A Peer-to-Peer Marketplace for Agent-Resource Matching and Truthfulness in Transportation Services

Jane Lin*
Department of Civil and Materials Engineering &
Institute for Environmental Science and Policy
University of Illinois at Chicago
janelin@uic.edu

Ouri Wolfson
Department of Computer Science
University of Illinois at Chicago
wolfson@cs.uic.edu

Number of words: 7056
Number of tables and figures: 3*250 = 750
Total number of words: 7756

Submitted to the 2017 Transportation Research Board Annual Meeting, August 1st, 2016

*Corresponding author

Abstract

Traffic congestion (and delay) is caused by limited availability of transportation resources (in the form of physical infrastructure such as road space and parking) and/or spatio-temporal mismatch between transportation resources and demand. Limited resource availability is often a hard constraint due to natural resource scarcity (e.g., limited land) or financial infeasibility that is outside the control of a transportation entity. This paper focuses on the latter, i.e., how to improve spatial and temporal allocation/assignment of existing resources to demand. In this paper we introduce a general virtual marketplace, called Spatio-Temporal rEsources Marketplace (STEM), that enables peer-to-peer financial transactions to guarantee that every user is not worse off than in User Equilibrium (UE) in terms of the cost s/he pays and at the same time the overall social welfare (system optimum, SO) is maximized. We show that many transportation services can be viewed as an agent-resource matching problem and formulated by the proposed STEM model. We propose a peer-to-peer Guarantee-Agent-Gain (GAG) payment scheme that is pareto-improving and revenue-neutral if all necessary user (agent) information is true and known to STEM. We then introduce a pricing scheme called TRUTH to incentivize truth-telling or to disincentivize cheating because agents would see no gain by lying in TRUTH. Some thoughts of future research directions are also discussed in the paper.

1. Motivation and Objective

On average, people traveling during morning and evening rush hours in urban areas experienced 34 hours of delay annually in 2010; in urban areas with population over 3 million that delay goes up to 52 hours [1]. In one business district of Los Angeles, researchers found that vehicles searching for parking traveled a distance equivalent to 38 trips around world, produced 730 tons of carbon dioxide, and burned 47,000 gallons of gasoline in one year [2]. Congestion (and delay) is caused by (1) limited availability of transportation resources (in the form of physical infrastructure such as road space and parking) and (2) spatio-temporal mismatch between transportation resources and demand. Limited resource availability is often a hard constraint due to natural resource scarcity (e.g., limited land) or financial infeasibility that is outside the control of a transportation entity. Hence, our proposed research focuses on the latter, i.e., how to improve spatial and temporal assignment/match of existing resources to demand.

In transportation literature, two most well-known forms of assignment (or match) between demand and resource are the so-called User Equilibrium (UE) and System Optimum (SO). Simply speaking, UE is a stable match between users and the resources that the users are seeking such that all users receive their best pay-offs in this match. Intuitively, this means that the system is settling into a state in which no user can unilaterally improve her performance. In other words, UE is what every user selfishly wishes to be. We have shown that UE is a form of stable marriage match (assignment) [3]. SO aims at maximizing the overall social welfare. In other words, SO is what we would like the transportation service to be. Unfortunately we know that UE often times results in worse off social welfare than SO. Moreover, the gap between UE and SO is potentially huge. Specifics depend on the particular system. But, for example, we have shown that for parking the gap between optimum and equilibrium is unbounded in the worst case [4], and is about 20% on average [5]. Imagine the potential of reducing travel-time by 20%!

Researchers have proposed to alleviate these problems by bridging the gap between UE and SO assignments in congestion pricing (e.g., [6-14]) and parking pricing (e.g., [4][5][15-21]). These studies are resource specific, i.e., focusing on a specific type of transportation resource such as road space and parking space. The proposed pricing schemes are often resource specific – price is set for specific resources independent of users (e.g., road tolls, parking rate), because individuals' valuation structure and preferences are typically unknown to the central management authority who sets the price. On the other hand, rapid advancement in mobile computing and wide penetration of personal mobile devices such as smartphones make it possible to have users declare or reveal their information in advance such that user specific pricing schemes in continuous time are possible.

In this paper we demonstrate a framework to bridge the gap between UE and SO assignments in the general context of spatio-temporal match of transportation resources to agents (users) that are seeking the resources. Such resources are not limited to road space but may include many transportation infrastructure facilities, for example, parking slots, public transit vehicles, shared bikes, shared bike racks, ride-sharing, electric vehicles charging stations, and landing slots at an airport. Specifically, we present a virtual marketplace that enables peer-to-peer (P2P) financial transactions to guarantee that every user is not worse off than in UE in terms of the cost s/he pays and at the same time the overall social welfare is maximized. This virtual marketplace is called *Spatio-Temporal rEsources Marketplace* (STEM). Previously we have introduced STEM in the context of agents seeking parking slots [22]. In [22] we showed that moving from equilibrium towards optimum by peer-to-peer (P2P) financial transactions that guarantee that every user will not be worse off than in equilibrium; and each user will be better off. Note that in [22] we did not take into account the cost associated with using/occupying a parking slot; only the cost of travel time to the parking slot was considered. Building on [22], this paper introduces STEM in a general context of transportation resource matching.

The main idea of STEM is illustrated through a parking example as follows. Assume a set of drivers looking for curbside parking in a downtown area; the area has a set of available parking slots. At a given time T_0 all drivers report their current location, final destination, value of time, and valuation structure and preferences to STEM. STEM computes the SO assignment and a UE assignment. Next, STEM matches each driver u with a parking slot coinciding with her slot in SO, and guarantees a cost to driver u that is not higher than the cost of her slot in UE. It does so through the following mechanism. If the difference between driver u's costs in UE and SO is positive, i.e. her cost is reduced when moving from UE to SO, then u pays the other drivers the difference; otherwise the other drivers pay u this difference. This pricing scheme is revenue positive, and the profit can be redistributed back to drivers to further reduce their costs. This scheme involves only peer-to-peer financial transaction and requires no toll or tax of some sort on curbside parking slots. The amount each driver pays or gets paid is driver-specific and dependent on the drivers' spatial location relative to the available parking slots at T_0.

2. Relevant Work

2.1 Pareto-improving, revenue-neutral Peer-to-Peer payment mechanisms

Pricing scheme or mechanism design is a common economic intervention to regulate demand for or behavior toward use of certain resources so that a preferred outcome can be achieved. In transportation, tolling or congestion pricing in road networks is a prominent case of such interventions (e.g. [6-14]). A preferred outcome in congestion pricing is often defined by reduced or minimized total network travel time by switching some drivers to different routes via pricing. Parking is another area of transportation that has seen active pricing research in recent years [4][5][15-22].

