Technologies for Safe & Efficient Transportation

THE NATIONAL USDOT UNIVERSITY TRANSPORTATION CENTER FOR SAFETY

Carnegie Mellon University | UNIVERSITY of PENNSYLVANIA

Smart Parking

PI: Robert C. Hampshire

Research team: Daniel Jordon, Kats Sasanuma, Numeritics LLC.

Contract No. DTRT-12-GUTC-11

Table of Contents

The problem

A study by UCLA economist and urban planner, Donald Shoup, found that in a 15-block area of Westwood, cruising for parking generates 950,000 excess vehicle-miles of travel, wastes 47,000 gallons of gas, 100,000 hours and produces 730 tons of greenhouse gas carbon dioxide per year. Furthermore, cities have systematically mismanaged on-street parking by underpricing it which encouraging excessive searching for on-street parking. This pattern of excessive cruising for parking is replicated in every city throughout the world.

To remedy this excessive searching, two primary solutions have been proposed: *pricing* and *information*. Shoup has advocated that on-street parking prices should be adjusted to achieve a goal of 85% occupancy, or approximately one empty space per block at all times of day. Economists have developed simple models of parking search behavior and pricing. In this study, we examine currently operating parking information and pricing system.

Many cities are currently undertaking parking information pricing programs to decrease cruising. Our research team, with the aid of many partners, has developed a parking information system for Pittsburgh that enables many of the results described in this report. ParkPGH is a smart parking system that uses historical parking and event data in a prediction model to provide real-time information on the availability of parking within downtown Pittsburgh. The program enhances 19 existing off street parking facilities by providing real time information using a host of information delivery methods that includes an iPhone application, traditional and mobile website, text messaging and an interactive voice response system. The primary goals of the program are to reduce search time and search time variability when finding a parking space within the Cultural District and to make the District a more desirable destination for patrons by reducing the anxiety and uncertainties related to parking issues. In a study, included with this report and partially funded by the T-SET UTC, we find that cruising for parking in downtown Pittsburgh has decreased due to the *information* provided by ParkPGH.

The city of San Francisco has recently deployed a $20 million parking information and pricing program called SFPark of which I am member of the technical advisory committee. This program is the first large scale deployment to combine both time of day pricing and information aimed at reducing excessive searching for parking. This program is expected to improve public transit service by reducing road congestion caused by those searching for parking, reduce greenhouse gas emissions, improve neighborhood livability, enhance San Francisco's economic vitality, and make parking more convenient. Parking sensors will be installed in 6,000 on-street parking spaces and 11,500 off-street parking spaces. The data generated by the sensors will enable the thorough evaluation of new pricing structures. SFPark will distribute information about parking to drivers before and during their trip. Real time parking information will be made available via variable message signs, static wayfinding signs, web, PDSs, and text messages (SMS). In a study, included with this report and partially funded by the T-SET UTC, we estimate that cruising for parking has decreased in San Francisco due the SFPark program.

While SFPark has led to decreases in road congestion caused by cruising for parking, the program may be too expensive to implement for most cities. The goal of this study is to investigate an **inexpensive** parking information and management systems based on *crowdsourcing*. Vehicle-to-Vehicle(V2V) and Vehicle-to-Infrastructure(V2I)communications is the enabling technology for the proposed crowd sourced parking information system.

Our goal is to develop and analyze a cost effective *decentralized crowdsourced* parking information system by leveraging the existing deployment of ParkPGH,org, a centralized, parking information system.

Approach

Asystems engineering approach is adopted to develop and analyze a viable crowdsourced parking information approach which is enabled by V2X communications. The first step in the systems engineering process is understanding the needs of the relevant stakeholders and ascertaining the functional requirements of the crowdsourcing approach. To that end, we have conducted an extensive stakeholder assessment. The goal of the stakeholder assessment is to identify the salient parking challenges in the city and to illicit the role of a technology solution to address these challenges.

Next, we present a study of the effectiveness of the *information* currently provided by ParkPGH.org. Any decentralized crowdsourced scheme in Pittsburgh needs to build on the centralized ParkPGH.org system. So it is imperative to establish the effectiveness of centralized systems, such as ParkPGH. Next, we also present our study that establishes the effectiveness of *price* changes to decrease cruising for parking in San Francisco.

Finally, we combine the stakeholder analysis, the information and pricing studies, to develop an algorithm and simulation of a crowdsourced parking information system.

The major findings from each of these 4 steps in the systems engineering process are described below. The text of these four studies is included in their entirety in the appendix of this report.

Methodology

As outlined above, we combine qualitative, simulation and analytic models to analyze the problem of congestion due to cruising for parking. The problem is subdivided into 4 studies: 1) stakeholder assessment, 2) impact of information, 3) impact of pricing and 4) crowdsourced parking information system. The background of each study and summary of the major findings of each of these 4 studies are presented below.

Stakeholder Analysis

This report summarizes the approach and findings of the needs assessment and environmental scan of the parking situation within the city of Pittsburgh. The study's primary objective is to reflect stakeholders' input in the design of the integrated parking application project, an initiative that employs both centralized and decentralized systems in providing parking information within the City of Pittsburgh. By conducting interviews with key stakeholders and carrying out detailed data analysis, we are able to determine what issues and concerns exist around parking within the City of Pittsburgh. Not only does the report document these issues, it also highlights the key drivers of the demand for parking and provides insights that will inform the design and conceptualization of the integrated parking application project. The research employs a user-centric approach that emphasizes the centrality of stakeholders and end users in the design process. We also draw on the concept of socio-technical systems in creating a framework for the design process. The framework provides a platform on which stakeholders can reflect and contribute to the design process through a series of interactive methods and discuss their expectations of the project with the product development team. The platform also facilitates the examination of the political, institutional and cultural context within which the system will be implemented. This robust approach fosters community buy-in,

informs successful design and implementation strategies, builds credibility and ensures that the product addresses the deficits identified by the stakeholders.
We draw on a multitude of data sources in painting a rich picture of the parking and transportation ecosystem within the city of Pittsburgh. These include primary data from the semi-structured interviews, secondary data from local publications, U.S. Census data on workforce and commuting patterns and document review of relevant literature. An appreciable degree of the data analysis is directed at commuters. The rationale for this is two–fold: the need to focus on daytime parking when most of the peak demands in parking were observed, and the city's workforce size relative to its resident population. Pittsburgh's workforce to residential population ratio is 0.92, the highest of all the cities analyzed. On any workday, Pittsburgh's daytime population increases to 463,186. This net gain of 155,702 is as a result of workers commuting to the city and is equivalent to a 50.6% increase in the city's overall population[1].

The research effort brought to fore a series of findings. While the issue at present may not be as much of a supply deficit as the inability of patrons and commuters to be able to park in close proximity to their destination, a deficit in supply of parking spaces is expected on the horizon given Pittsburgh's favorable workforce growth trend. Compared to 2012 parking demand levels, our analysis revealed a projected estimate of 20,000 increased demand for parking spaces across the city by January 2018. Given the workforce composition trends, this increase will come solely from commuters who are not resident in the city. We recognize that a strategy that is primarily supply-driven is not feasible, thus our approach has been to embrace a menu of initiatives that will influence both commuters' demand for parking spaces and their commuting behavior. The proposed strategy section seeks to reflect these initiatives in the design and in subsequent phases of the integrated parking application project.

The insights obtained from the study are classified broadly into two sections – one is product specific and the other, policy related. We have used these insights to provide specific guidelines on the product development process further downstream and provided a condensed list of these guidelines and recommendations in Table E.1. Taking a cue from the interviews we had with stakeholders and the review of existing documents that highlighted the benefits of ParkPGH, we recommend that the smart parking app should serve as the core of the integrated parking application project. Added functionalities can be reflected either by building on ParkPGH's open source platform or by exploring synergies between the app and other existing initiatives. This is demonstrated by showing how to target the more than 210,000 non-city residents that commute to Pittsburgh on any work day by using Variable Message Signs (VMS) placed at major transportation arteries and relaying information sourced from ParkPGH.

Arguably, the most insightful realization we came away with is the potential impact the predictive module, presently conceived as having both a long term and short term predictive components, may have in shifting the populace towards utilizing a multi-modal transportation system. It will not only influence how individuals demand parking spaces but more importantly, but how they modify their travel demand pattern. This is achieved by allowing drivers to proactively plan their trips and explore the options available to them. A Pittsburgh Cultural Trust patron going to the Cultural District to see a matinee show in a week's time could use the long term predictive component to calculate the probability of finding a parking space. In a similar light, an individual who is heading downtown from Oakland in an hour or two could use the short term module to make a decision whether to drive or head to the East busway station to catch a bus. However, the benefits of the predictive module go beyond the demand side. On the supply side, garage operators could use the predictive information to better manage their facilities. For example, a predicted higher than normal demand for parking spots could allow a garage operator to artificially increase the facility's capacity by making provisions for valet parking. Further downstream, the information provided by the predictive module could be used to dynamically price parking spaces.

On the policy side, we examine a host of issues and provided suggestions on how they could be addressed. Some of these issues are price related while some address the factors that condition the parking market. A specific example is how to incentivize commuters to exercise parking choices that are socially optimal. Achieving this goes beyond pricing and the information provided by a smart parking application. One suggestion is decoupling parking privileges from the contract some organizations and corporations have with upper echelon employees and instead monetize these parking privileges. By freeing up the employee to park anywhere, this removes the friction such contracts create in the market. Secondly, the movement to a "pay as you use" regime moderates commuters' consumption of the service compared to leases' buffet pricing strategy that encourage over consumption.

Table E.1: Guidelines and Recommendations

Product Design Issues

Build on ParkPGH

- *Predictive parking*
  - ✓ Implement fully functional long and short term predictive modules;
  - ✓ Integrate predicted parking information with traffic flow patterns and estimated arrival times;
  - ✓ Influence commuters' travel behavior by linking predicted parking information with real time information for the public transit system
- *Expand coverage and add extra functionalities*
  - ✓ Expand the coverage of ParkPGH to surface lots and on-street parking;
  - ✓ Provide extra functionalities that include online reservations and the ability to lock in prices assuming a dynamic pricing regime exists

Explore synergistic opportunities

- Use variable message systems (VMS) to relay information provided by the application to the public;
- Decide on where the VMS could be strategically placed. Candidate options include I-376, I-279 and Route 28
- Increase the utilization of fringe parking garages by enabling them to function like Park & Ride outlets

Fine-tune design

- Create and demonstrate a prototype of the application before a group of six to eight key stakeholders that are highly networked, control essential resources and have legitimacy within Pittsburgh's parking industry. Where feasible, reflect their feedback in subsequent iterations of the design.

Policy Related Issues

Price/Proximity issues

- Incentivize individuals who park for extended period of time to use fringe parking facilities. One way to achieve this is to encourage institutions to decouple parking privileges from (upper echelon) employees' contract and instead monetize the privilege;
- Remove the distortion created by allowing price to vary for on-street parking while keeping it fixed for public off-street parking assets;

Others

- Invest in achieving better connections from the fringe parking facilities to the urban core;
- Rewrite existing parking ordinances in such a way that makes them more socially optimal;
- Sensitize policy makers as to the effect of local policy pronouncements;
- Invest more in public transit system since it holds more promise compared to getting the driving public to transition to a higher vehicle occupancy

Figure 1 This table summarizes the findings from the stakeholder assessment.

