2011 IEEE Forum on Integrated and
Sustainable Transportation Systems
Vienna, Austria, June 29 - July 1, 2011

A Simulation Study of Peer-to-Peer Carsharing

Robert C. Hampshire and Srinath Sinha

***Abstract*— Many studies have shown that carsharing reduces environmental pollution and the transportation costs for a large segment of the population. Car sharing also reduces the number of private vehicles on the road because members do not purchase their own car. However, the traditional carsharing business model is difficult to scale geographically to neighborhoods with lower population densities because the operator must bear the upfront fixed cost of purchasing or leasing the vehicles in the fleet. In contrast to traditional carsharing, Peer-to-Peer (P2P) carsharing allows car owners to convert their personal vehicles into shared cars which can be rented to other drivers on a short-term basis. This model leverages the fact that most privately owned vehicles sit idle over 90% of the day. This paper presents a simulation study and a reservation control policy (RCP) to increase the revenue generated from P2P carsharing. The results show that rejecting reservations, even when the time slot is available, increases revenue when the demand is sufficiently high.**

I. INTRODUCTION

National priorities are focused on reducing the energy consumption and greenhouse gas emissions from the transportation sector. There are many potential supply side and demand side solutions. Car sharing is one such demand side energy saving innovation. Car sharing reduces the environmental impact of driving and reduces private transportation costs for some drivers with only intermittent need for vehicle transportation. Carsharing is both environmentally friendly and cost efficient. Previous studies have demonstrated that each new share car added to existing carsharing fleets removes 4.6 to 20 private vehicles from the road. This reduction is because members of carsharing services are much less likely to purchase their own cars and may even sell a car after joining a carsharing service, [1][2]. Car sharing changes the economics of driving by converting vehicle transportation from a fixed cost into a variable cost. Car sharing has been shown to reduce mode adjusted vehicle miles traveled (MVMT) among members by 67% [3]. The average member of the City CarShare carsharing service in San Francisco spends only about $540 per year on automotive transportation [3]. This represents a tenfold cost savings when compared to owning a small sedan [1]. A range of market demand studies conducted in the US and Europe have estimated cost savings alone would drive between 3% and 25% of the driving population to forego car ownership, or to replace their privately owned cars, and instead take up membership in a carsharing service [4]. Other research estimates that if a sufficient number of conveniently located vehicles were available, then 10% of the individuals over the age of 21 in metropolitan areas of North America would adopt carsharing [5].

Carsharing is important economically as it provides access to mobility for those without a car. Many studies (see Litman [6], Raphael et al. [7], and Raphael and Rice [8]) have shown that lack of car access negatively impacts employment and health outcomes. This is particularly true for low income households that often lack access to a car due to the high cost of car ownership. The traditional carsharing business model is difficult to scale geographically to neighborhoods with lower population densities because the operator must bear the high upfront fixed cost of purchasing all of the vehicles in the fleet. These less dense neighborhoods are also typically under-served by public transportation, many of which are low income.

In contrast to traditional carsharing, Person-to-Person (P2P) carsharing allows car owners to convert their personal vehicles into shared cars which can be rented to other drivers on a short-term basis. This business model leverages the fact that most privately owned vehicles sit idle over 90% of the day [9]. Person-2-Person carsharing alleviates upfront costs and scales more economically than traditional carsharing. Thus, P2P carsharing provides greater potential for car accessibility than traditional carsharing. P2P carsharing extends the reach and potential benefits of carsharing. There are several new service companies dedicated to P2P carsharing: WhipCar, Relayrides, GetAround, Spride Share and Go-Op.

The first author's previous work explores the economic incentives and potential market size of P2P carsharing [10]. Given the recent economic downturn, P2P carsharing is particularly relevant to car-owners who can generate an additional income stream from an asset they already own. In this paper, we explore the operational aspects of P2P carsharing. The fundamental operational trade-off is between car owner revenue and renter satisfaction. The car owner revenue is directly related to the utilization of their car. Renter satisfaction is directly related to the availability of reservations. This paper uses simulation to explore this trade-off. We present a reservation admission control policy that increases car utilization and applies to both traditional and P2P carsharing.

This paper makes two main contributions to our understanding of P2P carsharing. First, this is the first study to

This work was supported by the iLab located at Heinz College, Carnegie Mellon University, and NSF CMMI 1055832 .

