Real-time Bidding based Vehicle Sharing

(Extended Abstract)

Yinlam Chow*
Stanford University
Stanford, USA, 94305
ychow@stanford.edu

Jia Yuan Yu
IBM Research Ireland
Dublin, Ireland
jiayuanyu@ie.ibm.com

ABSTRACT

We consider one-way vehicle sharing systems where customers can pick a car at one station and drop it off at another (e.g., Zipcar, Car2Go). We aim to optimize the distribution of cars, and quality of service, by pricing rentals appropriately. However, with highly uncertain demands and other uncertain parameters (e.g., pick-up and drop-off location, time, duration), pricing each individual rental becomes prohibitively difficult. To overcome this difficulty, we propose a new approach for vehicle sharing based on a bidding mechanism reminiscent of Priceline or Hotwire.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Planning and Scheduling—Planning under Uncertainty

General Terms

Algorithms, Theory, Management

Keywords

One-way vehicle sharing; Dynamic rebalancing; Intelligent transportation management

1. INTRODUCTION

One-way vehicle sharing system is an urban mobility on demand (MOD) platform which effectively utilizes usages of idle vehicles, reduces demands to parking spaces, alleviates traffic congestion during rush hours, and cuts down excessive carbon footprints due to personal transportation. The MOD vehicle sharing system consists of a network of parking stations and a fleet of vehicles. Customers arrive at particular stations can pick up a vehicle and drop it off at any other destination station. Existing vehicle sharing examples include Zipcar , Car2Go and Autoshare for one-way car sharing, and Velib and City-bike for one-way bike sharing.

Despite the apparent advantages of one-way vehicle sharing systems they do present significant operational problems. Due to the asymmetric travel patterns in a city, many stations will eventually experience imbalance of vehicle departures and customer arrivals. To maintain the quality of service, many existing fleet management strategies empirically redistribute empty vehicles among stations with tow trucks or by hiring crew drivers. Still, this solution is adhoc and inefficient. In some cases, these scheduled re-balancing strategies may cause extra congestion to road networks as well.

In the next generation one-way vehicle sharing systems, demand-supply imbalance can be addressed by imposing incentive pricing to vehicle rentals. A typical incentive pricing mechanism would be each station adjusts its rental price based on current inventory and customers' requests. Rather than passively balancing demand and supply by adjusting rental prices at each station, here we study a bidding mechanism to vehicle rentals where at each station customers place bids based on their travel durations and destinations, and the company decides which bids to accept.

There are several methods in literature to address demand-supply imbalance in one-way vehicle sharing system by relocating vehicles. The first suggested way is by periodic relocation of vehicles among stations by staff members. This method had been studied by [1], using discrete event simulations. [3] explored a stochastic mixed-integer programming (MIP) model with an objective of minimizing cost for vehicle relocation such that a probabilistic service level is satisfied. Experimental results showed that these systems improved efficiencies after re-balancing. Similar studies of static rebalancing in vehicle sharing can also be found in [2], However with empirical re-balancing strategies, improvements in throughput performance are unstable, and this approach increases the sunk cost by hiring staff drivers. This motivates our research on designing a next-generation one-way ride sharing platform based on choosing customers' bids.

2. MATHEMATICAL MODEL

Suppose the company has C vehicles, indexed from $1,\dots,C$, and S stations, indexed from $1,\dots,S$. The company's policy only allows each passenger to rent for a maximum of $\overline{T}$ time slots and the maximum fare for each rental period is $\overline{F}$.