Smart Parking: Impact of Information

This study documents the methodological approach and findings of an evaluation process for a smart parking application that provides real time information on parking availability. The initiative is in response to the increased demand for parking spaces within the Pittsburgh Cultural District and the desire to improve patrons' parking experiences. Primary data, obtained through semi structured interview, in-person 5 and online surveys of patrons were utilized for the stakeholders' analysis, baseline data, process evaluation and outcome evaluation phases. Secondary data that utilized count data obtained from website use logs was employed for the output evaluation phase. The contributions of the evaluation framework are the insights it provides on how the key challenges created by the unique environment within which the system was deployed were addressed and how the framework could be employed in tackling response shift bias through the use of a binary system approach that uniquely identifies distinct cohorts of respondents. The report is especially timely given the prohibitively expensive cost of employing a supply side approach in addressing cities' parking problems, the ease of replicating the evaluation framework and product design and the wealth of information it provides to the body of knowledge in the evaluation of technological products.

Tables below document the major congestion mitigation and financial impacts of ParkPGH.

Table 4: Outcome related measures

DOCUMENTED OUTCOME	%
ParkPGH has made finding parking spaces easier	
% of respondents with positive response	57.2
Specific reduction in search time	
% of respondents reporting a reduction in search time	48.6
% of respondents with 1-3min reduction	17.1
% of respondents with 4-6min reduction	22.9
% of respondents with more than 6 min reduction in search time	8.6

Table 5: ParkPGH Estimated Impact

Impact Type	*Form of Measure*	*$/Unit*	*# of Unit*	*Savings ($)*
Time Value	Hour	20.44[6]	5746.6	117,460.5
Gas Expenditure	Gallon	3.50	2873.3	10,056.56
Cumulative Savings				**127,517.06**

Smart Parking: Impact of Pricing

The city of San Francisco is undertaking a large-scale controlled parking pricing experiment. San Francisco has adopted a performance goal of 60% to 80% occupancy for its metered parking. The goal represents an heuristic performance measure intended to reduce double parking and cruising for parking, and improve the driver experience; it follows a wave of academic and policy literature that calls for adjusting on-street parking prices to achieve similar occupancy targets. In this study, we evaluate the relationship between occupancy rules and metrics of direct policy interest, such as the probability of finding a parking space, the amount of cruising, and show how cruising and arrival rates can be simulated or estimated from hourly occupancy data. Further, we evaluate the impacts of the first two years of the San Francisco program, and conclude that rate changes have helped achieve the City's occupancy goal and reduced cruising by 50%.

The contributions of the study are:

- We evaluate the impacts of San Francisco's parking experiment, SF*park*
- We develop methods to infer cruising and the probability that a driver finds a space

Our major findings are

- SF*park* is slowly achieving its goal of moving occupancy into a target range of 60-80%
- SF*park* has reduced cruising for parking by about 50%

Smart Parking: CrowdSourced Parking Information System

Several cities are undertaking ***expensive*** parking management and pricing programs. For example, San Francisco has recently deployed a $20 million parking information and pricing program called SFPark. The goal of this study is to develop an **inexpensive** parking information and management system by leveraging Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications. Our approach to leveraging V2V and V2I to develop a parking management system extends our previous work in parking management systems. We have developed a novel parking prediction scheme. We propose using data from V2V and/or V2I to infer the three key inputs used in our previous research. Each driver looking for parking has a belief about the current availability of parking. When the driver comes into contact with other drivers, updates his belief about the current availability of parking.

One of most frustrating aspects of driving throughout urban centers is parking. On top of waiting through congested intersections, one must also search for usually scare on-street or off-street parking. One cause of frustration is the fact that each person looking to park must independently observe the parking landscape, which increases congestion on the roads. This is very wasteful, for if everyone could exchange their information we could greatly reduce the amount of time spent cruising for parking.

We added an information model on top of a network of queues to capture how a vehicle-tovehicle information mechanism might effect congestion. The reason for the use of a queueing model is simple: even during times of low congestion one must often wait before proceeding to the next part of the network. For this reason, it is not unnatural to view modern city traffic systems as networks of queues, that is, stations where one must wait before being served and moving on. The parking infrastructure can also be thought of as a queue, even though its underlying characteristics appear different from that of a classical queueing system.

Each component of the transportation infrastructure will be represented by a different type of queue in a queueing network. Our transportation network is composed of roads, garages, and destinations. We model the network as a graph where each node is a queue that represents one of these three components. Queues are typically described by a process that specifies the nature of any arrivals to the queue, and a process that specifies the service times when the server is in use. Nodes that represent the road network will be modeled using a single-server queue. Road queues will form an inhomogeneous Poisson processes, that is, arrivals will form a Poisson process with an arrival rate that depends on time (roads with k lanes will be modeled with multi-server queues with k servers). Garages will be modeled with time-varying finite-capacity loss queues. Loss systems turn arrivals away when the system is full. By using finite capacity queues for garages, we are able to capture part of the reasons drivers often cruise for parking: lack of availability[1]. Lastly, destination nodes will be modeled much like road queues, except the arrival rates will depend on the types of events that occur at that particular destination. We note that few nodes will receive arrivals from outside the network, but those that do will have time dependent arrival rates to capture time of day effects in transportation.

Each driver arrives to the network with a particular destination in mind and a fixed route on how to get there. When a driver arrives at their destination they choose where to park by selecting one of the adjacent garage nodes. After departing from their parking spot they then choose a new destination by sampling from some distribution d[2].

Drivers also observer the current state of the queue that they depart from, and note the time of their observation. These observations server as the information that is shared with other drivers in the network. This allows drivers to accumulate information about the state of the network as they travel without having to traverse the entire network. Information is exchanged when two drivers are concurrently located at a node in the network, and drivers incorporate new information into their belief about the state of the system[3]. Drivers use this information when deciding where to park after reaching their destination. Each driver chooses their garage by drawing from the multinomial distribution with probabilities $p1,...,p_n$ where n is the total number of garages near the destination, and pk is the fraction of all vacant parking spaces located in garage k.

---

[1] On-street parking is modeled as just another garage in this model. To distinguish it from an actual garage we can change its distance to destination nodes, or its costs relative to a garage node.

[2] For the simulations discussed here, the distribution d is taken to be the uniform distribution.

[3] One way to incorporate information is with Bayesian updating. Another way is for drivers to completely adopt information that is more up-to-date than their own and reject information that is older than their own.

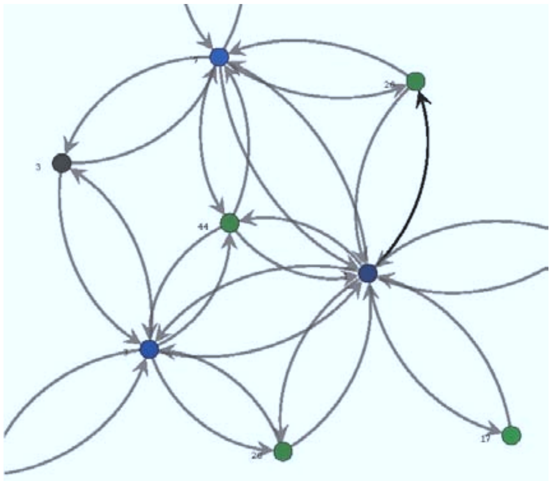


Figure 1 Segment of a sample transportation network. Grey nodes represent road queues, blue nodes represent destination queues, and green nodes represent garage queues. The dark arrow shows a driver parking at a garage that is near their destination.

Under this setup, this model is similar to other networks of queues. For example, using a classed Jackson network or a Kelly networks, one could represent a drivers destination and level of information using classes [2, 1]. Unfortunately, in a Kelly network drivers are not able to change their class to flect new information. Some models, such as one presented by Massey in [3], allow drivers to change classes but not in a way that is congruent with our information mechanisms. Other models, such as the one given by Serfozo in [4], allow some routing based on the state of the network, but place restrictions on routing to the shortest queue (which is what we do in our model). Also, in our model drivers do not have access to the true state of the system, and rely on information that is not always the most up-to-date. Some of the other differences between our model here and a classical classed Jackson network is the inclusion of loss queues and time varying arrival rates.

We ran several preliminary simulations of the above model, trying to ascertain how the level of drivers capable of exchanging information affects the behavior of the system. The percentage of drivers capable of exchanging information, denoted p, was one of the following values: $p \in \{0, 0.25, 0.5, 0.75, 1\}$. Drivers that do not share information choose their parking garage uniformly at random. We use the scenario where no driver shares information, $p = 0$, as the baseline of comparison. As mentioned above, drivers that have information select their parking garage by drawing from the multinomial distribution with probabilities $p_1, \ldots, p_n$ where n is the total number of garages near the destination, and p_k is the fraction of all vacant parking spaces located in garage k. If a driver does not have information on the availability of a particular garage they assume the garage is half-empty (or half-full, depending on your mood) and calculate p_k [4]. After parking, drivers pick a new destination node and head there.

Each simulation was initialized to an empty network where one node accepted arrivals from the outside world and did so until the network reached a predetermined number of drivers. The total garage capacity was set so that it could accommodate two-thirds of all drivers. Destination nodes were located throughout the grid and each had multiple garages nodes that we adjacent. If two destination nodes were adjacent to one another, they often shared at least one garage node [5]. The departure rate for each

[4] When no information is available, another alternative would be to calculate p_k based on historical availability.

non-garage node was fixed to 3, and did not vary with time. For each simulation the departure rate, µ, of the garages was fixed to one of the following two values: µ ∈{0.05, 0.15}.

We measure the amount of time the average driver spends looking for parking for all combinations of departure and participation rates mentioned above. Figure 2 shows the results of the simulation when the departure rate of each garage is set to µ =0.15. Drivers spend 25% and 31% of their time looking for parking. As the proportion of drivers exchanging information increases, the amount of time drivers spend looking for parking decreases. Note that the level of improvement over the baseline of p = 0 is about 6 percentage points, which is a 20% reduction in cruising time.

We find in Figure 3 the results when µ =0.05. In this scenario drivers spend much more time cruising for parking. The availability of information helps but not to the same degree as we found when µ =0.15. Lastly, Figure 4 shows different results from the two scenarios discussed above.

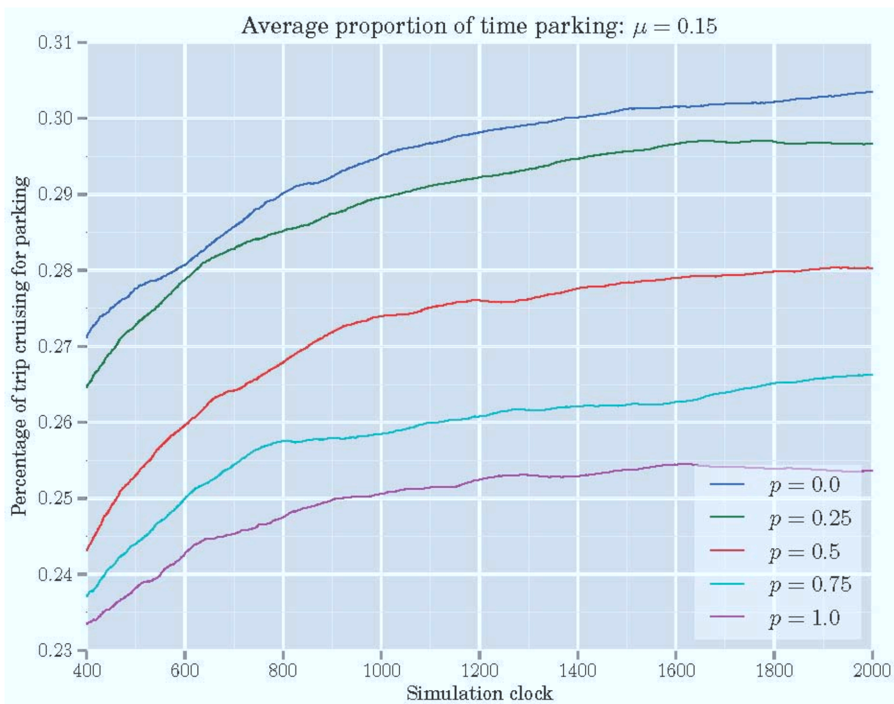


Figure 2 Plots the percentage of time drivers spend looking for parking as the system settles to equilibrium. Each line represents the differing numbers of drivers participating in information sharing. Information sharing reduces congestion.