R.C. Hampshire is an Assistant Professor of Operations Research and Public Policy, H. John Heinz III College, Carnegie Mellon University, Pittsburgh, PA, hamp@cmu.edu

S. Sinha is with the Heinz College, Carnegie Mellon University, Pittsburgh, PA.

[1]USEPA. Emissions Facts: Greenhouse Gas Emissions from a Typical Passenger Vehicle. US Environmental Protection Agency. [Online] 2005. http://www.epa.gov/OMS/climate/420f05004.htm.

present an operational and simulation model of P2P carsharing. Particularly, we explore the main operational tradeoff of balancing car utilization with reservation availability. Secondly, we propose a reservation admission control policy for carsharing, and P2P carsharing specifically, that generates more revenue for car owners.

The remainder of the paper is organized as follows. In the next section we review the literature on carsharing and discuss how the contributions of this paper relate to that literature. Section III describes the operations and pricing structure of P2P carsharing. The reservation control policy (RCP) is introduced in Section IV. A discrete event simulation of P2P carsharing is presented in Section V along with the implementation of the reservation control policy. The RCP is evaluated via simulation under four supply and demand scenarios in Section VI. Finally, we conclude and summarize the results in Section VII

II. LITERATURE REVIEW

There is only one previous research paper the authors are aware of that directly considers P2P carsharing. The first author's previous work examined the economic incentives and market for P2P carsharing [10]. Additionally, it presents a framework to estimate the supply and demand for P2P carsharing at the census block group level. Finally, the framework is applied to a case study of Pittsburgh, PA. This paper complements [10] by investigating some the operational mechanics taken for granted previously.

The literature on carsharing focuses on the behavioral, economic and environmental impacts of carsharing. Particularly, these papers consider the demographics of carsharing members and their motivations for joining a carsharing organization [3]. Another stream of research examines the neighborhood characteristics that foster carsharing [11],[12], and [4].

Led by Shaheen and her coauthors, there is now a rich literature establishing the positive environmental and economic impacts of carsharing [1], [5], [2]. Cumulatively, this research documents the long term affects of carsharing on members. Household vehicle ownership decreases due to members selling an existing car or forgoing purchase of a car. Also, the evidence shows that carsharing members travel less and have a smaller carbon footprint than groups with similar characteristics before joining carsharing.

While most of the existing research on carsharing considers the environmental or economic impacts of carsharing, there are several papers that examine the operational mechanics of carsharing. Barth et al. [13] , and Nakayama [14] analyze the tradeoffs associated with one way carsharing trips using simulation. They present a simulation study to evaluate management strategies for carsharing and characterize the tradeoffs between utilization and car availability. This paper presents a similar perspective for P2P carsharing.

III. P2P CARSHARING

In contrast to traditional carsharing, Peer-to-Peer (P2P) carsharing allows car owners to convert their personal vehicles into shared cars which can be rented to other drivers on a short-term basis. This business model leverages the fact that most privately owned vehicles sit idle over 90% of the day [9]. Person-2-Person carsharing alleviates upfront costs, and scales more economically than traditional carsharing. Thus, P2P carsharing provides greater potential for car accessibility than traditional carsharing.

P2P carsharing services facilitate the rental process by providing insurance, gas, a method to access the car, and an online reservation system. Typically, the car owner receives approximately 70% of the rental revenue, while the remaining goes to the service provider to cover insurance, telematics, other expenses and profit. Currently the rental price structure is similar to that of nonprofit traditional carsharing services with an hourly rate of roughly $5 per hour and $.35 per mile. The P2P carsharing organization can afford to adopt the non-profit rates because the P2P model removes roughly 50% of the cost of business from the traditional carsharing model (see Zipcar S-1 filing [15]).

This lower cost business model also allows P2P providers to place cars more profitably in areas with lower population densities. The users of P2P in less dense areas may prove to have different usage characteristics than users in more dense areas. For the time being, we assume that P2P renters behave identically to traditional carsharing members. Both the pricing and operational procedures of P2P carsharing are slightly different than traditional carsharing as we describe below.

A. Pricing

Currently, the carsharing sector does employ price differentiation based on weekday vs weekend, type of car, and some have long term or overnight pricing. The hourly rental rates range from approximately $5 per hour, for some nonprofit carsharing organizations, to $20 per hour for high end cars like BMW's. There does seem to be some price differentiation based on location, but this practice appears to be rare. Further research is needed to systematically investigate pricing based on location of the car and is the subject of future research.