In recent years, research has been focused on finding Pareto-improving and revenue-neutral (PIRN) pricing schemes (e.g., [6], [11-13]). A Pareto-improving scheme means no user in the scheme is worse off than without it. A revenue-neutral scheme does not require external financial flow into the system; in other words, a revenue-neutral scheme is a financially self-sustaining one. For example, [6] shows that for a transportation network with homogeneous travelers, a Pareto-improving O–D-specific scheme for refunding total toll revenue to all travelers exists if and only if the pricing scheme reduces the total system travel time. In [11] the authors investigate revenue neutral tradable credit schemes among road users in user equilibrium, system optimum, and elastic demand conditions and show there exist unique solutions in which everyone is no worse off. In [12] the study concerns a tolling/subsidy scheme between a single O-D, two-mode transportation network. The two modes are highway automobiles and transit. Assuming highway users are always tolled positively and transit users are always tolled negatively, the study essentially presents possible revenue-neutral subsidy mechanisms from highway tolls to subsidize transit service. [13] builds on [12] to further examine how users' value of time (VOT) may affect the existence of a PIRN toll scheme and under what conditions PIRN may be guaranteed.

One common feature in this area of transportation research is a resource-specific pricing mechanism. For example, in congestion pricing literature, the same toll is set at a selected roadway segment that applies to all road users equally. The underlying thinking is that individual VOT values are typically unrevealed and hard to observe and thus toll differentiation across user classes is unrealistic and difficult to implement in reality. Of course the advantage of a resource-specific pricing mechanism is that it is easy to implement and still possible to achieve PIRN.

However, the conditions to achieve PIRN tolling are often hard to meet in reality. For example, [13] points out that the existence of a PIRN scheme is not guaranteed in general and external subsidies may still be required to ensure Pareto-improving even after revenue refund to road users. [6] demonstrates that to ensure the existence of a class-anonymous (i.e., without specifying individuals' VOT) Pareto refunding scheme the discrepancy in travel time changes among the various OD pairs resulting from the pricing scheme should not be too large.

In addition, tolling is perceived by the public as a form of taxation and a "Big Brother" (government) invention of one's daily life. [11] investigates a PIRN tradable credit scheme that still would require government initially distributing the credits among users and careful design of the total amount of credits and link specific credit charges.

2.2 Truthfulness of User Provided Information

A system like STEM is vulnerable to strategic manipulation, e.g., agents lying about their location or final destination in order to gain an advantage. Appropriate design and implementation of mechanisms to prevent false information reporting have been studied in the literature. Under the mechanisms an agent will find herself not better off by lying about her valuation, i.e. truth telling is incentivized. Among many existing mechanisms, the Vickery-Clark-Groves (VCG) and Myerson mechanisms [23-26] are most commonly used to allocate public and private goods that maximize respectively social welfare and profit. Current applications of VCG are predominantly in fields such as computer science, auctions and procurement [27-30] than in transportation service.

To the best of our knowledge, there are only a handful of references that apply the principles of truth telling to transportation problems. [31] considers VCG auctions to allocate railway paths. Bidders make bids and pay the system revenue difference with and without their bidding set. [32] explores the sufficient and necessary conditions for airlines to unilaterally deviate from truth telling under a voting scheme to provide consensus advice to an air traffic service provider (i.e. the central authority for air traffic flow management). [33] proposes two model-free, online mechanisms which schedule user access to plug-in hybrid electric vehicle charging points, and conclude that implementation of the proposed mechanisms can result in 50% increase in charging capacity at the same fuel cost compared to a simple randomized policy.

Previously we have investigated truth telling mechanisms in parking [20][21]. In [20], we devised new mechanism designs to induce truth telling of drivers' valuation in both static and dynamic parking games and proved that with a monotonic allocation rule in the mechanism an appropriate payment scheme, drivers have no incentive to lie about their true valuation and time information. In [21], we studied a smartphone-based parking reservation system that manages a finite number of curbside parking spaces located at different places in a downtown area, and applied the Vickrey-Clark-Groves mechanism to determine the allocation of parking spaces and parking fees to minimize the total social cost while ensuring all drivers to report truthfully their final destinations.

Given the paucity of literature in the field of transportation resource allocation using mechanism design, the increasing sharing economy of mobility service, and the growing reliance on large streams of information and data in transportation planning and management, we envision that mechanism design will become a crucial element of a future transportation system to prevent strategic manipulation of the system by users to their advantage.

3. Problem Definition

3.1 Model Configuration for STEM

We introduce STEM in the context of general spatio-temporal transportation resources. These are resources in geo-space, or time intervals, that may be available or unavailable to a user depending on other users. That a resource is unavailable may be due to the fact that it is occupied (e.g., parking slot) or that it incurs huge delay that a user is not willing to pay for (e.g., roadway congestion). Broadly speaking there are two types of transportation resources: single-occupancy and multiple-occupancy. Many transportation resources are single-occupancy, for example, parking slots, shared bikes, shared bike racks, electric vehicle (EV) charging stations, and airport runways. Roadways, ride-sharing, and public transit vehicles are examples of multiple-occupancy transportation resources.

First, we define the model configuration for STEM. A configuration consists of a set of *mobile* agents - these are resource seekers in vehicles or other modes, $\mathbf{V}=\{v_i, i=1, 2,..,n\}$ in geo-space and a set of available *stationary* resources (e.g. parking slots) $\mathbf{R}=\{r_j, j=1, 2, ...,m\}$ at a given time point T_0. Agents do not have an extent, thus at any time they are located at points in geo-space. The resources are either all spatial or all temporal. If spatial, then they are static and occupy point locations in geo-space. Temporal resources are time intervals. For example, airport runway is a spatial resource; and landing time-slots on an airport-runway are temporal resources. A single-occupancy resource can be used only by a single agent at a time; a multiple-occupancy resource can be used by multiple agents simultaneously. An assignment is a mapping of agents to resources for a duration of time.

The locations of the resources are known to STEM and thus to the agents. STEM may reside centrally in the cloud, or a copy of it may reside in a tamper-resistant fashion in the mobile device of each agent. STEM may detect agents' locations but agents may choose not to disclose it. In other words, agents do not necessarily know other agents' locations in our research setting.