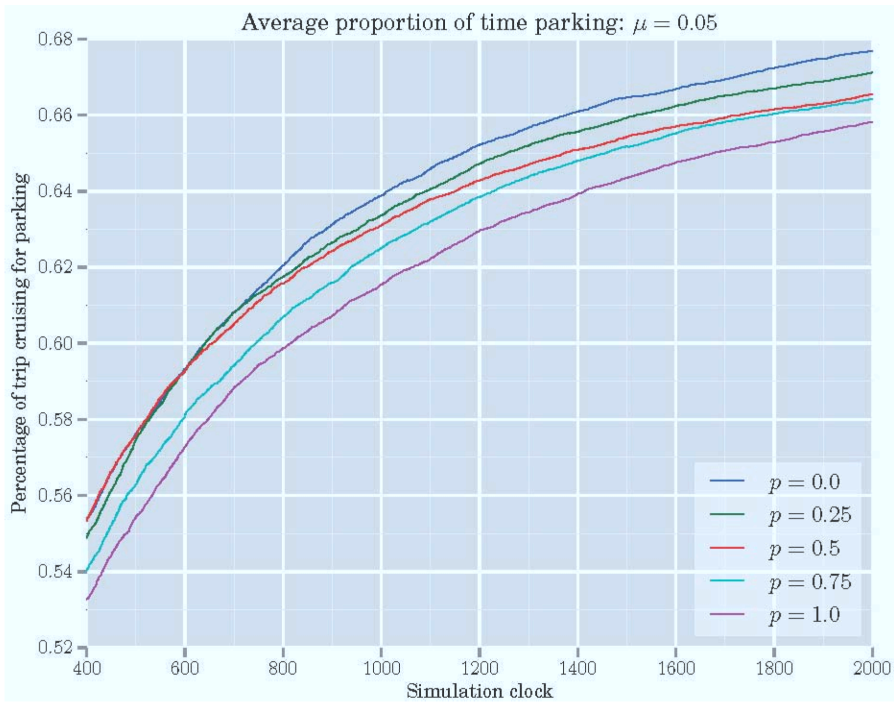


Figure 3: Plots the percentage of time drivers spend looking for parking as the system settles to equilibrium. Here, the departure rate for the garages is much lower than in the simulation used in Figure 2, leading to much more cruising.

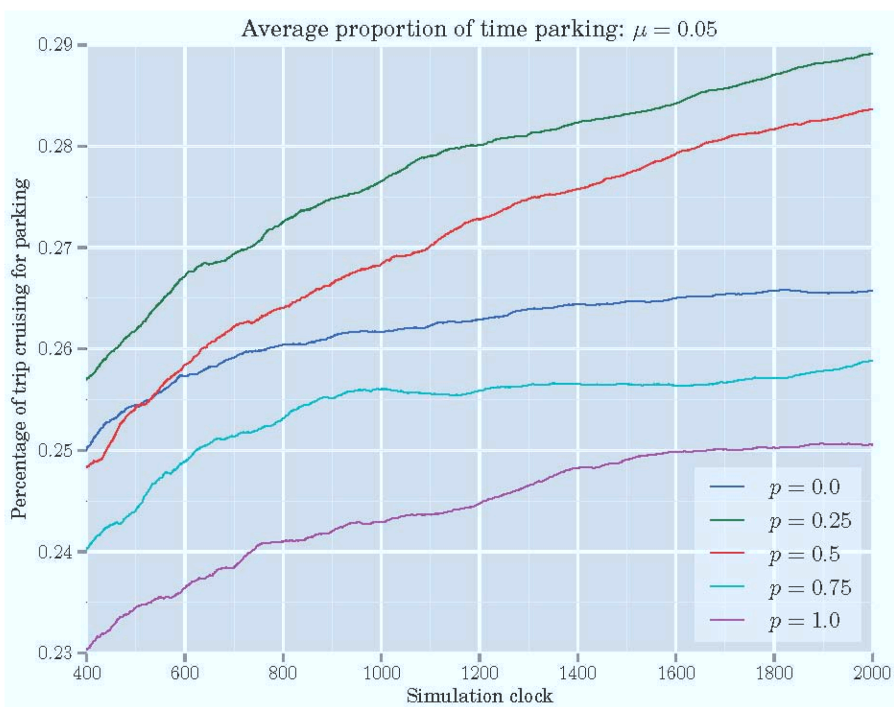


Figure 4 Plots the percentage of time drivers spend looking for parking as the system settles to equilibrium. Performance decreases when there is a small number of people sharing information and increases as more people share information.

The simulation was run on an entirely different graph than the first two. Performance decreases when a small number of people participate in information sharing, but performs well when the percentage of the population participating is 75% or 100%.

The results thus far indicate that large amounts of information improves efficiency, allowing drivers to quickly locate available parking. One of the caveats to this finding is that performance is very sensitive to both the topology of the network and calibration to the parameters in the network. Also, we find varying results when specifying how drivers interact with information. If drivers always park at the garage that has the most vacancies, then the system can have worse performance as the percentage of people sharing information increases. This implies that these findings are by no means robust. The way users engage with information matters, and differing implementations of information sharing leads to very different results. Also, different transportation networks have differing outcomes as well, making it very difficult to generalize to all networks. The results presented so far show that under certain circumstances, the sharing of information greatly reduces congestion.

References

[1] F. P. Kelly. "Networks of Queues". In: Advances in Applied Probability 8.2 (1976), pp. 416–432.

[2] F. P. Kelly. "Networks of Queues with Customers of Different Types". In: Journal of Applied Probability 12.3 (1975), pp. 542–554.

[3] W. A. Massey. "Open Networks of Queues: Their Algebraic Structure and Estimating Their Transient Behavior". In: Advances in Applied Probability 16.1 (1984), pp. 176–201.

[4] R. F. Serfozo. "Markovian network processes: Congestion-dependent routing and processing". English. In: Queueing Systems 5.1-3 (1989), pp. 5–36. doi: 10.1007/BF01149184.

Research Papers

The 4 studies presented in this report are attached here, as an appendix.

1. Hampshire, R.C. and T. Fabusyi, ``Needs Assessment for the Integrated Parking Application Project," 2013
2. Hampshire, R.C. and T. Fabusyi, ``Evaluation of a Smart Parking System," *Transportation Research Record: Journal of the Transportation Research Board*, 2013.
3. A. Millard-Ball, R. Weinberger and R.C Hampshire, ``Is the curb 80% full or 20% empty? A Dynamic Parking Pricing Experiment in San Francisco," under review at *Transportation Research Part A.*
4. D. Jordon, ``On the Modeling of Parking with Dynamic Arrival Rates: Incorporating Information"

NUMERITICS

Client: Traffic21, Carnegie Mellon University.

September 2013

Needs Assessment for the Integrated Parking Application Project

Tayo Fabusuyi, *Numeritics*
&
Robert Hampshire, *Heinz College, Carnegie Mellon University*

The authors would like to express their gratitude to the stakeholders that participated in the semi-structured interview sessions.

EXECUTIVE SUMMARY

This report summarizes the approach and findings of the needs assessment and environmental scan of the parking situation within the city of Pittsburgh. The study's primary objective is to reflect stakeholders' input in the design of the integrated parking application project, an initiative that employs both centralized and decentralized systems in providing parking information within the City of Pittsburgh. By conducting interviews with key stakeholders and carrying out detailed data analysis, we are able to determine what issues and concerns exist around parking within the City of Pittsburgh. Not only does the report document these issues, it also highlights the key drivers of the demand for parking and provides insights that will inform the design and conceptualization of the integrated parking application project.

The research employs a user-centric approach that emphasizes the centrality of stakeholders and end users in the design process. We also draw on the concept of socio-technical systems in creating a framework for the design process. The framework provides a platform on which stakeholders can reflect and contribute to the design process through a series of interactive methods and discuss their expectations of the project with the product development team. The platform also facilitates the examination of the political, institutional and cultural context within which the system will be implemented. This robust approach fosters community buy-in, informs successful design and implementation strategies, builds credibility and ensures that the product addresses the deficits identified by the stakeholders.

We draw on a multitude of data sources in painting a rich picture of the parking and transportation ecosystem within the city of Pittsburgh. These include primary data from the semi-structured interviews, secondary data from local publications, U.S. Census data on workforce and commuting patterns and document review of relevant literature. An appreciable degree of the data analysis is directed at commuters. The rationale for this is two–fold: the need to focus on daytime parking when most of the peak demands in parking were observed, and the city's workforce size relative to its resident population. Pittsburgh's workforce to residential population ratio is 0.92, the highest of all the cities analyzed. On any workday, Pittsburgh's daytime population increases to 463,186. This net gain of 155,702 is as a result of workers commuting to the city and is equivalent to a 50.6% increase in the city's overall population[1].

The research effort brought to fore a series of findings. While the issue at present may not be as much of a supply deficit as the inability of patrons and commuters to be able to park in close proximity to their destination, a deficit in supply of parking spaces is expected on the horizon given Pittsburgh's favorable workforce growth trend. Compared to 2012 parking demand levels, our analysis revealed a projected estimate of 20,000 increased demand for parking spaces across the city by January 2018. Given the workforce composition trends, this increase will come solely from commuters who are not resident in the city. We recognize that a strategy that is primarily supply-driven is not feasible, thus our approach has been to embrace a menu of

[1] These figures are based on 2011 data. It also bears stating that of the 15 cities that featured in the multi city analysis, none comes remotely close to the percentage increase figure cited.

initiatives that will influence both commuters' demand for parking spaces and their commuting behavior. The proposed strategy section seeks to reflect these initiatives in the design and in subsequent phases of the integrated parking application project.

The insights obtained from the study are classified broadly into two sections – one is product specific and the other, policy related. We have used these insights to provide specific guidelines on the product development process further downstream and provided a condensed list of these guidelines and recommendations in Table E.1. Taking a cue from the interviews we had with stakeholders and the review of existing documents that highlighted the benefits of ParkPGH, we recommend that the smart parking app should serve as the core of the integrated parking application project. Added functionalities can be reflected either by building on ParkPGH's open source platform or by exploring synergies between the app and other existing initiatives. This is demonstrated by showing how to target the more than 210,000 non-city residents that commute to Pittsburgh on any work day by using Variable Message Signs (VMS) placed at major transportation arteries and relaying information sourced from ParkPGH.