To the authors' knowledge, no carsharing companies set prices based on how far in advance a renter makes a reservation. The prevailing pricing structure in the carsharing industry does not employ the revenue management techniques found in other service sectors, i.e airlines, rental car services, and hotels see [16]. Also to the authors' knowledge, all carsharing companies accept reservations based on a first come first serve (FCFS) basis. In the revenue management literature, there is a recognized duality between admission control and pricing policies [16],[17]. In the following section, we present an admission control policy for carsharing based on time of the rental request.

IV. RESERVATION CONTROL POLICY

The effectiveness of traditional carsharing and peer-to-peer carsharing services depend on their reservation system. Both the renters' quality of service, and the car owners' profitability is related to providing high car availability to renters, while maintaining high efficiency of the car. We now present a reservation control policy for accepting or rejecting renter reservation requests. Following the work of Luss [18],[19], Aalto [20], and Virtamo [21] on the optimization of reservation systems, we develop a reservation control policy (RCP) for carsharing.

To introduce the policy, consider a single car in isolation. Our car is accepting reservations for a future date T time units in the future. The reservation book initially has 24 available hourly slots. The renter demand arrives randomly according to a non-homogeneous Poisson process with rate $\lambda(t)$. The average remaining renter demand at time t is $\Lambda_t = \int_t^T \lambda(s)ds$. Each arriving renter has associated with it an independently distributed *mark* (see [22]) $R = (\Gamma, H)$ representing a uniformly distributed desired renter start time Γ, and H is distributed according to g_h a geometric distribution. A rental request of length h with start time τ is accepted if a contiguous block of slots of length h is available starting at the $\tau - th$ slot and rejected otherwise. A contiguous block of available reservation slots is called an *island*. Luss [18] and Virtamo [21] show that the time evolution of the reservation book is a Markov Process. The state descriptor of the process is the locations and sizes of *islands* in the reservation book.

Virtamo [21] develops a reservation control policy whose objective is to maximize the utilization of islands in the system. To accomplish this, a dynamic programming formulation is employed. The policy maximizes utilization by appropriately rejecting a rental request even when an island of the desired size is available. The rationale behind these rejections is that accepting the "wrong" request creates an island of an undesirable size given the distribution of rental durations.

We summarize the approach here. The Bellman value function, $V_l(\overline{\lambda})$, is a function of the size of an island and average remaining renter demand $\overline{\lambda}$, and represents the final value of the utilization of that island. There is a value function for every possible size of island. Given that we are considering only one vehicle, there are 25 possible island sizes. The dynamics of the value function are

$$\frac{dV_l(\overline{\lambda})}{d\overline{\lambda}} = \sum_{h=1}^{l-1} g_h \sum_{j=1}^{l-h} (h + V_{l-(h,j)}(\overline{\lambda}) - V_l(\overline{\lambda})) \qquad (1)$$

for $l = 0, 1, \ldots, 24$, where $l - (h, j)$ is the size of an island produced by accepting a request of size h into an island of size l which starts at position j within the island. The dynamics of islands upon accepting a request play an important role in computing the optimal reservation policy. For the simple 24-hour case that we have where the availability is binary, we can see that a request of length h divides an island of type l into 2 smaller islands of length j and $l - h - j + 1$,

$$V_{l-(h,j)}(\overline{\lambda}) = V_j(\overline{\lambda}) + V_{l-h-j}(\overline{\lambda}). \qquad (2)$$

The initial conditions for this set of differential equations are $V_l(0) = 0 \, \forall l$ and $V_0(\cdot) = 0$. This set of differential equations can be solved recursively starting for $l = 0$.

The resulting decision rule to accept a rental request follows directly from 1. If $h + V_{l-(h,j)}(\overline{\lambda}) > V_l(\overline{\lambda})$, then we should accept the request and reject it otherwise. This decision rule results in a set of threshold value $\lambda_{h,j}$, and if the expected remaining rental demand λ_t^T is greater than $\lambda_{h,j}^l$, then the request is rejected. The interested reader may see [21] for more details.

V. SIMULATION

In the previous section, we considered one car in isolation. In this section, we describe a discrete simulation approach to capture the dynamics of many cars. This simulation framework allows us to analyze the tradeoffs between car utilization and rental availability under several reservation control policies and car supply location distributions. The purpose of the simulation is to explore the key tradeoffs of utilization and quality of service in a stylized setting. A more robust approach is needed to apply the results directly the carsharing context.

A. Baseline Policy

For the baseline simulation, we represent the P2P system as a 2-dimensional space with car and renter location generated by spatial Poisson processes. First, the car supply appears randomly according to a non-homogeneous spatial Poisson process with density function $\Lambda_O(x, y)$. Each atom of the car owner location process has an independent mark associated with it, $O = (A_1, A_2, \ldots, A_{24})$ representing the hourly availability of the car over the day.