Suppose that at T_0, all agents in $\mathbf{V}$ are located at given distances to any resource in $\mathbf{R}$. In other words, an agent may need to travel to reach the resource in order to use it. We call that travel time <u>*access time*</u> and denote it by d_{ij} for agent v_i ($\in\mathbf{V}$) to reach resource r_j ($\in\mathbf{R}$). There may be additional costs associated with agent v_i using resource r_j. For example, in the case of parking, additional costs may be the cost of parking and/or the cost of walking time from the slot to the driver's final destination. We define the time agent v_i spends using resource r_j as <u>*usage time*</u>, denoted t_{ij}, and other time associated with using the resource as <u>*egress time*</u>, denoted τ_{ij}, e.g., walking time from the parking slot or bus stop to office. Denote agent v_i's value of time (VOT) by α_i. Then at T_0 the total cost associated with agent v_i obtaining and using resource r_j, C_{ij}[1], is defined as follows:

$$C_{ij} = \alpha_i d_{ij} + \beta t_{ij} + \alpha_i \tau_{ij} \quad (1).$$

If β is resource specific (i.e., not related to individual agents), then $\beta=\beta_j$. For example, the charge rate of parking is typically fixed for all users; the charge rate of a bike-sharing program is

[1] For simplicity the time dimension is dropped in all letter notations in this proposal. One should bear in mind when reading that they are all time dependent.

typically fixed for all users; bus fare is route specific. For another example, current congestion pricing (tolling) schemes are link specific tolls for all users traveling on those links. That is what is typically assumed and studied in the existing relevant literature. The reason is noted in [6] that toll differentiation across user classes is unrealistic and difficult to implement in reality because VOT is reported observationally indistinguishable. Furthermore, the access time and egress time are not considered in the existing congestion pricing literature. In other words, total cost reduces to $C_{ij} = \beta t_{ij}$ in the network/congestion pricing literature.

We show that transportation services in general can be viewed from the perspective of spatio-temporal resource assignment/allocation. Resources are the service agents (users) seek to obtain. For example, in bus service, buses (or bus lines) are the resources. Depending on when riders (agents) arrive at a bus stop, they may take different buses (or bus lines). For another example, in bike-sharing service, available bikes in different stations are the resources and their availability depends on when riders (agents) arrive at a station.

Furthermore, we consider the case where $\beta=\alpha_i$ in this research. In other words, the cost associated with using a resource depends on who is using it. That is,

$$C_{ij} = \alpha_i d_{ij} + \alpha_i t_{ij} + \alpha_i \tau_{ij} \quad (2).$$

At the outset, each agent v_i sends STEM the information necessary to compute d_{ij}, t_{ij}, τ_{ij}, and C_{ij}. Such information may include the agent's current (or starting) location, final destination, and VOT (α_i). When receiving this information from all the agents, STEM computes all d_{ij}'s t_{ij}'s, τ_{ij}'s, and C_{ij}'s, and then determines an assignment and a payment scheme for each individual agent.

An assignment is essentially a mapping of agents $\mathbf{V}=\{v_i, i=1, 2,..,n\}$ to available resources $\mathbf{R}=\{r_j, j=1, 2, ...,m\}$. In a one-to-one assignment, if the number of agents is greater than the number of available resources, i.e., n>m, then there are agents left unallocated at a given time. In a many-to-one assignment, there are agents unallocated if the number of agents demanding the resource exceeds the capacity of the resource. An unallocated agent incurs a very high cost, ω. Therefore, if the *cost* of an agent v_i ($\in\mathbf{V}$) in an assignment $\mathbf{A}$, denoted $C(i,\mathbf{A})$, is defined the same way as in Eq. (2), then at a given time T_0,

$$C(i,\mathbf{A}) = \begin{cases} C_{ij}, & if\ (v_i, r_j) \in \mathbf{A}, \forall v_i \in \mathbf{V}, r_j \in \mathbf{R} \\ \omega, & if\ (v_i, r_j) \notin \mathbf{A}, \forall v_i \in \mathbf{V}, r_j \in \mathbf{R} \end{cases} \quad (3).$$

The total cost of an assignment $\mathbf{A}$ is $\sum_{\forall i \in \mathbf{V}} C(i,\mathbf{A})$.

In this paper, we assume the following in the process of matching agents and resources:

(1) at a given time point T_0, not all agents in $\mathbf{V}$ are necessarily allocated;

(2) unallocated agents at T_0 continue to seek resources at the subsequent time points when previously occupied resources may become available.

The time points may be pre-determined in STEM (e.g., every 5 minutes) or triggered by certain events (e.g., significant change in traffic conditions).

Now we formally define the UE and SO assignments in the context of STEM.

Definition 1. An assignment $\mathbf{M}$ is a SO assignment if any other assignment $\mathbf{B}$ has a total cost higher than that of $\mathbf{M}$. That is,

$$\sum_{\forall i \in \mathbf{V}} C(i,\mathbf{M}) \le \sum_{\forall i \in \mathbf{V}} C(i,\mathbf{B}), \text{ for } \forall \mathbf{M}, \mathbf{B} \quad (4).$$

In [4] we have shown that given a finite set of agents and a finite set of resources, a SO assignment can be computed in strongly polynomial-time by representing it as a minimum-cost network flow on a bipartite graph [34].

Definition 2. An assignment **E** is a UE assignment if for every agent v_i and for any other assignment **B** that differs from **E** only in the assignment of v_i this relationship holds:

$$C(i,\mathbf{E}) \le C(i,\mathbf{B}), \text{ for } \forall \mathbf{v}_i \in \mathbf{V}, \text{ and } \forall \mathbf{B} \text{ such that } \mathbf{B}_{i-} = \mathbf{E}_{i-} \quad (5),$$

where $\mathbf{B}_{i-}$ or $\mathbf{E}_{i-}$ represents the remaining assignment in **B** or **E** after excluding agent v_i. In [5] we have shown that an equilibrium assignment can also be found in polynomial time using the Gale-Shapley deferred acceptance algorithm.

Note that Definitions 1 and 2 are the cost-based UE and SO, whereas in transportation network analysis, time-based disutility measures have long been accepted as standard system performance metrics. In the current transportation literature, both time-based and cost-based disutility measures are used and studied. It is easy to show that the time-based UE and SO are a special case of Definitions 1 and 2 respectively.

Observe that in a one-to-one assignment, if the number of agents is higher than the number of resources, i.e., n>m, then different sets of agents may be allocated the resources in **E** and **M**. In other words, different sets of agents may be unallocated in the two assignments. For example, consider Figure 1 where there are two EV charging slots (resources) S_1 and S_2, and three EVs (agents) v_1, v_2, and v_3; the arc values are costs associated with using that resource by the agent, i.e., C_{11}=1, C_{12}=2, C_{21}=5, C_{22}=8, C_{31}=10, C_{32}=7. In this configuration, the optimum assignment $\mathbf{M}$={(v_1,S_2), (v_2,S_1)} has a total cost of 7+ω with $C(1,\mathbf{M})$=2, $C(2,\mathbf{M})$=5, and $C(3,M)$=ω (unallocated); the equilibrium assignment $\mathbf{E}$={(v_1,S_1), (v_3,S_2)} has a total cost of 8+ω with $C(1,\mathbf{E})$=1, $C(2,\mathbf{E})$= ω (unallocated), and $C(3,\mathbf{E})$=7. So v_3 incurs a very high cost in **M** and v_2 in **E**. When simply moving the system from **E** to **M**, the total cost is reduced by 1. On the other hand, v_3 is the victim of this movement and v_2 is the beneficiary. In reality, v_3 is unlikely to voluntarily give up his/her position in **E**.