Arguably, the most insightful realization we came away with is the potential impact the predictive module, presently conceived as having both a long term and short term predictive components, may have in shifting the populace towards utilizing a multi-modal transportation system. It will not only influence how individuals demand parking spaces but more importantly, but how they modify their travel demand pattern. This is achieved by allowing drivers to proactively plan their trips and explore the options available to them. A Pittsburgh Cultural Trust patron going to the Cultural District to see a matinee show in a week's time could use the long term predictive component to calculate the probability of finding a parking space. In a similar light, an individual who is heading downtown from Oakland in an hour or two could use the short term module to make a decision whether to drive or head to the East busway station to catch a bus. However, the benefits of the predictive module go beyond the demand side. On the supply side, garage operators could use the predictive information to better manage their facilities. For example, a predicted higher than normal demand for parking spots could allow a garage operator to artificially increase the facility's capacity by making provisions for valet parking. Further downstream, the information provided by the predictive module could be used to dynamically price parking spaces.

On the policy side, we examine a host of issues and provided suggestions on how they could be addressed. Some of these issues are price related while some address the factors that condition the parking market. A specific example is how to incentivize commuters to exercise parking choices that are socially optimal. Achieving this goes beyond pricing and the information provided by a smart parking application. One suggestion is decoupling parking privileges from the contract some organizations and corporations have with upper echelon employees and instead monetize these parking privileges. By freeing up the employee to park anywhere, this removes the friction such contracts create in the market. Secondly, the movement to a "pay as you use" regime moderates commuters' consumption of the service compared to leases' buffet pricing strategy that encourage over consumption.

Table E.1: Guidelines and Recommendations

Product Design Issues

Build on ParkPGH

- *Predictive parking*
  - ✓ Implement fully functional long and short term predictive modules;
  - ✓ Integrate predicted parking information with traffic flow patterns and estimated arrival times;
  - ✓ Influence commuters' travel behavior by linking predicted parking information with real time information for the public transit system
- *Expand coverage and add extra functionalities*
  - ✓ Expand the coverage of ParkPGH to surface lots and on-street parking;
  - ✓ Provide extra functionalities that include online reservations and the ability to lock in prices assuming a dynamic pricing regime exists

Explore synergistic opportunities

- Use variable message systems (VMS) to relay information provided by the application to the public;
- Decide on where the VMS could be strategically placed. Candidate options include I-376, I-279 and Route 28
- Increase the utilization of fringe parking garages by enabling them to function like Park & Ride outlets

Fine-tune design

- Create and demonstrate a prototype of the application before a group of six to eight key stakeholders that are highly networked, control essential resources and have legitimacy within Pittsburgh's parking industry. Where feasible, reflect their feedback in subsequent iterations of the design.

Policy Related Issues

Price/Proximity issues

- Incentivize individuals who park for extended period of time to use fringe parking facilities. One way to achieve this is to encourage institutions to decouple parking privileges from (upper echelon) employees' contract and instead monetize the privilege;
- Remove the distortion created by allowing price to vary for on-street parking while keeping it fixed for public off-street parking assets;

Others

- Invest in achieving better connections from the fringe parking facilities to the urban core;
- Rewrite existing parking ordinances in such a way that makes them more socially optimal;
- Sensitize policy makers as to the effect of local policy pronouncements;
- Invest more in public transit system since it holds more promise compared to getting the driving public to transition to a higher vehicle occupancy

SECTION
ONE

1 INTRODUCTION

This report provides an overview of the methodology used for the needs assessment and stakeholder analysis of the parking situation within the city of Pittsburgh. The methodology utilized two key approaches – one, the needs assessment conducted with stakeholders' input examines the present and the desired state of parking using input from key stakeholders. The second situates the responses obtained from stakeholders within the broader environment by conducting an environmental scan[2]. The environmental scan was conducted not only in a static sense but by also projecting into the near future to provide an assessment of the prospective state assuming the status quo continues.

The needs assessment will establish if deficit exist in systems' performance and document the nature and extent of the deficit. Complementing this is the environmental scan that provides the necessary context that adequately reflects the peculiarities of the Pittsburgh environment. The synthesize information is subsequently used to identify the best option in a menu of product designs that best address the shortcomings identified. The analysis is carried out by identifying the key stakeholders and scheduling interviews with them to identify the system's shortcomings. The interviews also include an assessment of what the ideal system should be. This is more qualitative in nature. Apart from stakeholders' identification, parking related data was also collected and analyzed. This complements the problem identification addressed in the earlier phase. The objective here is to situate the information obtained from the stakeholders in a broader context. The analysis is also used to identify structural constraints, synergistic opportunities within the system that could be explored and key levers that could be utilized during the product design phase.

The information obtained from both the stakeholders' interview and the environmental scan was subsequently distilled into a concise whole that provides insight on the design of the planned integrated parking application. The result of the exercise is expected to inform the exploratory design of the product development phase. Issues addressed include the examination of the forms by which the identified shortcomings in systems performance could be addressed and questioning the initial set of assumptions made by the product development team – for example, given the nature of the deficit, is a demand side intervention the ideal policy response?

Our approach is a user centric one - this ensures that the deficit is defined by end users. This unique insight, provided by key stakeholders, fosters community buy-in, informs successful design and implementation strategies, builds credibility and ensures that the product addresses the deficits identified by the stakeholders. Borrowing from comments from stakeholders, we have framed the needs assessment as a gap analysis with the objective being to improve current performance or correct a deficiency. However, in examining the feasible strategies, we have

[2] Environmental scan is used here as a component of a strategy development process.

chosen not to examine the perceived deficit in isolation. Rather, we have couched the design approach within the context of the broader environmental constraints and issues. This is crucial in ensuring that the program intervention will be effective in addressing the perceived shortfalls in system performance.

The report is divided into five sections. Section two documents the methodology used to identify the shortcomings in the existing system. It also examines the feasibility of addressing these shortcomings given the broader structural factors. The third section focuses on the interviews with the stakeholders. It identifies the stakeholders within Pittsburgh who have influence and interest on parking issues. It also focuses on designing the protocol and developing the instruments that will be used for the in-person interview, refining the instrument designed as to content, field testing and finalizing the instrument design. The interviews are conducted for each identified stakeholder and summary report generated that document the process and results of the stakeholders' semi structured interviews.

Section four addresses transportation system constraints and key concerns that impact on parking. It is driven by a combination of data elements and document review that address both parking demand and supply side issues. This combination of data sources and document review paints a rich picture of the parking and transportation ecosystem within the City of Pittsburgh. Section five, the strategy section situates the input from key stakeholders within the broader context and local peculiarities of the City of Pittsburgh provided by the environmental scan of Section four. The new insight obtained both from the needs assessment and the environmental scan will be used to provide substance on the tentative strategy that informed the integrated parking application project.

SECTION
TWO

2 METHODOLOGY

In order to have a robust framework, we have employed a socio-technical system approach to the design of the integrated parking application project. These are a class of engineering systems made up of both a physical domain where the technical system resides and an institutional sphere that defines the context within which the physical domain is implemented (1). In addition, we have also emphasized a user centric design, a design process in which user requirements are considered from the get-go and included all through the product development cycle (2). Stakeholders and end-users input are obtained and reflected in the design process through a series of interactive methods. This process creates a platform on which stakeholders could reflect on the key issues, table their concerns and discuss their expectations of the project with the product development team. These are examined for feasibility and if possible, they are reflected in subsequent designs of the socio-technical system.

The International Standards Organization (ISO) *Human Centred Design for Interactive Systems* (3) specifies six principles of a user centered design approach:

- The design is based upon an explicit understanding of users, tasks and environments.
- Users are involved throughout design and development.
- The design is driven and refined by user-centered evaluation.
- The process is iterative.
- The design addresses the whole user experience.
- The design team includes multidisciplinary skills and perspectives.

2.1 Panoramic View of the Methodology[3]

Incorporating the recommendations above, we have placed the users squarely at the core of both the design process and product implementation. We have actively sought the suggestions and input of key stakeholders in framing the design and intend to reflect their input with regards to usability and evaluating the product's value added post deployment. The key advantage of the user-centric design is that a more thorough understanding of the non-technical factors that affect the use of the technology to be deployed emerges by involving stakeholders and users. This ensures that the product is effective – in terms of addressing the deficit it is intend to correct, and efficient – in terms of usability issues. The iterative process between users and the design team also promotes buy-in and a sense of ownership. In addition, carrying stakeholders and end users along and making them an integral part of the process allows for a better management of their expectations. Figure 2.1 provides a diagrammatic explanation of the process.

[3] The methodology addresses not only the needs assessment phase of planned project. It also provides insight on all stages deemed relevant in the design and implementation of the smart parking application project.

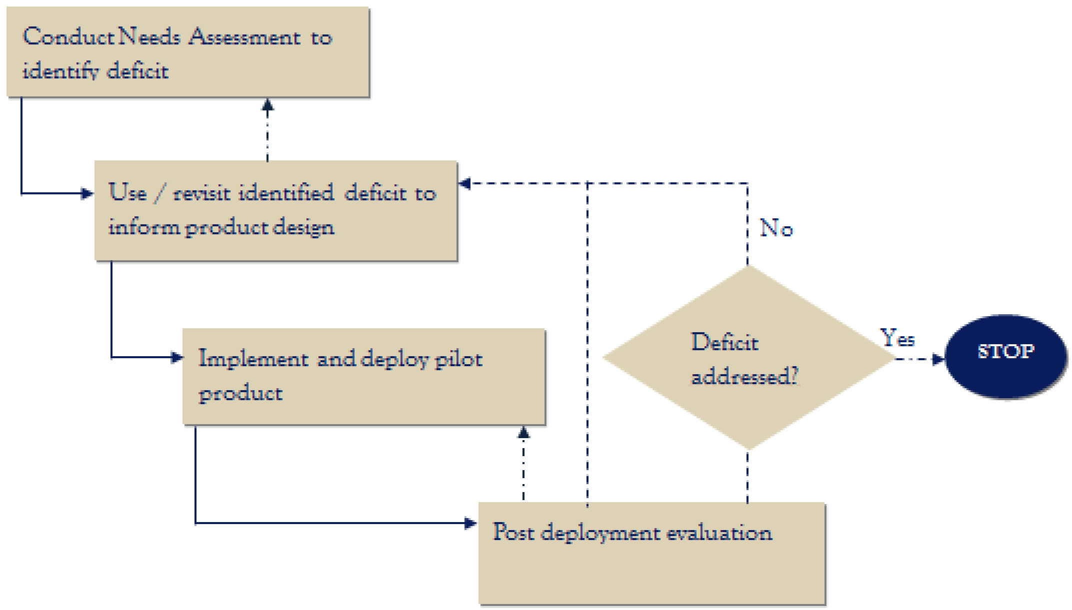


Figure 2.1: Overview of the Methodological Framework

Figure 2.1 presents the overview of the methodological framework. It is made up of four stages of a broadly conceived product development life cycle itemized below:

- Specify the nature and if possible, magnitude of the present deficit;
- Design of the socio-technical system;
- Implementation of the design and;
- Post Deployment evaluation.

Stage 1 is the focus of the present research effort and entails the identification of key stakeholders and obtaining input from them with regards to the existing parking situation with the City of Pittsburgh. In addition, information is sourced from them with regards to their expectations of the planned application. This information is subsequently used to specify the nature and magnitude of existing system deficits. In stage 2, the profile of the deficit constructed is passed to the product development team whose objective is to reflect this insight in the product's design. Oftentimes, this will be a two-way street in that various iterations of the design, for example, paper prototypes or a simulated, non-operational software prototypes are shared with the stakeholders and the back and forth process ceases only when stakeholders feel sufficiently comfortable with the design[4]. On the part of the design team, this process fosters a deeper understanding of the intended use of application while stakeholders end up having a greater sense of ownership.