Next, renters arrive according to a homogeneous (in time) Poisson process over an interval of length T. Each renter has an independent random mark $R = (\Gamma, H)$ representing reservation start time and length. The distribution of the spatial location of these renters is assumed to be uniform. The reservation start time is assumed to be uniform between 1 and 24, and the length is geometrically distributed with mean 4.

The car owner process divides space into a random tessellation (i.e. open covering) of convex sets called the Possion-Voroni tessellation (see [22]). Next, each of the arriving renters is matched to the closest car and requests a reservation. If all of the requested time slots are available, then the request is accepted, otherwise it is rejected.

We are interested in the spatial statistics generated from this process. Particularly, we report the car utilization as a function of location and the reservation acceptance rate as a function of renter location.These two summary statistics capture the trade-off between car owner revenue and renter satisfaction.

B. Reservation Control Policy

Our implementation of the reservation control policy (RCP) assumes that each car in the system implements the policy independently. Renter requests at each car are accepted or rejected based on the threshold developed in the previous section. Given that the renter locations are uniformly distributed, the total expected number of arrivals at

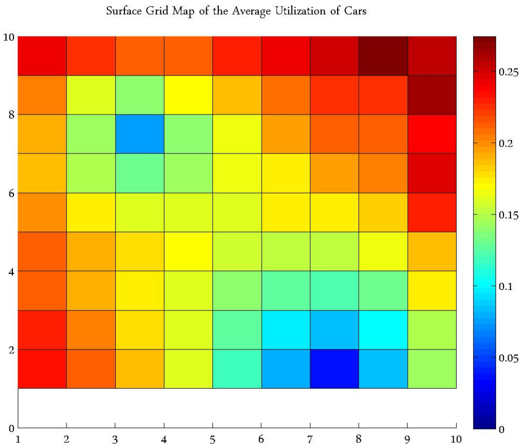

Fig. 1. Spatial Utilization for Car Locations with $a = 8$ and expected demand of 2750 under the RCP policy

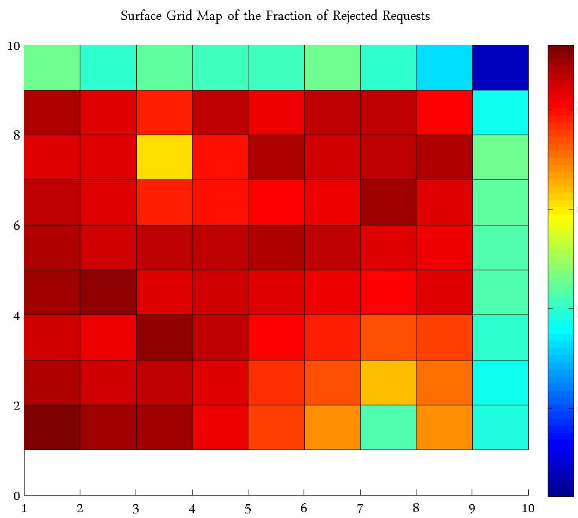

Fig. 2. Spatial Acceptance Rates for $a = 8$ and expected demand of 2750 under the RCP policy

each location is the same. Thus, the rejection thresholds are independent of location of the car. In the general setting, the rejection thresholds are a function of location. In addition to the car utilization and reservation acceptance rate, we collect the conditional rejection rate when there is space available in the reservation book.

VI. RESULTS AND DISCUSSION

We calibrate the renter characteristics to those found in the carsharing literature. Cervero's five year study of the impacts of City CarShare's car sharing service in San Francisco found that the average renter completed 1.31 trips each month. The average duration of each trip was found to be 3.93 hours [3]. For the simulation, we assume the trip duration is geometrically distributed with mean of 4 hours.

For the simulation, we assume a 10 by 10 spatial grid. The locations of the supply of cars is governed by the density function $\lambda(x, y)$. We consider a non-uniform density with two hotspots at locations $(3, 7)$ and $(7, 3)$ and with intensities a and b,

$$\lambda(x, y) = \frac{a}{\sqrt{(x-3)^2 + (y-7)^2}} + \frac{b}{\sqrt{(x-7)^2 + (y-3)^2}}. \tag{3}$$

We simulate the system with 10,000 realizations. For simplicity, we assume $b = 2a$. Figure 1 shows the average spatial car utilization for the case of the nonuniform car locations for with $a = 8$ and the expected total demand is 2750 under the RCP policy. The revenue per accepted reservation is \$5 per hour. Figure 2 displays the corresponding spatial acceptance rates. We see that the car utilization is higher under the RCP policy and the acceptance rate is lower. The utilization of the cars closer to the hotspots is lower due to the fact that the user demand is located uniformly. The RCP policy generates 4.9% more revenue than the unoptimized case. Note, this simulation represents one day in the operations of the P2P carsharing service, So, a RCP yields a 4.9% revenue increase for every day of operations.