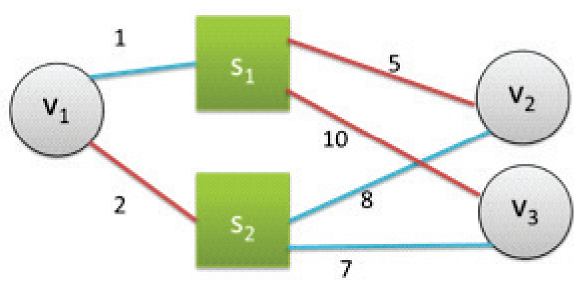

Figure 1: A configuration of 3 EVs (agents) and 2 available charging slots (resources).

Now if v_2 is willing to pay an amount of (ω-5) to v_3 to compensate v_3 for postponing getting the resource at this point and an amount of 1 to v_1 for moving to the more costly resource S_2, then we could achieve the SO assignment $\mathbf{M}$={(v_1,S_2), (v_2,S_1)} and at the same time the adjusted costs for v_1, v_2, and v_3 are now 1, ω, and 5 respectively. In this case, v_1 and v_3 are better off and v_2 is no worse off than in the UE assignment **E**. In this process, no central authority is involved; it is simply Peer-to-Peer financial transactions among the three agents; all agents are guaranteed no worse off; and no external financial flow is required. This example illustrates the essence of our proposed Guaranteed-Agent-Gain (GAG) payment scheme to be described in Section 3.2.

3.2 Design of Pareto-Improving and Revenue-Neutral Peer-to-Peer Payment Mechanism

In this section, we present a PIRN payment scheme called Guaranteed-Agent-Gain (GAG) in which the payment amount varies by user not only due to the heterogeneity in user's VOT and valuation structure but also dependent on users' spatial and temporal positions relative to the resources over time. This is seen in the way the individual cost is defined in Eq.(2). It is a key divergence from the existing transportation pricing literature. The payment transactions are enabled in STEM.

Simply speaking, GAG is a Peer-to-Peer payment scheme that converts a UE assignment (**E**) to a SO assignment (**M**) in such a way that no agent is worse off by moving from **E** to **M** and that the scheme is revenue neutral. GAG works in a general context of spatio-temporal transportation resource allocation. We know that road tolling essentially attempts to bridge the gap between optimum and equilibrium [35,36]. So Intuitively this PIRN GAG exists and has been demonstrated in the example depicted in Figure 1.

Why would agents cooperate? First of all, no one is worse off and the total social welfare is maximized. All agents may feel good about their good karma. Secondly, some agents get paid for his/her good karma; the others obtain his/her preferred resources, so the payment scheme is nothing out of the ordinary in practice. Thirdly, it is unlikely that the agents would perceive the payment scheme as a toll (or some form of tax) so there is little resentment to it. Fourthly, there is no central authority involvement so agents do not feel being told what to do. Lastly, as mobile apps are already well accepted in everyday life, this will be viewed as just another "cool" app.

3.2.1 Guaranteed-Agent-Gain (GAG) payment scheme

In [22] we introduced a payment scheme called Guaranteed-Agent-Gain (GAG), and proved that, under the time-based UE and SO, STEM transactions are guaranteed to leave every user, and society overall, in a better off situation than UE. In this research, we generalize GAG and prove that GAG also works in the cost-based UE and SO. That is, GAG is a payment scheme that guarantees to each agent $v_i \in V$ that its cost in **M**, $C(i,\mathbf{M})$, will not be higher than its naturally expected cost in **E**, $C(i,\mathbf{E})$. We denote the difference between the two costs by D_i, i.e.,

$$D_i = C(i,\mathbf{E}) - C(i,\mathbf{M}) \tag{6}$$

This is how GAG works:

i. If for some agent v_i, D_i is negative, then STEM pays v_i an amount equal to $|D_i|$ to compensate the increase in v_i's cost by moving from **E** to **M**.
ii. If D_i is positive, that means v_i benefits from some other agents "sacrificing" what they could have had in **E**. Then v_i pays back STEM the amount of D_i and its overall cost in **M** is still no worse than that in **E**.

Thus, the GAG payment scheme guarantees that each agent v_i incurs an adjusted cost, i.e. $C(i,\mathbf{M})+D_i$, which is not higher than v_i's naturally expected cost in equilibrium, $C(i,\mathbf{E})$.

Assume now that STEM proceeds with assignment **M** and the GAG payment scheme, i.e. it announces these to the agents, only when the *total income* (I), i.e. the sum of $|D_i|$'s received from the agents in (ii), is not lower than the *total outcome* (O), i.e. the sum of $|D_i|$'s paid out to the road users in (i). Otherwise STEM does not mediate the competition, and tells the road users to compete for the roadway resources as they currently do, i.e. without the mechanism proposed in this research.

<u>*Definition 3.*</u> The GAG payment scheme is *revenue neutral* if and only if the total income is no less than the total outcome, i.e., $I \geq O$.

Theorem 0: For every configuration of agents and resources, the GAG payment scheme combined with assignment **M** is revenue neutral.

Proof: The proof follows from Theorem 4 in [5], and is based on the fact that the total system cost of assignment **M** is not higher than the total system cost of assignment **E**. That is, the following inequality always holds:

$$\sum_{\forall i \in \mathbf{V}} C(i, \mathbf{M}) \leq \sum_{\forall i \in \mathbf{V}} C(i, \mathbf{E}) \tag{7}$$

Then

$$\sum_{\forall i \in \mathbf{V}} [C(i, \mathbf{E}) - C(i, \mathbf{M})] \geq 0 \tag{8}$$

$$\text{i.e.,} \qquad \sum_{\forall i \in \mathbf{V}} D_i \geq 0 \tag{9}$$

We rewrite (9) into the following:

$$\sum\nolimits_{+} D_i + \sum\nolimits_{-} D_i \geq 0 \tag{10}$$

where $\sum_{+} D_i$ represents the summation of all positive D_i's and $\sum_{-} D_i$ all negative D_i's. Based on Definition 3, $\sum_{+} D_i$ is the total income I of STEM from the agents and $\sum_{-} D_i$ is the total outcome O from STEM to the agents. Eq.(10) says $I \geq O$. Therefore, the GAG payment scheme combined with the SO assignment **M** is revenue neutral. []

3.2.2 Design of GAG in STEM

Observe that, for the purpose of computing the assignments and the payment scheme, it does not matter whether STEM is implemented centrally in the cloud, or distributed on the mobile devices of the agents. If distributed, all mobile devices will receive the same information and compute the same assignment.