[4] This involves the consideration of ends in such a way that takes into consideration the structural issues and the means (resource constraints) by which the ends will be achieved. This mutual adjustment of ends and means helps to match what is desirable (in terms of stakeholders' expectations) with what is feasible. Typically, this will be an inferior set of stakeholders' wish list that reflects the structural/environmental constraints and limitations of the product design team.

The next stage will be the deployment of an operational prototype for the pilot deployment phase. The objective here is to observe how end users interact with the product, evaluate usability metrics, and address efficiency issues before the application is scaled up. We envisage surveying between 500 -1000 end users to collect data on these issues. Some of these issues could be addressed by modifying the product's design in its present iteration while others may be more involved, requiring changes to be made to the product's design. A baseline of relevant performance metrics will also be collected before product deployment. Stage 4 focuses on the product's effectiveness. Once the product[5] is rolled out, post deployment metrics are calculated and compared to the baseline ones in order to establish the product's value-added. This latter part is done in a summative sense and could be couched as answering the question – has the application been successful in addressing the identified deficit?

[5] Before the product development can proceed beyond the pilot phase, there is the need to ascertain that all formative issues have been resolved. We could classify this broadly into two categories – formative issues that are structural (those that speak to the fundamental issues the product is meant to address) in nature and those that are quality related (aesthetics, ease of use, etc.). We agree that this categorization is artificial in nature since a quality type issue, for example the granularity of the information provided to commuters, depending on the noise/signal ratio, may end up being structural one.

SECTION
THREE

3 SEMI-STRUCTURED INTERVIEWS

3.1 Overview

Section three; the summary report of the semi-structured interviews documents the process and findings of a series of semi-structured interviews conducted for a group of stakeholders between Feb14th and 21st, 2013. The objective of the interviews was to establish stakeholders' assessment as regards the present parking situation within the City of Pittsburgh. The platform was also used to ascertain any specific expectations as regards the planned integrated parking project.

A check list of questions related to the subject was utilized. Provision was also made to entertain follow-up questions or questions deemed relevant to the discussion by the interviewee. This allows for much richer insight and often times, enables the stakeholder to lead the evaluation team in a different, yet discerning direction not previously thought of. The responses were summarized into the main discussion points. The summary notes were subsequently categorized into a limited number of sections.

A wide range of stakeholders were interviewed including individuals and organizations who utilize parking spaces and those who provide or manage them. On the suppliers' side, we talked to both management and owners of off-street parking garages. On the demand side, we interviewed organizations such as the Pittsburgh Cultural Trust (PCT), who often required bulk parking spots. The checklist or questions were slightly modified to adequately address the issues and concerns of the category of the individual or agency being interviewed.

3.2 Stakeholders' Identification and Protocol Design

Stakeholders were identified based on their roles and legitimacy, the resources they control or the responsibilities they have and finally, the relationship they have within the parking community or greater transportation ecosystem. In all, ten organizations were invited to participate.[6] Eight confirmed their interest; however due to scheduling difficulties interviews were only conducted for seven of these organizations. Questions addressed during the interviews include:

- What are your major concerns as regards the parking situation within the City of Pittsburgh? From your own perception and from that of your patrons, would you say that there is a lack of available parking downtown/Oakland/East Liberty/Shadyside/South Side/Other? Please elaborate.

[6] Invitations were sent out to the Pittsburgh Cultural Trust (PTC); Benter Foundation; Hillman Family Foundation; ALCO Parking; Pittsburgh Parking Authority; Pittsburgh Downtown Partnership (PDP); City of Pittsburgh; South Western PA Commission; Urban Redevelopment Authority of Pittsburgh; Oakland Business Improvement District (OBID) and East Liberty Development Inc. (ELDI).

- What preconditions, limitations or problems do you foresee may affect the implementation or the effectiveness of the integrated parking application project? Are there specific issues or areas of concern that you suggest we focus on?

- What impact, if any, do you think an initiative like IPAP will have on the public? How best do you think we could engage the community on this initiative?

- What is your perception of the role of technology in finding a parking space? Would you say there may be legitimate concerns about individuals not being able to get parking information because of usability or restricted access issues? If so, would you have suggestions as to how these concerns could be addressed?

- Could you make suggestions as regards other stakeholders that are active in this space (stakeholders with strong legitimacy, and/or strongly networked and/or that exercise control over essential resources) that you think it will be helpful for us to talk to?

- Would you know of any similar or complementary initiatives in the pipeline within the Pittsburgh transportation ecosystem? If so, is there someone you would recommend we contact to discuss such initiative?

- What specific issues do you think the Integrated Parking Application Project could help address? Are there any specific expectations, needs, additional ideas or functionalities you or your agency have as regards the project?

- Looking forward, how best do you think we could build stronger linkages to other components of Pittsburgh transportation ecosystem?

3.3 Results

The nature of the interviews and the instrument used allowed for focused dialogues. By providing some flexibility as regards the issues to be explored, we were able to get rich insights on parking related issues. In some situations, the individual being interviewed was given some leeway as regards specific issues she feels are relevant and that deserves more attention. On aggregate, interviewees were open and engaged throughout the interview process. Specific issues addressed for the individuals interviewed are provided in Table 3.1 and the subsequent section presents detailed results of the interviews with the responses categorized into separate sub-sections.

Table 3.1: Semi- Structured Interviews

Organization / Agency	*Individuals Interviewed*	*Issues Addressed*
Pittsburgh Parking Authority (PPA)	Dave Onorato and Christopher Speers	• Perception on the generally held view of not enough parking spots; • Policy environment and possible lack of political will; • How best to engage surface lot owners in the discussions; • Need for standardization across garage operators as regards software/hardware that are often incompatible; • The public's assessment of the new on-street parking meters; • Challenge of coordinating across the disparate agencies or organizations that make up the parking industry.
City of Pittsburgh	Patrick Roberts	• The importance of data in positioning Pittsburgh as a city of the future; • Zoning Ordinances; • Perception of parking as a binding constraint; • IBM Report on the Smarter Cities Challenge (4).
City Lab	Eve Picker	• Achieving a healthy mix of residential and commercial uses downtown; • Lack of a strategic framework when the City deals with developers; • The need for a more proactive way of thinking on the part of developers with regards to the needs of potential tenants; • Embracing a shift to a truly multimodal transportation system.
ALCO Parking	Merrill Stabile	• ParkPGH • Interoperability issues • Reservation and pre-selling of parking spaces • Low turnover and the right incentives to address this.

Table 3.1 *(contd.)*

Organization / Agency	*Individuals Interviewed*	*Issues Addressed*
Pittsburgh Cultural Trust (PCT)	Marc Fleming	• Leases as a prime commodity; • Planned expansion to ParkPGH; • Challenges with implementing dynamic pricing; • Specific suggestions on improving ridership of the public transit system; • The centrality of the City of Pittsburgh in the discussion process; • Making provision for patrons who are not tech-savvy;
Hillman Foundation	Dave Rogers	• Need to delineate perception driven viewpoints from ones that are data driven; • Suburbanites and their perception of safety especially around the downtown area; • Challenges with engaging the City in the process; • Ascertaining the extent to which technological products are being used; • Limiting factor analysis.
Oakland Business Improvement District (OBID)	Alex Coyne	• Turnover and parking duration; • Tech related initiatives that are currently being implemented; • How best to leverage on the assets that large entities can bring onto the table; • Public transit system and the Bus Rapid Transit; • Perception of parking as a binding constraint.

Perception of the parking situation

While most of the individuals we spoke to felt that there are not enough parking spots, they agreed that the issue is less about the shortage of parking spaces and more about the deficit of parking spots in close proximity to their destination. Several examples were provided to buttress this point. One respondent said that he did not understand why spaces would be available at Grant Street parking garage for $5 and yet patrons would be willing to pay upwards of six times that amount to park closer to see a Steelers game. He further posed the question – is it the proximity issue or is it that they do not know that the Grant Street option exists?

Following up on the aforementioned, individuals surveyed in an earlier study related to parking availability in downtown Pittsburgh cite safety as a key issue (5). There may be significant negative misperceptions regarding the safety of walking downtown. In addition, a 3 minute walk to the event venue could be perceived as appreciably lengthier with users. This may be more of the case when individuals are coming for events – opera, matinees, black tie etc. where these individuals may not want to walk long distance due to their dressy attire.

The negative security assessment was more pronounced among suburbanites who work in the city – primarily downtown - or come to Pittsburgh frequently. They may rarely venture outside their comfort zone when they come downtown. Getting these individuals to change their parking behavior from one of utilizing prime parking spots to using the fringe parking facilities – for example, the Grant Street Parking Garage or the parking assets on the North Shore may be an uphill task.

Another concern mentioned frequently by businesses is that there is little turnover of parking spots. In the downtown area, this is primarily attributed to employees parking in prime spots, while students are chiefly responsible for the little or no turnover in the Oakland area. Finding a way to incentivize people who park long term to relocate their cars could go a long way in addressing the perceived deficit.

Political Environment and Policy Options

While not intentionally so, many of the deliberations we had with stakeholders revolved around the subject of policy options and the prevailing political environment. For a host of reasons, the consensus is that it is imperative that the City be brought more on board. For one, there are assets owned by the City that are crucial to the intelligent parking system - for example, on street road sensors that are at present not turned on. Some of the issues identified include the rate structure for publicly owned parking assets, zoning ordinances and the associated red tape.

.

One of the concerns we heard over and over is the inability of the City to have a more comprehensive view of parking. At times this has led to sub-optimal outcomes and lost synergistic opportunities. A prime example is making the case for the recent varying rate structure for on-street parking, a rate structure that is being implemented in parallel with the fixed price regime for off-street parking. While a variable rate may be ideal, how can this be justified given that the pricing regime for on-street parking is totally divorced from off-street parking even though they are close substitutes?

Finally, there may be need for organizational changes to improve efficiency. For example, it may be more effective having one organization oversee both parking and transit to explore synergies that such an organizational structure facilitates - San Francisco presents an excellent example of this.

With regards to the policy framework, the consensus across the stakeholders is that there is the need to have extensive discussions on zoning ordinances.[7] The consensus among our interviewees was that if it is not in the zoning ordinance, it does not get done. There was a fire incident where three houses burned down because emergency vehicles couldn't get through the road. While only tangentially related to parking, these issues merit an examination. For example, could this have been averted assuming a zoning ordinance designating only one side of the street for parking exists?

In addition, interviewees said dealing with government entities is not always simple. For example, with regards to real estate development, some of the respondents felt that there was neither a common platform nor a strategic framework in place to deal with real estate developers. Rather things are done on a case by case basis and that by so doing the city had left a lot of money on the table by not having a uniform approach in addressing developers. The lack of uniformity as regards these bilateral deals unnerves some developers, particularly the smaller players who feel like they may have to jump through extra hoops when negotiating with the City.

New initiatives and public's receptiveness

One of the issues we raised with stakeholders is the public's receptiveness to new initiatives that are technology based. What got the most buzz is the new "pay by license plate" on-street parking meters. While the assessment of the initiative has been generally positive, we were reliably informed that there have been some complaints as regards punching in the wrong plate number and the expectation of an automatic receipt being provided, which is actually optional. Confusion with the new system is expected to taper off over time. In another new initiative, the Pittsburgh Parking Authority (PPA) is working on providing a feature on their website that allows individuals to reserve parking spaces online. The feature is currently being fine-tuned and is expected to be made available to the public as soon as the kinks are addressed.

Oakland Business Improvement District (OBID) is also running a test pilot where drivers could pay using their cell phones. Some patrons have expressed concerns that their cellphones could be stolen and subsequently used to pay. In addition, OBID is in the midst of installing posts along Forbes Av. These will provide way-finding and other information on parking. Other types of information that could be included are event times around Oakland and student arrival week. A pilot study using this information was on the verge of being launched when we were conducting these interviews so we have no information on public receptivity to the project.