In this paper, we consider a discrete time model $t = 0, 1, \dots,$. At time $t \geq 0$, there is a multi-variate (four-dimensional) stationary probability distributions Φ with domain $\{1,\dots,S\}\times\{1,\dots,S\}\times[0,\overline{T}]\times[0,\overline{F}]$, representing the customers' origin station, destination, rental duration and proposed travel fare. We assume the multi-variate probability distribution Φ is known in advance. If the multi-variate distribution is unknown, it can easily be empirically estimated by kernel estimation. Since the vehicle sharing system can at most accept C requests, we generate C i.i.d. random variables from Φ: $((\mathbf{O}_t^1,\mathbf{G}_t^1,\mathbf{T}_t^1,\mathbf{F}_t^1),\dots,(\mathbf{O}_t^C,\mathbf{G}_t^C,\mathbf{T}_t^C,\mathbf{F}_t^C))$. If $\mathbf{T}_t^k = 0$, it represents that there are no customers picking the k^{th} vehicle at time t. For $j \in \{1,\dots,S\}$, denote by $\mathcal{A}_t^j$ the number of customers arriving at time t who wish to travel to station j. Based on the definition of random variable $\mathbf{T}_t^k$, one easily sees that this quantity can be expressed as $\mathcal{A}_t^j := \sum_{k=1}^C \mathbf{1}\{\mathbf{T}_t^k > 0, \mathbf{G}_t^k = j\}$.

This model captures both concepts of renting and rebalancing. Notice that the random price offered by the customer k, i.e., $\mathbf{F}_t^k$ for $k \in \{1,\dots,C\}$ can either be positive or negative. When this quantity is positive, it means that the customer is willing to paying $\mathbf{F}_t^k$ to rent a vehicle for $\mathbf{T}_t^k$ periods to travel from station $\mathbf{O}_t^k$ to $\mathbf{G}_t^k$. If this quantity is negative, it means that the company is paying $\mathbf{F}_t^k$ to the k^{th} customer, if a vehicle is needed to re-balance from station $\mathbf{O}_t^k$ to $\mathbf{G}_t^k$ in $\mathbf{T}_t^k$ periods.

Since $(\mathbf{O}_t^1,\mathbf{G}_t^1,\mathbf{T}_t^1,\mathbf{F}_t^1),\dots,(\mathbf{O}_t^C,\mathbf{G}_t^C,\mathbf{T}_t^C,\mathbf{F}_t^C)$ are i.i.d. ran-

*Part of the work is completed during the author's internship in IBM Research Ireland.

Appears in: *Proceedings of the 14th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2015), Bordini, Elkind, Weiss, Yolum (eds.), May 4–8, 2015, Istanbul, Turkey.*

dom vectors, intuitively there is no difference in assigning any specific vehicles to corresponding potential customers if the customers' information is not known in advance. Rather, based on the vehicle biding mechanism in our problem formulation, the company obtains the stochastic customer information vector ω_t before deciding any actions on renting, parking or rebalancing. Therefore at each destination station, it has a pre-determined passenger ranking function to select "better customers", i.e., customers which maximize revenue (or minimize rebalancing cost) and minimize vehicle usage. We define f^j_{rank} as the customer ranking function for destination station $j \in \{1, \dots, S\}$ based on the price-time ratio: $\mathbf{1}\{\mathbf{F} \geq 0\}\mathbf{F}/\mathbf{T} + \mathbf{1}\{\mathbf{F} \leq 0\}\mathbf{F}\mathbf{T}$ for $\mathbf{T} \neq 0$. Specifically, for any arbitrary customer information vector

$$\omega = ((\mathbf{O}^1, \mathbf{G}^1, \mathbf{T}^1, \mathbf{F}^1), \dots, (\mathbf{O}^C, \mathbf{G}^C, \mathbf{T}^C, \mathbf{F}^C)),$$

the customer ranking function $f^j_{\text{rank}}(\omega)$ assigns score $-\infty$ to the elements with $\mathbf{T}^k = 0$ or $\mathbf{G}^k \neq j$, for $k \in \{1, \dots, C\}$ in ω, and assigns score $\mathbf{1}\{\mathbf{F}^k \geq 0\}\mathbf{F}^k/\mathbf{T}^k + \mathbf{1}\{\mathbf{F}^k \leq 0\}\mathbf{F}^k\mathbf{T}^k$ to other elements whose destination station $\mathbf{G}^k = j$ for $k \in \{1, \dots, C\}$.