We explore a range of scenarios under which to examine the RCP policy described in the previous section. These scenarios correspond to varying the car supply intensity from $a = 1$ to $a = 17$ where $b = 2a$, and the total expected demand from 1000 to 5000 in steps of 250. The resulting percent revenue gains from the RCP over the baseline range from -15% to 5%, see Figure 3.

The revenue for each scenario is the spatial average weighted by the probability of a car appearing in that location. Similarly, Figure 4 is the percent utilization change under the RCP compared to the baseline. The utilization for each scenario is the spatial average utilization weighted by the probability of a car appearing in that location. Here, we observe that the RCP performs better in high demand conditions, both at low and high supply.

VII. CONCLUSION

Carsharing is both environmentally and economically sustainable. An extension of traditional carsharing called peer-to-peer (P2P) carsharing has the potential to vastly extend these benefits. We present a reservation control policy to improve the operational efficiency of P2P carsharing. This policy also is applicable to traditional car sharing. A simulation setting is used to evaluate this policy in comparison to other plausible schemes.

We find that reservation control policy yields large increases in revenue when the service is popular. Most existing car sharing organizations do not employ a reservation admission control policy. In fact, most carsharing companies are non-profits, and the for profit organizations have yet to achieve profitability. The policy developed in this paper respresents an opportunity for carsharing organizations to generate more revenue with their existing assets. These operational improvements could benefit the entire sector, and perpetuate the positive environmental and economic benefits of carsharing.

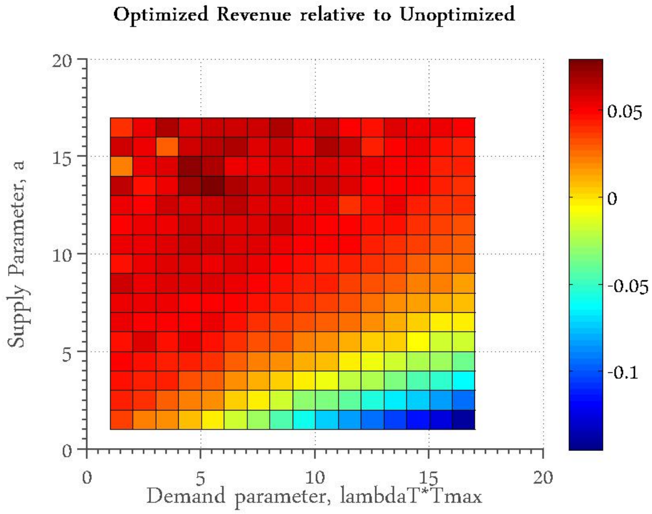

Fig. 3. Gain in Revenue under RCP policy over Baseline for various Supply and Demand Scenarios

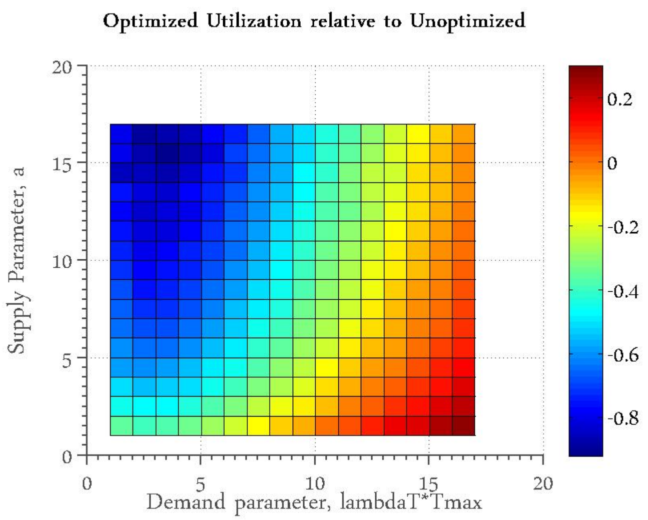

Fig. 4. Gain in Utilization under RCP policy over Baseline for various Supply and Demand Scenarios

While these preliminary results are promising, the simulation setting is simplified and makes many assumptions. Our future work includes relaxing many of these assumption in the simulation, and providing a rigorous framework for the analysis.