Some of the discussions revolved around how the integrated parking application project could piggyback on the aforementioned initiatives, in a way that complements and adds value to the existing initiatives. One strategy may be to accelerate the planned expansion of ParkPGH as regards the geographical area covered and in adding more features. The PCT informed us that one of the things they are thinking of doing is using ParkPGH as a platform in moving towards

[7] Zoning ordinances could be at the district or City level or county wide. With regards to real estate, in contrast to commercial developments, there are no zoning requirements for residential parking downtown. However, apartments are more attractive if this option is bundled in and even banks take this into consideration in granting loans.

a holistic parking system that integrates both on-street and off-street, way-finding and variable message signs VMS system. However, at present they do not have the capacity to implement it.

Broadening the dialogue

Some of the deliberations also revolved around how best to bring additional large organizations onto the table. Specifically, what resources of theirs could be used creatively to help achieve the goals and objectives of the integrated parking application program? Some of these organizations are good corporate citizens, and perhaps with a little persuasion could be nudged to do more. For example, UPMC opened their Oakland parking lot to non-UPMC commuters for a small fee of $40 a month and made its shuttle available to them as well. Such decisions could help immensely with the utilization of fringe parking assets.[8]

On a broader level, with regards to multi-modal transportation issues and how to improve ridership of the public transit system, an option that could be explored is bundling PCT and Port Authority Transit (PAT) tickets. The idea here is to get the PCT patrons to change their commuting behavior by encouraging concert goers to take the public transport by allowing them to ride the buses or the T for free with their ticket. The arrangement that the University of Pittsburgh and Carnegie Mellon University have with PAT could also be extended to organizations with large workforces, where a flat annual fee is paid to PAT per employee for the privilege of unrestricted access to PAT buses and the T Connector. These initiatives could go a long way in addressing the multi-modal issue.

Addressing occasional parking bottlenecks during peak periods or events could also have immense benefits. Introducing an adaptive traffic control system similar to the East Liberty pilot is one way to address the queue as it builds up. Pittsburgh's downtown offers a good laboratory to test this out. A test bed could be created for patrons exiting the Theater Square garage after an event. A question that would need to be answered is how to get the traffic signal in front of the garage to be responsive to the long queues that build up?

Access to parking information as a public good

Given the cost to both individuals and society when individuals drive for extended period of time while looking for a parking spot, we have approached the issue of parking from the perspective of a public good. One of the issues we discussed was on how to ensure accessibility of information for those who may be technologically challenged or who do not have access to smart phones.

One solution could be to provide a feature that allows users to call into a designated phone line and then assisting them with their enquiry. The feature could be designed to be user-friendly for the targeted population. ParkPGH includes some information channels – for example SMS Texts that were created and supported even though they have low utilization. The decision to continue supporting these lower utilized channels can be justified based on the philosophy of open-access and the concept that parking information should be available to the public.

---

[8] One of the respondents proposed the idea of incentivizing employees to bike more by these organizations and agencies having locker room/changing & shower facilities. The question is - how feasible and effective will this be?

Economic Health and Vitality

Economic health and vitality concerns revolve around two main issues. The first is that parking problems can be seen as a constraint to economic growth. The second involves how economic activities affect parking and vice versa. As location decisions for businesses take into consideration the availability of parking spaces, respondents were asked if they could recall any situation where a potential development was no longer pursued because of the parking requirement attached to the proposal. Examples given include LA Fitness and Saks – projects that were either jettisoned or forced to relocate because of the inability of meeting dedicated parking space requirements. In the Oakland section of Pittsburgh, parking is not seen as a binding constraint – at least not now, or in the immediate future. However, specific mention was made of American Eagle Outfitters that chose not to relocate to Oakland because of corporate policies that specified proximity to a theater and a minimum parking space availability.

Other creative approaches were discussed. These would be those not mandated by zoning ordinances that could be employed in proactively shaping demand for parking spaces in the future. One of the hallmarks of a thriving area is a healthy mix of residential and commercial uses. In such an area, even after office hours there are still a lot of activities going on late into the early mornings and in the weekends. Recent demographic trends indicate that the younger population is less car-dependent than previous generation. Given this knowledge, a creative approach could be to offer the younger population lease contracts without a guaranteed parking spot in close proximity or one that offers them the right incentive to utilize fringe parking garages. One respondent said she has observed a marked shift in tenants' attitude with regards to having cars compared to what used to be the norm 10 to 15 years ago. This change in attitude has resulted in less demand for parking spots with newer tenants demanding fewer parking spots per apartment[9]. Thus, it may be easier to accommodate this population given the higher elasticity of demand for parking spot for this cohort. The use of other incentives may also be effective – for example, parking much further away or unbundling the cost of parking and the apartment rent.

Attitudinal and Behavioral Changes

Building on the nascent changes observed with parking behavior from ParkPGH, one area of interest we wish to explore is how providing parking information to the public changes their attitude and behavior when it comes to finding parking spaces. To that end, we asked respondents if they have evidence, either personal or anecdotal, of the increased use of parking garages at the periphery and/or whether they have suggestions on potential ideas that may incentivize drivers to exercise a more socially optimal option. It was mentioned that there is increased utilization of fringe garages and several of the respondents confirmed that ParkPGH has altered their behavioral pattern when looking for parking spaces in downtown Pittsburgh. For example, if the app is showing that parking facilities in core downtown are already filled up, he/she may then proceed to the Grant Street garage, a parking facility on the fringe.

[9] Some cities are making amendments to their zoning code as a result of this trend. An example is Cincinnati that recently eliminated parking requirements for residential developments in some parts of the city's downtown area (6).

On activities that may further change the public's attitude and behavior on parking demand, a pricing strategy could be used to free up the core downtown area with prime parking spots by incentivizing employees who typically park for long stretches of time to park elsewhere. The same could be done with lease holders – this should be a more viable strategy compared to imposing lease quotas given that leases are prime commodities in downtown Pittsburgh. In addition, these attitudes could be changed by transitioning to a functional and effective multi-modal transportation system. This, coupled with the right incentives could radically change the transportation ecosystem within the city. Finally, on the real estate side, a proactive shift in developers' mindset by making provision for smaller apartments or employing different forms of contracts may spell a move in a direction that gets people thinking differently regarding their parking demand needs.

Data Analytics and Issues Further Downstream

The area of greatest consensus among the individuals interviewed is the importance of data and how effective good data analysis could be in shaping the region's transportation ecosystem. Following up on the previous section, such information could be used to validate or refute the anecdotal evidence on employees parking for long stretches of time, or to establish the magnitude of individuals who engage in this behavior. The information obtained could subsequently be used to encourage people to change their behavior possibly via various means. The information could also be used to inform the modifications to be made to policy measures or zoning ordinances.

Having said this, there are challenges. A *siloed* approach to collecting and analyzing data will produce sub-optimal performance. The challenge then is two-fold – convincing the relevant organizations to make the required data available and secondly, warehousing them in a format amenable to being analyzed. This is not a trivial task. At present we have a situation involving disparate data stores on often incompatible software and hardware systems, making it quite difficult to integrate all these data into one coherent whole.

SECTION

FOUR

4 ENVIRONMENTAL SCAN

This section addresses transportation system constraints that impact on parking. It is driven by a combination of data sources – primary data from the semi-structured interviews, secondary data from recent local publications, US Census data on commuting pattern and document review of relevant literature to paint a rich picture of parking and the transportation ecosystem within Pittsburgh. The insight obtained from this section will be used to deliberate on the feasibility of the stakeholders' goals and expectations given the system constraints identified.

The approach to the environmental scan is a holistic one that includes both supply and demand factors. The supply side issues will address parking or transportation-related initiatives that are currently active, in the planning stage or presently being mainstreamed. The conversations with key stakeholders and a host of publications will be the primary sources for this sub-section. Demand side analysis focuses on commuting patterns to ascertain what the nature of parking demand will look like in the near future. The analysis will employ data triangulation by analyzing data from multiple sources that include the US Census public use microdata sample data on commuting pattern (7), the Local Employment and Household Dynamics (8) and the Quarterly Workforce Indicators (9).

4.1 Supply Side Issues

Within the City of Pittsburgh, the ownership and management of parking facilities is managed by both the public and the private sectors. The biggest players within this space are the Pittsburgh Parking Authority (PPA), which is publicly owned and ALCO Parking, a private sector parking entity. Parking assets are categorized as *off-street*, metered parking lots that employs both single and multi-space meter technologies and *on –street* metered spaces. The off-street category includes both garages and non-metered parking lots. Table 4.1 provides estimates of the parking inventory[10].

Table 4.1: Inventory of Parking Assets (by Type) for the City of Pittsburgh

Parking Facilities	Magnitude	Percentage
Off-Street		
Garages	33,508	63%
Lots	12,778	24%
On-Street		
Single & Multi-metered	6,937	13%
Total	53,223	100.0%

[10] We would like to express our gratitude to Christopher Speers of the Pittsburgh Parking Authority (PPA) for making available PPA's yearly market rate survey of parking facilities.

In conducting the inventory, we have excluded some parking facilities. These include facilities dedicated primarily for retail purposes – for example, the Target parking lot in East Liberty. We have also excluded parking facilities with restricted access – for example, garages and lots meant solely for permit holders like the Carnegie Mellon University parking lot on Morewood.

A significant proportion of these facilities are located in the downtown area as shown in Table 4.2. However, other neighborhoods within the City of Pittsburgh including Oakland, Shadyside, East Liberty, Bloomfield and the South Side have an appreciable parking capacity. Often times, this is due to the presence of a major institution or employer in the neighborhood. This is the case for Bloomfield given the presence of West Penn Allegheny Health Systems and Oakland, given the location of the University of Pittsburgh Medical Center (UPMC), University of Pittsburgh and Carnegie Mellon University.

Table 4.2: Inventory of Parking Assets (by geographical area) for the City of Pittsburgh

Parking Facilities	Downtown Area		Other Neighborhoods	
	Magnitude	%	Magnitude	%
Off-Street				
Garages	**21,495**	**78%**	**12,013**	**47%**
Lots	**5,321**	**19%**	**7,457**	**29%**
On-Street				
Single & Multi-metered	**674**	**3%**	**6,263**	**24%**
Total	**27,490**	**100**	**25,733**	**100**

Furthermore, recent developments may impact the available number of parking spaces within the City in the near future. On the positive side, East Liberty Development Incorporated (ELDI) is currently working with *Walker Parking Consultants*, to assist in implementing the Circulation and Mobility Vision project (10) that was undertaken in the latter half of 2012. Other supply side related projects include the completion of the North Shore Connector that will facilitate access to parking spots on the North Shore and the Target parking garage in East Liberty with a capacity of 600 spaces[11]. At the same time, significant attrition in parking supply is expected. As a result of these planned developments, it is inevitable that some surface lot spaces will be eliminated. A report commissioned by the Urban Redevelopment Association (URA) estimates that 646 parking spaces from surface lots will be eliminated in East Liberty (11). In the same vein, the downtown area is expected to witness reduction in parking supply from new construction and the repurposing of existing parking facilities.

[11] Strictly speaking, this figure should not be included in the total inventory of parking spots open to the public since these parking spaces are meant for Target customers. This is not any different compared to the PNC garage downtown with limited or no public access. However, their existence reduces the demand burden that PNC staff or Target customers place on the publicly available parking spaces.