2.1 State Variables

The operator makes decisions based on the stochastic inputs generated from the environment and the following system observations of each vehicle in the fleet:

- For $i \in \{1, \dots, C\}$ and $t \geq 0$, $q^i_t \in \{1, \dots, S\}$ is the destination station and $\tau^i_t \in \{0, 1, 2, \dots, \overline{\mathcal{T}}\}$ is the current travel time remaining to destination of the i^{th} vehicle. Also define $q_t = (q^1_t, \dots, q^C_t)$ and $\tau_t = (\tau^1_t, \dots, \tau^C_t)$ as the stochastic state vectors of $\{q^i_t\}$ and $\{\tau^i_t\}$ respectively.

2.2 Decision Variables

At any time slot t, the company makes a decision to park, rebalance or to rent vehicle to any potential passengers:

- For each station $j \in \{1, \dots, S\}$, $\mathbf{u}^j_t \in \{0, 1, \dots, C\}$ is a decision variable that represents the number of vehicles to dedicate to destination station j at time t. Also define the decision $\mathbf{u}_t = (\mathbf{u}^1_t, \dots, \mathbf{u}^S_t)$ as the operator's decision vector.

These decision variables have the following constraint to upper bound the decision variable at time $t \geq 0$: $\mathbf{u}^j_t \leq \mathcal{A}^j_t$, $\forall j \in \{1, \dots, S\}$. Furthermore, the number of vehicle assignment equals to C, i.e., $\sum_{j=1}^S \mathbf{u}^j_t = C$, $\forall j \in \{1, \dots, S\}$.

2.3 State Dynamics

Before stating the state dynamics of (q_t, τ_t), we start by constructing a destination allocation function for each vehicle. Define the quota index $\mathbf{Q} = (\mathbf{Q}^1, \dots, \mathbf{Q}^S)$ whose domain lies in $\{0, 1, \dots, C\}^S$. For each $k \in \{1, \dots, S\}$, $\mathbf{Q}^k$ is a quota index that counts the number of vehicle assignments to destination station k. Recall the arbitrary information vector ω. At any origin $j \in \{1, \dots, S\}$, construct an allocation function $\mathcal{G}(\omega, \mathbf{Q}, j) : \Omega \times \{0, 1, \dots, C\}^S \times \{1, \dots, S\} \rightarrow \{1, \dots, S\} \times \{1, \dots, S\} \times [0, \overline{T}] \times [0, \overline{F}]$ for which this function examines the current origin station of each request and outputs the corresponding information based on the available quota and maximum score. Specifically, let $\omega^j = \{(\mathbf{O}, \mathbf{G}, \mathbf{T}, \mathbf{F}) : (\mathbf{O}, \mathbf{G}, \mathbf{T}, \mathbf{F}) \in \omega,\ \mathbf{O} = j\}$ be a sub-vector of ω whose elements have origins at $j \in \{1, \dots, S\}$. Then, define $\text{Assign}(f^{j'}_{\text{rank}}(\omega^j)) = (\mathbf{O}, \mathbf{G}, \mathbf{T}, \mathbf{F})$ as a function that finds an element in ω^j with maximum score corresponding to destination station j', where $\{v^{j'}\}_{j' \in \{1, \dots, S\}}$ is a shorthand notation for vector $(v^1, \dots, v^S)$. If there exists a destination station $j' \in \{1, \dots, S\}$ with $\mathbf{Q}^{j'} > 0$ and $\max f^{j'}_{\text{rank}}(\omega^j) \neq -\infty$, then

$$\mathcal{G}(\omega, \mathbf{Q}, j) = \underset{j' \in \{1, \dots, S\}: \mathbf{Q}^{j'} > 0}{\arg\max} \left\{ \text{Assign}(f^{j'}_{\text{rank}}(\omega^j)) \right\}_{j' \in \{1, \dots, S\}}.$$

Otherwise, $\mathcal{G}(\omega, \mathbf{Q}, j) = (\text{NIL}, \text{NIL}, \text{NIL}, \text{NIL})$. Then, we have the following algorithm that assigns state updates $(q^i_{t+1}, \tau^i_{t+1})$ for each vehicle.