This is how STEM works. At a given time point T_0, STEM

1. receives from agents (users) the following information: resource to be sought after, agent's current location, destination, transportation modes, value of resource to the agent, VOT, preference on the resource (e.g., in the vicinity of current location or destination), and usage time of the resource;
2. forms the current agent set **V**, which is a combination of the new agents at T_0 and the existing agents who sent their requests at the previous time points before T_0 and have not found one at T_0;
3. identifies the available resource set **R**;
4. computes the cost C_{ij} for each agent $v_i \in \mathbf{V}$ to each available resource $r_j \in \mathbf{R}$;
5. performs assignments **E** and **M**, and determines the costs for each agent v_i in **E** and **M**, i.e., $C(i,\mathbf{E})$ and $C(i,\mathbf{M})$, $\forall\ v_i \in \mathbf{V}$;
6. computes D_i for each agent $v_i \in \mathbf{V}$;
7. matches agents to their assigned resources in **M**;
8. collects payments from agents with a positive D_i or provides compensations to agents with a negative D_i.

Repeat steps 1-8 at the subsequent time points.

3.2.3 Incorporating other payment items into GAG

We could further implement a refund scheme when $I>O$. Distributing the profit (I-O) evenly among the agents is one such a refund scheme. In this case, each agent receives a refund amount of $(I\text{-}O)/n$. In the end, each agent's GAG-based adjusted cost is $C(i,\mathbf{M})+D_i$ $-(I\text{-}O)/n=C(i,\mathbf{E})\text{-}(I\text{-}O)/n \leq C(i,\mathbf{E})$. Therefore, no agent is worse off from what he/she naturally expects to pay and it is revenue neutral. As an example, for the configuration of Figure 2, Table 1 summarizes the above steps of determining the GAG-based adjusted cost.

Table 1. Overall cost to agents in GAG in Figure 2 with even refund.

Agent	$C(i,\mathbf{E})$	$C(i,\mathbf{M})$	D_i	Even refund	Total add'l cost	GAG-based adjusted cost
v_1	+1	+3	-2	-0.5	-2.5	0.5
v_2	+10	+6	+3	-0.5	+2.5	+8.5

Observe that although some central coordination occurs through STEM, due to the refund scheme STEM does not make a profit, i.e., all the money paid by agents is paid out to agents, and in this sense the transactions are Peer-to-Peer. However, observe that in the general case, these are not necessarily binary transactions. This means that the payment of one agent may be paid out to more than one other agent, or the combined payment of three agents may be paid out to four other agents.

A future extension of GAG could be to incorporate environmental costs, e.g., fuel cost and greenhouse gas emission costs, to the calculation of C_{ij}'s. We have demonstrated how these costs may be determined in [37-40].

3.3 Truthfulness of Users

In the previous section we assumed that the agents provide STEM with the correct information to compute the D_{ij}'s and C_{ij}'s. Agents can gain from being untruthful. Consider an example in Figure 2. There are two vehicles (agents) v_1 and v_2 looking for parking and there are currently two available parking slots (resources) S_1 and S_2. The labels on the arcs are the respective access times d_{ij}'s, i.e., d_{11}=1, d_{12}=2, d_{21}=5, d_{22}=8. Both v_1 and v_2 prefer S_1 because it is closer. The egress times from the parking lots to agents' final destinations are noted on S_1 and S_2, i.e., τ_{11}=0, τ_{12}=1, τ_{21}=1, and τ_{22}=2. Assume both vehicles park the same amount of time and pay the same amount for parking. Thus the cost associated with parking can be excluded in the assignment. Assume both agents have the same VOT of unity, without loss of generality. Then the costs are C_{11}=1, C_{12}=3, C_{21}=6, C_{22}=10. The SO assignment $\mathbf{M}$={(v_1,S_2), (v_2,S_1)} has a total cost of 9, in which $C(1,\mathbf{M})$=3 and $C(2,\mathbf{M})$=6; the UE assignment $\mathbf{E}$={(v_1,S_1), (v_2,S_2)} has a total cost of 11, in which $C(1,\mathbf{E})$ =1 and $C(2,\mathbf{E})$=10. In GAG, v_1 gets paid an amount of 2 and v_2 pays an amount of 4. Now suppose that v_2 lies about his/her final destination so that τ_{21}=0 and τ_{22}=0, and all other egress times remain the same. The **M** and **E** assignments do not change but now v_2 pays an amount of 3 instead of 4 to use his/her preferred resource S_1. And the total net income to STEM is reduced to 1.

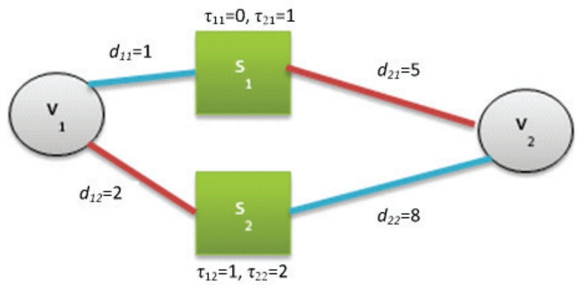

Figure 2: A configuration of vehicles (agents v_1 and v_2) and parking slots (resources s_1 and s_2), where the arc-labels denote respective access times to the parking slots.

Some information such as location is relatively easy to detect nowadays. What is hard to detect is agents' valuation structure (VOT and utility). They are typically assumed to be known to the central authority and left mostly unquestioned in the current literature. That is obviously not the reality. So an agent could strategically provide false valuation information to gain unfair advantage in the above GAG scheme.

One way to combat cheating is to give STEM direct access to agent's GPS readings. This authorization may be combined with the authorization to impose fines if cheating about the agent's current location or final destination is detected. However, this method would not help in the case of lying about an agent's valuation structure (VOT and utility), which is hard to detect.

An alternative way is based on Vickrey-Clarke-Groves (VCG) mechanisms that price the resources in a way that incentivizes truth telling. The adaptation of such a mechanism to the transportation resource assignment problem was discussed in [22] in the context of time-based disutilities. Here we adapt a similar VCG to the cost-based disutilities defined in this research.