4.2 Demand Side Issues

Our approach to the demand side analysis focuses primarily on the workforce population and commuting patterns. This approach is informed by Pittsburgh's relatively high *workforce to residents' population ratio,*[12] observed peak occupancy periods, neighborhoods with high occupancy rates and commuters who parked for considerable length of time. The heat map below shows differences in workforce concentration across the city. In addition to the heat map, workforce magnitudes are also provided in form of colored circles. Not surprisingly, the downtown and Oakland areas account for the highest density areas.

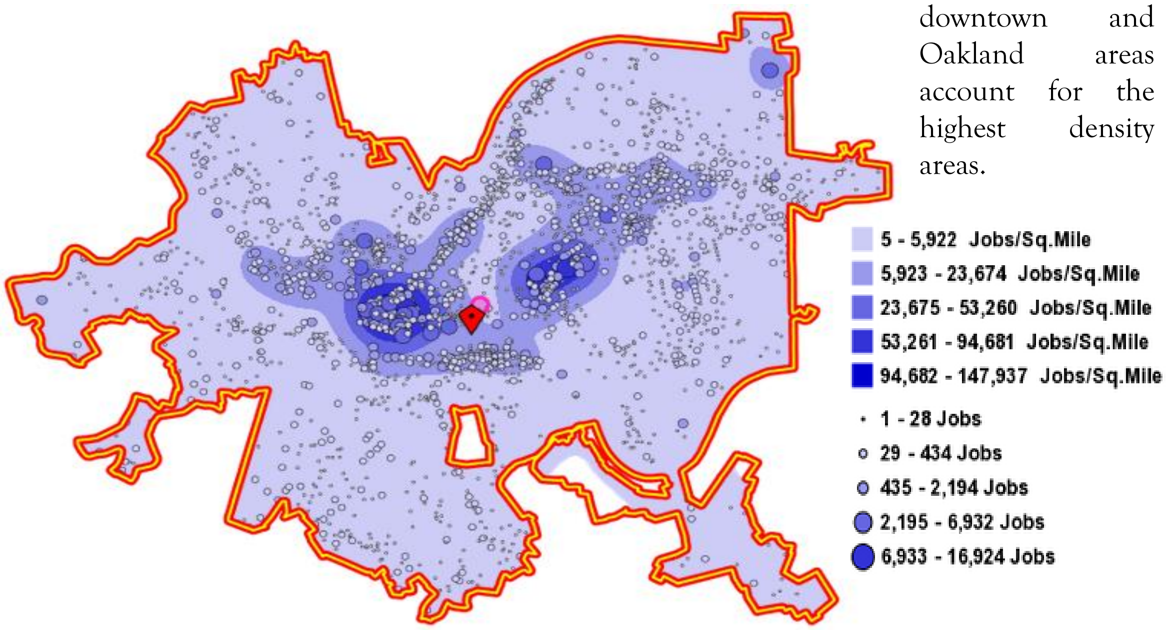


Figure 4.1: Heat map representation of Pittsburgh's Workforce.

While the residents' population and workforce population figures reveal some insight with regards to parking demand, what is truly relevant is the inflow and outflow traffic pattern. We have addressed this in multiple ways. We start by providing information on the magnitude of inflow and outflow of workers in 2011. Over and above this, we have examined these commuters by both direction and commuting distance. Finally, we conducted an analysis of the means of transportation and vehicle occupancy for both the City of Pittsburgh and Allegheny

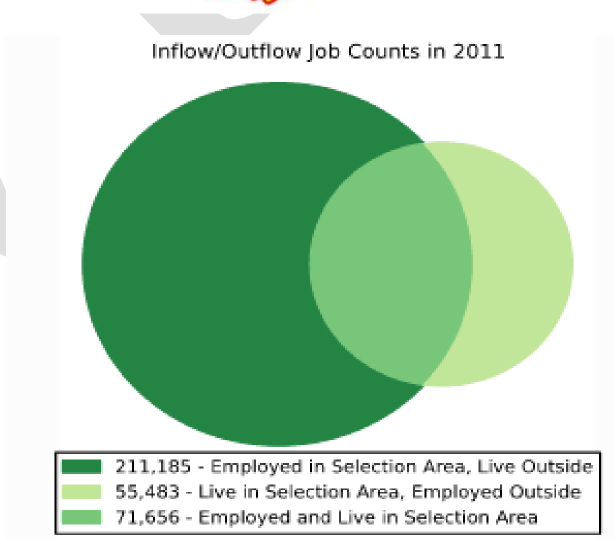


Figure 4.2: Inflow/Outflow Job Counts in 2011

[12] Of the 15 comparable cities we analyzed, Pittsburgh, bar none, has the highest *workforce to resident population* ratio. For every 100 residents, Pittsburgh has 92 workers while Tucson occupies the other end of the spectrum at 43 workers for every 100 residents. The appendix section presents the figures for each city analyzed and we address the tax implications of this for Pittsburgh in the next page.

County. We subsequently use our findings to make plausible assumptions about the commuting behavior of the identified cohorts of the workforce population.

The Venn diagram in Figure 4.2 shows the inflow and outflow of job counts in 2011. The darker oval shaped diagram on the left represents the subset of the city's workforce population who do not call the city home while the lighter one represents the population of employed individuals who call the city home but are employed outside of the city. The ratio of the former compared to the latter gives a good indication of how attractive the city is as a place to work relative to living. The intersection of the two shapes is the subset of the population that work and live within the city.

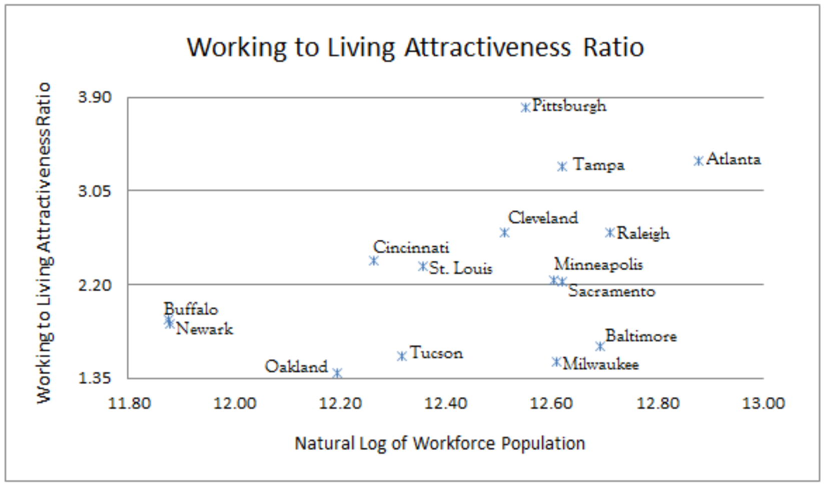


Figure 4.3: Working to Living Attractiveness Ratio

Another way of analyzing the situation is looking at the *working relative to living attractiveness* ratio. We have chosen to analyze this from two dimensions – across time and geographical area. One looks at the trend pattern of this ratio starting from 2002 and the other compares the City of Pittsburgh to comparable workforce investment areas (WIA). Figure 4.3 shows the latter while figures for the former ranges from a low value of 3.4 in 2002 to 3.81[13] in 2011.

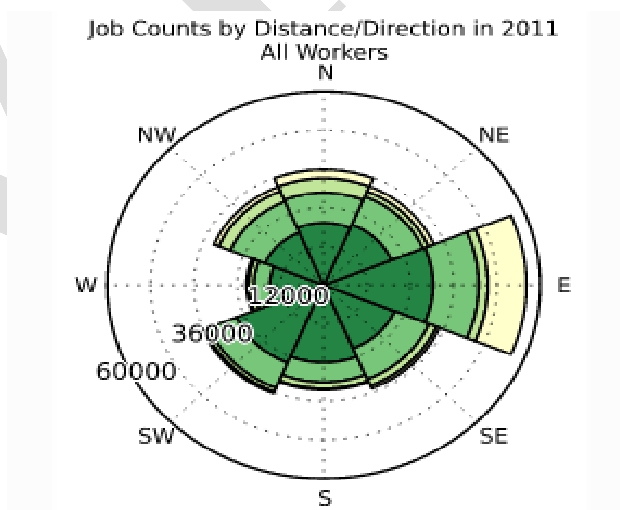


Figure 4.4: Job Counts by Distance/Direction in 2011

[13] It is obvious that Pittsburgh is the outlier in Figure 4.3.given that no other City crosses the 3.5 mark. The 3.5 level means for every 7 commuters who work in the city but live outside, only 2 individuals live in the city and work outside. Only Orlando, FL (which is not shown in the appendix) with its economy primarily dependent on tourism scaled this threshold at 3.59. More insightful though is the tax implications of the workforce composition.

Analysis on distance and direction
The radial diagram in Figure 4.4 provides information on the direction and the associated magnitude of workers commuting from work census block to home. The direction, at close of business, seems to be towards the east, north, north east or south west direction. The direction east accounts for close to 60,000 employees, or expressed differently, approximately 30% of the working population who are not city residents. Each ring of the radial represents 12,000 individuals.

We have complemented this analysis by providing commuting distance information as shown in Table 4.3. The commuting distance for approximately 90% of the population is 25 miles or less. We have used this information to make the assumption that most of the City's workers reside outside the City. That assumption provides some intangible insight on the travel pattern for the subset of the City's workforce population who are not city residents. We would also like to point out that the distance and direction analysis was carried out relative to the place of work.

Table 4.3: City of Pittsburgh - Jobs by Distance measured by Work Census Block to Home (2011)

Commuting Distance	Magnitude	Percentage
All Jobs	**282,841**	**100%**
Less than 10 miles	**174,002**	**61.5%**
10 to 24 miles	**71,030**	**25.1%**
25 to 50 miles	**18,941**	**6.7%**
Greater than 50 miles	**18,868**	**6.7%**

Transportation Means and Vehicle Occupancy
To obtain the real picture on the actual demand made on available parking spaces by employees, we have carried out an analysis on the means of transportation and vehicle occupancy for both the City of Pittsburgh and Allegheny County. We subsequently abstract from the results obtained by making the assumption that the commuting pattern of employees who work in the City but are not resident there are no different compared to the figures obtained for workers in Allegheny County excluding Pittsburgh[14]. In the same vein, we have made the assumption that the home to work travel pattern of workers who live and work in the city is not any different compared to the proportionate figures for workers who reside within the City of Pittsburgh[15]. The essence is to focus on individuals who drive to work as compared to other forms of transportation and then to, zero in on vehicle occupancy patterns.

Tables 4.4 and 4.5 provide estimated magnitudes and the associated errors at the 90% confidence interval level. These figures were generated from the 2009 – 2011 3 years US

[14] We had earlier provided justification for this by showing that close to 90% of the employees may be resident in Allegheny County.
[15] These are conservative estimates in that the demand for parking facilities is expected to be higher, on average, for the cohort of Pittsburgh residents who work outside the City boundary.

Census Public Use Microdata Sample (PUMS) population records[16]. The public use micro-data sample set provides an excellent resource for understanding commuting patterns at sub-regional level, a feat that was not possible in the past given the relatively small sample of existing surveys. For the present study, our analyses cover 10 public use micro-data areas (PUMAs) with each PUMA boundary drawn based on a population size of approximately 100,000 residents. The sample size for our analyses is 54,945, representing a population size of 1,224,537 with a sampling error of 2474.