Algorithm 1 State Updates at Time t

Input: Customer information vector ω_t and Decision variable $\mathbf{u}^1_t, \dots, \mathbf{u}^S_t$
Initialize quota index $\mathbf{Q} = (\mathbf{Q}^1, \dots, \mathbf{Q}^S)$ such that $\mathbf{Q}^j = \mathbf{u}^j_t$ at each station $j \in \{1, \dots, S\}$, available customer information $\omega = \omega_t$ and stage-wise revenue function $\mathbf{R}(q_t, \tau_t, \omega_t, \mathbf{u}_t) = 0$
for $i = 1, 2, \dots, C$ **do**
  for $j = 1, 2, \dots, S$ **do**
    Compute $(j, j^*, \mathcal{T}^i_t, \mathcal{F}^i_t) = \mathcal{G}(\omega, \mathbf{Q}, j)$
    if $q^i_t = j$ and $\tau^i_t = 0$ and $j^* \neq$ NIL **then**
      Set $(q^i_{t+1}, \tau^i_{t+1}) = (j^*, \mathcal{T}^i_t)$, $\mathbf{R}(q_t, \tau_t, \omega_t, \mathbf{u}_t) = \mathbf{R}(q_t, \tau_t, \omega_t, \mathbf{u}_t) + \mathcal{F}^i_t$,
      Update $\mathbf{Q}^{j^*} \leftarrow \mathbf{Q}^{j^*} - 1$ in $\mathbf{Q}$, replace the corresponding element $(j, j^*, \mathcal{T}^i_t, \mathcal{F}^i_t)$ in ω with $(j, j^*, 0, \mathcal{F}^i_t)$ and **break**
    else
      Set $(q^i_{t+1}, \tau^i_{t+1}) = (q^i_t, \max(\tau^i_t - 1, 0))$
    end if
  end for
end for
return State updates: (q_{t+1}, τ_{t+1})

2.4 Bidding Based Vehicle Sharing Problem

Recall the stage-wise revenue function from Algorithm 1, the total average revenue generated is given by

$$\lim_{T \to \infty} \frac{1}{T} \mathbb{E} \left[\sum_{t=0}^{T-1} \mathbf{R}(q_t, \tau_t, \omega_t, \mathbf{u}_t) \right].$$

We also impose the following set of service level agreement constraints that upper bounds the average number of customers at each station $j \in \{1, \dots, S\}$ for rental purposes, i.e.,

$$\lim_{T \to \infty} \frac{1}{T} \mathbb{E} \left[\sum_{t=0}^{T-1} \left(\sum_{i=1}^{C} \mathbf{1}\{\mathbf{G}^i_t = j, \mathbf{T}^i_t > 0, \mathbf{F}^i_t > 0\} - \mathbf{u}^j_t \right) \right] \leq \mathbf{d}^j,$$

where $\{\mathbf{d}^j\}_{j=1}^S$ is the vector of quality-of-service thresholds, pre-specified by the system operator.

Our objective for this problem is to maximize the expected revenue collected by renting vehicles while satisfying the customer service level agreement constraints at each station. More details can be found in our working paper.

3. CONCLUSIONS AND FUTURE WORK

In this project we proposed a detailed mathematical framework for bidding based one-way vehicle sharing systems. In contrast to existing approaches where the system operator at different stations dynamically set the price, we aim to control demand-supply imbalance via an active bidding approach. Derivations of solutions algorithms and implementations will be left as future work.

4. ACKNOWLEDGEMENT

This work was supported in part by the EU FP7 project INSIGHT under grant 318225.

REFERENCES

[1] M. Barth and M. Todd. Simulation model performance analysis of a multiple station shared vehicle system. *Transportation Research Part C: Emerging Technologies*, 7(4):237–259, 1999.

[2] R. Gunther et al. Balancing bicycle sharing systems: Improving a VNS by efficiently determining optimal loading operations. volume 7919, pages 130–143, 2013.

[3] R. Nair. Fleet management for vehicle sharing operations. *Transportation Science*, 45(4):524–540, 2011.