3.3.1 Maximum-total-net-value assignment

Before we introduce the VCG-inspired pricing scheme for truth telling, we first define a maximum-total-net-value assignment in addition to the UE and SO already described above.

Assume that each agent v_i may choose what information to disclose to STEM or it may disclose false information to STEM. Assume further that for each agent v_i there is a value associated with using a type of resource and that value is denoted B_i. Notice that B_i is agent specific and independent of the specific resource item obtained. For example, if an EV may choose between two EV charging slots, S_1 and S_2, then S_1 and S_2 would give the EV the same value because S_1 and S_2 are identical "goods". If the cost associated with using resource r_j by agent v_i is C_{ij} as defined before, then the net value to v_i of using resource r_j, called V_{ij}, is defined as

$$V_{ij} = B_i - C_{ij}\ , \quad for\ \forall i \in \mathbf{V}, j \in \mathbf{R} \tag{11}$$

Furthermore,

$$V_{ij} = \begin{cases} B_i - C_{ij}, & if\ B_i > C_{ij} \\ 0 \quad\quad\ , & if\ B_i \le C_{ij} \end{cases}, \quad for\ \forall i \in \mathbf{V}, j \in \mathbf{R} \tag{12}$$

Namely, if $C_{ij} \ge B_i$ then resource r_j is too costly and its cost exceeds its value to v_i such that v_i would rather not use it, and V_{ij} is set to zero. In other words r_j has no value to v_i.

<u>*Definition 4*:</u> if the net value to v_i of using resource r_j, V_{ij}, is zero, then we say r_j is *infeasible* for v_i, otherwise it is *feasible.*

Definition 5: maximum-total-net-value assignment, denoted **MN**, is one that maximizes the sum of agents' net values defined in Eq.(12). We denote by **MN**: {max $\sum_{\forall i,j} V_{ij}$ }.

Assume that STEM's objective is to maximize the total net value $\sum_{\forall i,j} V_{ij}$. This means maximizing the social welfare. We have the following proposition.

Proposition 1: the Maximum-total-net-value assignment **MN:** {max $\sum_{\forall i,j} V_{ij}$ } is equivalent to the system optimum assignment **M**: {min $\sum_{\forall i,j} C_{ij}$ }.

Proof: Observe that in $\sum_{\forall i,j} V_{ij} = \sum_{\forall i,j} B_i - \sum_{\forall i,j} C_{ij}$, $\sum_{\forall i,j} B_i$ is constant for a given set of agents and resources. Hence, maximizing $\sum_{\forall i,j} V_{ij}$ is equivalent to minimizing the total cost $\sum_{\forall i,j} C_{ij}$ for all feasible pairs (v_i, r_j).[]

Maximum-total-net-value can be solved by a maximum matching in the following bipartite graph G. G has resources and agents as nodes, and an edge between each pair of an agent v_i and a feasible resource r_j; this edge has a weight = V_{ij}. See maximum weighted bipartite matching in [41-43].

3.3.2 Pricing scheme to incentivize truth-telling

Now if agents do not reveal their true valuations to STEM, then we propose a pricing scheme TRUTH to incentivize truth telling from the agents as follows.

Let V_i^* be the net value of agent v_i in assignment **M**, i.e., $V_i^* = B_i - C(i, \mathbf{M})$. Let $V'_{k(i)}$ be the net value of agent v_k in an assignment **M'** of maximum total net value that includes all the resources but does not include agent v_i, i.e., **M'**: {max $\sum_{\forall k \neq i, \forall j} V_{kj}$.}. In other words, $V'_{k(i)} = B_k - C(k, \mathbf{M'})$ for $\forall v_k \in \mathbf{V} - \{v_i\}$.

Definition 6. Pricing Scheme TRUTH: Price paid by agent v_i to STEM in assignment **M** of maximum total net value, called PA_i, is $PA_i = \sum_{\forall k \neq i} V'_{k(i)} - \sum_{\forall k \neq i} V_k^*$.

Theorem 1: TRUTH is: (1) truthful, i.e., the best strategy for each agent is to declare its true valuation for each resource, (2) individually rational, i.e., $PA_i \leq V_i^*$, and (3) $PA_i \geq 0$, $\forall v_i \in \mathbf{V}$.

Proof: The theorem follows from the VCG theorem, with the Clarke pivot rule. More specifically, it follows from theorem 9.17 and Lemma 9.20 in [44]. 9.17 addresses a model in which there is a set **A** of alternatives (corresponding to the possible assignments in our model), and a valuation function $V_i(a)$ of each player (agent) for each alternative a in **A**. $V_i(a)$ corresponds to V_{ij}, where j is the resource assigned to agent i in assignment a. 9.17 indicates that a set of pricing schemes (mechanisms) is truthful, and 9.20 further refines these by indicating when these schemes are also individually rational and do not incur payments to the players. Intuitively, this happens when agent i pays an amount that is "equal to the damage that s/he causes the other players – the difference between the social welfare of others with and without i's participation. In other words, the payments make each player internalize the externalities that s/he causes [44]". In our model, these translate into our proposed pricing scheme TRUTH.[]

To see that payment scheme TRUTH induces truth-telling, consider again the configuration of Figure 2. We assume that the value of using a resource is \$11, and the value of time for each driver is \$1/minute. In this case the net value for each agent-resource pair is V_{11}=10, V_{12}=8, V_{21}=5, V_{22}=1. The net value for each agent in assignment **M** = {(v_1,S_2), (v_2,S_1)} is $V_1^* = 8$, $V_2^* = 5$, and the net value for v_1 without v_2 is $V'_{1(2)} = 10$, and vice versa $V'_{2(1)} = 5$. If STEM makes the maximum-total-net-value assignment **MN** (which is equivalent to **M**), then the TRUTH price paid to STEM by v_1 is $PA_1 = V'_{2(1)} - V_2^* = 5 - 5 = 0$, and the TRUTH price paid to STEM by v_2 is $PA_2 = V'_{1(2)} - V_1^* = 10 - 8 = 2$.

If v_2 lies and says she is very close to S_1, and v_1 tells the truth, assignment **MN** would not change, and v_2's TRUTH price would still be 2. Intuitively, the reason for this is that the TRUTH price paid by v_2 depends on the damage that her assignment in **MN** causes the other drivers. This is similar to Vickrey's second price auction, where the price paid by the winning player does not depend on the value she declared, but on the value declared by the 2nd highest bidder. In other words, the winner's price depends on the damage she causes the other players, which is the value to the 2nd highest bid. Similarly, if v_1 lies and says he is very close to S_1, his TRUTH price would still be 0 because assignment **MN** would still be the same.