References

[1] S. Shaheen, A. P. Cohen, and J. D. Roberts, "Carsharing in north america: Market growth, current developments, and future potential," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1986, 2005.

[2] S. Elliot Martin, Susan Shaheen and J. Lidicker, "Impact of carsharing on household vehicle holdings," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2143, no. 5, pp. 150–158, 2010.

[3] R. G. R. Cervero and A.Nee, "City carshare: Longer-term travel demand and car ownership impacts," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 51, no. 3, pp. 327 – 337, 2007.

[4] A. M.-B. Christine Celsor, "Where does carsharing work?: Using geographic information systems to assess market potential," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1992, no. 5, pp. 35–44, 2007.

[5] A. C. Susan Shaheen and M. Chung, "North american carsharing: 10-year retrospective," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2110, no. 5, pp. 35–44, 2010.

[6] T. Litman, "Evaluating carsharing benefits," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1702, 2000.

[7] K. A. S. Steven Raphael, Michael A. Stoll and C. Winston, "Can boosting minority car-ownership rates narrow inter-racial employment gaps?" *Brookings-Wharton Papers on Urban Affairs, (2001), pp. 99-145*, vol. 13, pp. 99–145, 2001.

[8] S. Raphael and L. Rice, "Car ownership, employment, and earnings," *Journal of Urban Economics*, vol. 52, no. 1, pp. 109 – 130, 2002. [Online]. Available: http://www.sciencedirect.com/science/article/B6WMG-4665KV7-6/2/0cdba7a8185581a47fac342a6e0db214

[9] D. Shoup, *The High Cost of Free Parking*. Planners Press: American Planning Press: American Planning Association, 2005.

[10] R. Hampshire and C. Gaites, "An analysis of person-2-person car sharing," in *Transportation and Development Conference*. American Society of Civil Engineers (ASCE), 2011.

[11] V. C. Grasset and C. Morcency, "Carsharing: Analyzing the interaction between neighborhood features and market share," *Transportation Research Record: 88th Annual Meeting*, 2009.

[12] T. S. Susan Shaheen and P. L. Mokhtarian, "Carsharing and the built environment," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2110, 2009.

[13] M. Barth and M. Todd, "Simulation model performance analysis of a multiple station shared vehicle system," *Transportation Research Part C: Emerging Technologies*, vol. 7, no. 4, pp. 237 – 259, 1999. [Online]. Available: http://www.sciencedirect.com/science/article/B6VGJ-3XRG736-4/2/b346dfedc8f93c40a16ae6eb754bf038

[14] R. K. Shoichiro Nakayama, Toshiyuki Yamamoto, "Simulation analysis for the management of an electric vehicle-sharing system: Case of the kyoto public-car system," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1791, pp. 99–104, 2002.

[15] Zipcar, "Form s-1 registration statement under the securities act of 1933," *http://www.sec.gov/*, Accessed June 2010.

[16] K. Talluri and G. van Ryzin, *The Theory and Practice of Revenue Management*. Kluwer Academic Publishers, 2004.

[17] G. Gallego and G. V. Ryzin, "Optimal Dynamic Demand Pricing over of Inventories Finite Horizons with Stochastic," *Management*, vol. 40, no. 8, pp. 999–1020, 2010.

[18] H. Luss, "A model for advanced reservations for intercity visual conferencing services," *Operational Research Quarterly (1970-1977)*, vol. 28, no. 2, pp. 275–284, 1977. [Online]. Available: http://www.jstor.org/stable/3009183

[19] ——, "A model for advanced reservations for large scale conferencing services," *The Journal of the Operational Research Society*, vol. 31, no. 3, pp. 239–245, 1980. [Online]. Available: http://www.jstor.org/stable/2581080

[20] S. Aalto, "Theory and methodology stochastic optimization of reservation systems," *European Journal Of Operational Research*, vol. 51, pp. 327–337, 1991.

[21] J. T. Virtamo and S. Aalto, "Stochastic optimization of reservation systems," *European Journal of Operational Research*, vol. 51, no. 3, pp. 327 – 337, 1991. [Online]. Available: http://www.sciencedirect.com/science/article/B6VCT-48NBFXJ-1PG/2/4a163f7a1510d2f17b690f2e63d65f34

[22] D. Stoyan, W. Kendell, and j. Mecke, *Stochastic Geometry and its Applications*. John Wiley and Sons., 1995.