Now observe that incentivizing truthfulness has its own price in STEM. Specifically, STEM's revenue suffers due to the incentive that it provides for truthfulness. To see this, we first define another pricing scheme as follows.

Definition 7: the Naïve pricing scheme NAIVE is one in which each agent v_i declares to STEM its true valuation and thus its net value for each resource r_j (i.e. V_{ij}), and pays the price, denoted PN_i, equal to the net value of v_i using the assigned resource r_h, i.e., $PN_i = V_{ih}$.

Because STEM makes assignment **MN**, and each agent declares its true valuation, based on proposition 1 we have $PN_i = V_i^*$. Hence the price of truthfulness for each agent v_i, denoted P_i, is the difference between the payment of v_i in TRUTH to incentivize truth telling and the payment in NAIVE in which all agents reveal their true valuations. That is,

$$P_i = PA_i - PN_i = \sum_{\forall k \neq i} V'_{k(i)} - \sum_{\forall k \neq i} V_k^* - V_i^* = \sum_{\forall k \neq i} V'_{k(i)} - \sum_{\forall i} V_i^* \quad (13)$$

Observe that in Eq.(13) P_i is always non positive, i.e., $P_i \leq 0$, because $\sum_{\forall i} V_i^*$ is the maximum total net value in **M**, whereas $\sum_{\forall k \neq i} V'_{k(i)}$ is the total net value of some assignment that does not include v_i. And a net value of an agent-resource pair is a non negative value based on Eq.(12). Therefore, $P_i \leq 0$. This means that each agent pays less to STEM under TRUTH than under NAIVE, and the difference is the price that STEM pays to induce each agent to be truthful. Again, this is similar to the situation in which the Vickrey second-price auction is compared with the naïve auction, i.e. the one where each agent declares and pays his value for the item; in the auction case, the winner also pays less in Vickrey auction than in naïve auction. Specifically, in Vicrey's 2nd price auction, the house revenue is not the highest bid, but the 2nd highest.

In TRUTH, each agent now incurs an adjusted cost of $C(i,\mathbf{M})+PA_i$ in assignment **M**. So the cost difference between **E** and **M** becomes:

$$D'_i = C(i,\mathbf{E}) - C(i,\mathbf{M}) - PA_i = D_i - PA_i \quad (14)$$

From Theorem 1 we have $PA_i \geq 0$ and thus $D_i^{'} \leq D_i$ and $\sum_{\forall i} D_i^{'} \leq \sum_{\forall i} D_i$. In other words, the total net income to STEM is reduced due to the price paid to incentivize truth telling. This finding is consistent with Eq.(13). Furthermore, from Theorem 1 we know that $PA_i \leq V_i^*$, so Eq.(14) can be rewritten as the following:

$$D_i^{'} \geq \left(D_i - V_i^* = C(i, \mathbf{E}) - B_i\right) \tag{15}$$

Eq.(15) implies that TRUTH does not guarantee Pareto-improving nor revenue neutral. So a future research question is “can we devise a mechanism that induces truth telling and at the same time is PIRN?” Is such a mechanism too good to be true? Intuitively speaking, agents may learn over time that lying does not always make them gain and in contrast being truthful can be PIRN, and thus self correct their behavior. So an iterative truth-telling mechanism may achieve PIRN over time.

4. Summary and Future Work

In this paper we have described an agent-resource matching problem for transportation resources and presented a peer-to-peer marketplace called STEM for general transportation resource matching. We showed that many transportation services can be viewed as an agent-resource matching problem. We have presented a peer-to-peer Guarantee-Agent-Gain (GAG) payment scheme that is pareto-improving and revenue-neutral if all necessary user (agent) information is true and known to STEM. We have then introduced a pricing scheme called TRUTH to incentivize truth-telling or to disincentivize cheating because agents would see no gain by lying in TRUTH. On the other hand, TRUTH is not PIRN, which points to a future research question, i.e., "can we design a mechanism that is PIRN and at the same time induces truth-telling?"

Another future research direction is the further generalizeability of the proposed STEM to an even broader set of transportation resources. Observe that an agent-resource matching problem is a typical bipartite graph, with resources and agents as nodes, and edges between all feasible agent-resource pairs (v_i, r_j). Each edge has a weight equal to the cost C_{ij} or the value V_{ij} associated with the agent acquiring and using the resource. For example, Figures 1 and 2 are bipartite graphs. In the case of a road network or a multimodal system, which is typically represented by a directed (multi-)graph, can the STEM model configuration defined in Section 3 still apply? Specifically, at any time point T_0, (1) what are the resources in a roadway network to allocate/assign? (2) how to define the access time (d_{ij}), usage time (t_{ij}), and egress time (τ_{ij}) in a roadway network? These are some of the questions to be addressed in our on-going and future research work.

Acknowledgement

This research was funded in part by the National Science Foundation grants DGE-0549489, IGERT: Graduate Program in Computational Transportation Science and CCF-1216096 ICES: Small: Collaborative Research: Dynamic Parking Assignment Games.

References:

[1]. Urban Mobility Report. 2015. Texas Transport Institute

[2]. Mathur, S. Jin, T., Kasturirangan, N., Chandrashekharan, J., Xue, W., Gruteser, M. and Trappe, W., 2010. Parknet: Drive-by sensing of road-side parking statistics. In *MobiSys*, San Francisco, CA, June 2010

[3]. Gale, D., and Shapley, L, S. 1962. College admissions and the stability of marriage, *The American Mathematical Monthly,* vol.69, pp.9-15

[4]. 4Ayala, D., Wolfson, O., Xu, B., Dasgupta, B., and Lin, J. 2011. Parking Slot Assignment Games. In *Proc. of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM GIS),* Chicago, IL, Nov. 2011, pp.299-308.

[5]. Ayala, D., Wolfson, O., Xu, B., Dasgupta, B., and Lin, J. 2012. Pricing of Parking for Congestion Reduction. In *Proc. of the 20th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM GIS)* Redondo Beach, CA, Nov. 2012.

[6]. Guo, X.L., Yang, H., 2010. Pareto-improving congestion pricing and revenue refunding with multiple user classes. *Transportation Research Part B: Methodological* 44 (8–9): 972–982.

[7]. Daniel, J. I., 1995. Congestion pricing and capacity of large hub airports: A bottleneck model with stochastic queues. *Econometrica: Journal of the Econometric Society*, 327-370.

[8]. Yang, H., and Huang, Hai-Jun, 1997. Analysis of the time-varying pricing of a bottleneck with elastic demand using optimal control theory. *Transportation Research Part B:Methodological*, *31*(6), 425-440

[9]. Brueckner, J. K., 2002. Airport congestion when carriers have market power. *American Economic Review*, 1357-1375.

[10]. Lou, Y., Yin, Y., and Lawphongpanich, S., 2010. Robust congestion pricing under boundedly rational user equilibrium. *Transportation Research Part B: Methodological*, *44*(1), 15-28.

[11]. Yang, H. and Wang, X., 2011. Managing network mobility with tradable credits. *Transportation Research Part B: Methodological* 45: 580-594.

[12]. Liu, Y., Guo, X., Yang, H., 2009. Pareto-improving and revenue-neutral congestion pricing schemes in two-mode traffic networks. *Netnomics* 10: 123-140.

[13]. Nie, Y. and Liu, Y., 2010. Existence of self-financing and Pareto-improving congestion pricing: Impact of value of time distribution. *Transportation Research Part A: Policy and Practice* 44: 39-51

[14]. Wie, B, W., and Tobin, R, L. 1998. Dynamic congestion pricing models for general traffic networks. *Transportation Research Part B – Methodological,* vol.32, pp.313-327

[15]. He, F., Yin, Y., Chen, Z., Zhou, J., 2015. Pricing of parking games with atomic players. *Transportation Research Part B: Methodological* 73: 1-12.

[16]. Guo, L., Huang, S., Zhuang, J., Sadek, A., 2013. Modeling parking behavior under uncertainty: a static game theoretic versus a sequential neo-additive capacity modeling approach. *Networks and Spatial Economics* 13, 327–350.

[17]. Kokolaki, E., Karaliopoulos, M., Stavrakakis, I., 2012. Leveraging Information in Vehicular Parking Games. *Technical Report,* July, 2012.

[18]. Qian, Z., Rajagopal, R., 2014. Optimal dynamic parking pricing for morning commute considering expected cruising time. *Transportation Research Part C* 48, 468–490.

[19]. Qian, Z., Xiao, F., Zhang, H., 2011. The economics of parking provision for the morning commute. *Transportation Research Part A* 45 (9), 861–879.

[20]. Zou, B., Kafle, N., Wolfson, O., Lin, J., 2015. A Mechanism Design Based Approach to Solving Parking Slot Assignment in the Information Era, *Transportation Research Part B: Methodological,* Vol.81 (2): 631-653

[21]. Chen, Z., Yin, Y., He, F., Lin, J., 2015. Parking Reservation for Managing Downtown Curbside Parking, *Transportation Research Record: Journal of the Transportation Research Board*, No. 2498, 12–18

[22]. Wolfson, O., and Lin, J. 2014. A Marketplace for Spatio-temporal Resources and Truthfulness of its Users, *Proceedings of the 7th ACM SIGSPATIAL International Workshop on Computational Transportation Science*, pp. 70-75.

[23]. Vickrey, W., 1961. Counterspeculation, auctions, and competitive sealed tenders. *The Journal of finance*, *16*(1), 8-37.

[24]. Clarke, E. H., 1971. Multipart pricing of public goods. *Public Choice*, *11*(1), 17-33.

[25]. Groves, T., 1973. Incentives in teams. *Econometrica: Journal of the Econometric Society*, 617-631.

[26]. Myerson, R. B., 1981. Optimal auction design. *Mathematics of operations research*, *6*(1), 58-73.

[27]. Dasgupta, S., and Spulber, D. F., 1990. Managing procurement auctions. *Information Economics and Policy*, *4*(1), 5-29.

[28]. Feigenbaum, J., Papadimitriou, C., Sami, R., & Shenker, S., 2005. A BGP-based mechanism for lowest-cost routing. *Distributed Computing*, *18*(1), 61-72.

[29]. Narahari, Y., Narayanam, R., Garg, D., & Prakash, H., 2009. Mechanism design for resource procurement in grid computing. In *Game Theoretic Problems in Network Economics and Mechanism Design Solutions* (pp. 1-28). Springer London

[30]. Chen, J., Huang, H., and Kauffman, R. J., 2011. A public procurement combinatorial auction mechanism with quality assignment. *Decision Support Systems*, *51*(3), 480-492.

[31]. Borndorfer, R., Grotschel, M., Lukac, S., & Mitusch, K., 2006. Auctioning Approach to Railway Slot Allocation, An. *Competition & Reg. Network Indus.*,*7*, 163.

[32]. Swaroop, P., 2013. *Problems and Models in Strategic Air Traffic Flow Management*. (PhD dissertation) University of Maryland.

[33]. Robu, V., Gerding, E. H., Stein, S., Parkes, D. C., Rogers, A., & Jennings, N. R., 2013. An Online Mechanism for Multi-Unit Demand and its Application to Plug-in Hybrid Electric Vehicle Charging. *Journal of Artificial Intelligence Research*.

[34]. Cook, W, J., Cunningham, W, H., Pulleyblank, W, R., and A. Schrijver.1998. *Combinatorial Optimization*. John Wiley & Sons.

[35]. Arnott, R., Palma, A, D., and Robin, L. 1990. Economics of a Bottle Neck. *Journal of Urban Economics, 27, 11-130*

[36]. Gonzales, E, J., and Daganzo, C, F. 2012. Morning commute with competing modes and distributed demand: User equilibrium, system optimum, and pricing. *Transportation Research Part B 46 (2012),* pp.1519–1534

[37]. Lin, J. Chen, Q., Kawamura, K. 2014. Logistics Cost and Environmental Impact Analyses of Urban Delivery Consolidation Strategies, *Networks and Spatial Economics,* available On-line First, April 2014, DOI 10.1007/s11067-014-9235-9.

[38]. Lin, J., Zhou, W., Du, L., under review. Green Same Day Delivery Service with Real-time Demand, *Transportation Research Part D: Transportation and the Environment.*

[39]. Zhou, W., and Lin, J., under revision. Is Electric Commercial Vehicle a Cost-effective Alternative to Diesel Commercial Vehicle in Urban Delivery? *Transportation Research Part E: Logistics and Transportation Review*

[40]. Lin, J., and Zhou, W., 2016. EV Routing Problem, to appear in *Transportation Research Procedia of the 9th International Conference on City Logistics*, DOI 10.1016/j.trpro.2016.02.007

[41]. West, Douglas Brent, 1999. *Introduction to Graph Theory* (2nd ed.), Prentice Hall.

[42]. Gibbons, A., 1985. *Algorithmic Graph Theory*, Cambridge University Press.

[43]. Tassa and Tamir, 2012. Finding all maximally-matchable edges in a bipartite graph. *Theoretical Computer Science* 423: 50–58,

[44]. Nisan, N., Roughgarden, T., Tardos, E, and Vazirani, V. 2007. Algorithmic Game Theory. *Cambridge University Press, New York, NY, USA*.