For this analysis, two types of weights were employed: person weight and replicate weights. The person weight is required for the point estimates and both person weight and the replicate weights are needed to calculate the standard errors. Of the total number of employees who live in Pittsburgh, the analysis shows that 90,127 (64%) commute to work either by car, truck or van. This figure however, ignores the variability in the estimates. If we take this into consideration, the calculated estimate ranges from a low of 87,572 to a high of 92,682 at the 90% confidence interval level. Breakdown of the estimates and their associated error margins for both the means of transportation and vehicle occupancy are provided in Tables 4 and 5. We have also provided detailed discussion of the methodology and the attendant limitations in the appendix.

Table 4.4: Means of Transportation to Work (relative to place of abode)

	City of Pittsburgh		Allegheny County (Excluding the City of Pittsburgh)	
Means of Transportation	Population Estimates	90% Confidence Interval	Population Estimates	90% Confidence Interval
Car, Truck or Van	**90,127**	**90,127 ± 2555**	**382,833**	**382,833 ± 3942**
Bus	**26,825**	**26,825 ± 1414**	**26,010**	**26,010 ± 1358**
Other Public Transit Forms	**1,173**	**1,173 ± 343**	**4,462**	**4,462 ± 637**
Bicycle	**2,016**	**2,016 ± 459**	**476**	**476 ± 160**
Walked or worked at home	**21,101**	**21,101 ± 1473**	**26,606**	**26,606 ± 1673**
Other transportation means	**601**	**601 ± 270**	**2,879**	**2,879 ± 571**

Estimates and the associated margins of errors were also calculated for individuals who used the public transit system, those whose place of work is in close proximity to home, individuals who biked and those who used other forms of transportation. These estimates were calculated for the City of Pittsburgh and for Allegheny County excluding the City of Pittsburgh. Finally, we have disaggregated the population that commute to work by car, truck or van by looking at vehicle occupancy. The analysis was done using three cohorts of vehicle occupancy – individuals who drive alone; 2 person carpools and 3 or more person carpools. For Pittsburgh residents, 84.7% of those who drove did so unaccompanied. For the same subset of the

[16] We could have used the latest 2011 1 year population records but the 3 years data provide better estimates. This, coupled with the fact that the travel behavioral pattern for any population typically takes a considerable length of time to change informed the decision to use the 3 years population records.

working population, a slightly higher percentage (89.4%) of unaccompanied drivers was observed for the rest of Allegheny County residents.

Table 4.5: Vehicle Occupancy for Journey to Work Trips

	City of Pittsburgh		Allegheny County (Excluding the City of Pittsburgh)	
Vehicle Occupancy	Population Estimates	90% Confidence Interval	Population Estimates	90% Confidence Interval
Drive Solo	76,311	76,311 ± 2253	342,153	342,153 ± 3880
2 person Carpool	11,437	11,437 ± 1189	34,873	34,873 ± 1828
3 or more	2,379	2,379 ± 500	5,807	5,807 ± 799

Estimated Demand for Parking Spaces

Using these results, we were able to calculate the demand for parking spots by workers in the City of Pittsburgh by applying the proportionate breakdown of the forms of transportation and vehicle occupancy to the relevant cohort – workers who reside in Pittsburgh and those who reside outside Pittsburgh. The results are shown in the table below and they were obtained by using the proportionate distribution of workers who commute to work using vehicles and subsequently applying that to the subsets of the workforce who live in or outside Pittsburgh. The equivalent number of vehicles was obtained by dividing the number of vehicles by the occupancy number while taking a conservative view by assuming that maximum occupancy for any vehicle is three.

Table 4.6: Estimate of the Present Demand for Parking Spaces by Pittsburgh Workers

Vehicle Occupancy	Proportionate %	Magnitude	Equivalent # of Vehicles
City Residents			
Drive Solo	53.8%	38,551	38,551
2 person Carpool	8.1%	5,804	2,902
3 or more	1.7%	1,218	406
Non-City Residents			
Drive Solo	77.2%	163,035	163,035
2 person Carpool	7.9%	16,684	8,342
3 or more	1.3%	2,745	915
Total			**214,151**

In total, approximately 214,150 parking spots are demanded on average, within the city on any working day. While it is virtually impossible getting the public to transition to a higher public transit ridership given the recent round of cuts in PAT services, it may be feasible to explore changes in attitude and mindset as regards car-pooling. A 5% reduction in the absolute number of individuals who drive unaccompanied translates to a reduction in demand of more than 5,000[17] parking spots – equivalent to 5 times the capacity of the Grant Street Center garage.

We would however like to mention that these reductions are optimistic. The presumptive mayor has made it a priority to encourage car-pooling and higher public transit ridership. However, our multicity analysis shows that commuters are reluctant to car-pool but they are more amenable to using the public transit system.[18] And here lies the conundrum – the only option that could be effective in achieving this witnessed a reduction in services in September 2012 and is slated for another round of cuts in June 2013.

Workforce Trend and Projected Demand for Parking Spaces

In order to provide a well-rounded picture of the parking situation not just from a static perspective, we have gone a step further by providing insights as to what the near future may look like. This was achieved by examining the trend pattern of the city's workforce and then subsequently using the trend to make projections of the City's workforce.

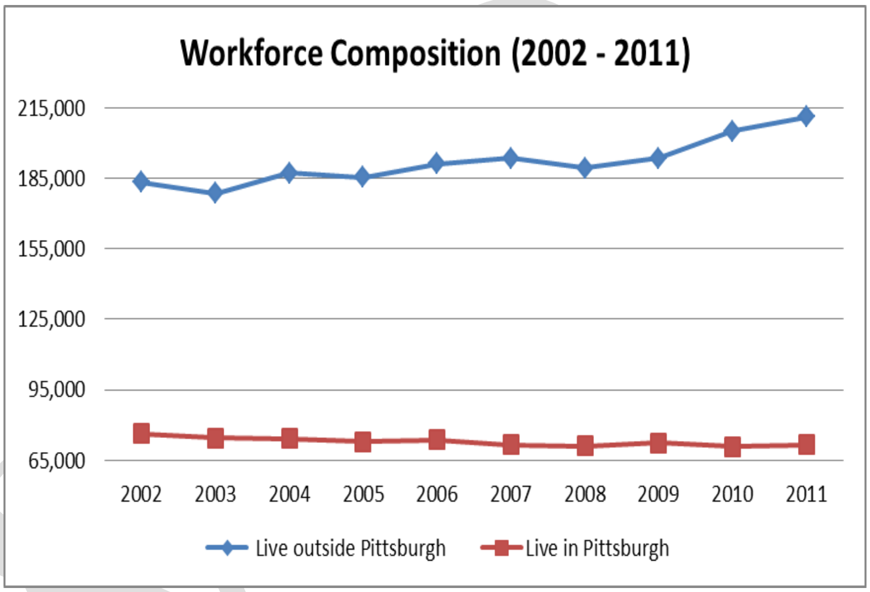


Figure 4.5: Pittsburgh's Workforce Composition using data from the US Census OnTheMap.

Figure 4.5 shows a 10 year trend of the city's workforce categorized broadly into two cohorts – employees who are city residents and those who are not. The rationale for this categorization is the difference in the commuting pattern observed across the two groups. As documented in Tables 4.4 and 4.5, Pittsburgh residents drive proportionately less unaccompanied and on average, use the public transit more compared to county residents. As could be seen from Figure 4.5, the proportion of the workforce that is made up of out of city residents is on the increase. Only 25.3% of the workforce lives in the city in 2011 compared to 29.5% in 2002.

---

[17] The exact figure is 5,086. This is obtained by assuming that among the cohort of individuals who reside within the City and who commute to work using vehicles, there is a reduction from the current 84.7% to 80% in the percentage of individuals who drive alone. In the same manner, we assumed that of the out-city residents who commute to work by vehicles into the city, there is a reduction in the percentage of individuals who drive unaccompanied from its present level of 89.4% to 85%. Vehicle occupancy estimates were obtained by top coding occupancy at three.

[18] The analysis used the US Census PUMS data from 2009-11 to calculate the population estimates of different means of transportation and vehicle occupancy for 15 cities.

This trend further exacerbates the pressure on parking spaces given that out of city residents cohort make more demand on the available parking spots compared to city residents.

Using the US Census Quarterly Workforce Indicators (QWI)[19] data, we provide forecasts of the workforce magnitude till the beginning of 2018 have projected Figure 4.6 provides the predicted result over a 24 quarter period with 2012 Q2 as the starting point. The estimated workforce magnitude in 2018 is 310,000. The estimate was obtained using a time series weighted moving average (MA) with weights that decrease exponentially going backwards in time. Figures on the Y axis represent the magnitude of the workforce while the X axis represent quarters with 2012 Q2 as the reference quarter, thus periods before 2012 Q2 will be negative. The sample path in red represents a continuum of projected figures over the 24 quarter period.

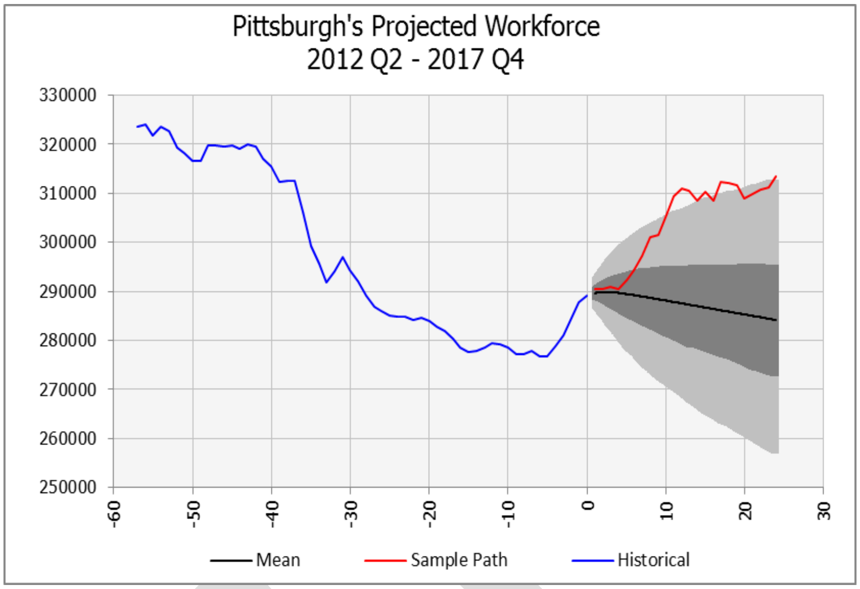


Figure 4.6: Pittsburgh's Projected Workforce using the US Census QWI data

We subsequently used the projected figure to calcuate the demand for parking spaces in January 2018. The computations were carried out under the assumptions that the commuting pattern shown in Tables 4.4 and 4.5 remains invariant and that 1 out of every 4 of the workforce reside in the city[20]. Table 4.7 provides a breakdown of the demand for parking spaces in 2018.

[19] We were not able to use the OnTheMap data that was used to create Figure 4.5 to generate the forecasts because we do not have enough data points to establish the presence or lack thereof, of stationarity in the time series data. This explains why we switched to the US Census QWI employment figures that are quarterly compared to the OnTheMap data that are provided annually. However, this comes at a price given that aggregation masks local realities - we do not have the luxury of tracking how each cohort – residents and non-residents of the workforce evolves overtime.

[20] The latter assumption is conservative given the trend shown in Figure 4.5. Consequently, we may end up underestimating the demand for parkign spaces given the average diffrence for parkign space across the two subsets of the working population.

Table 4.7: Projected Demand for Parking Spaces by Pittsburgh Workers by Jan 2018

Vehicle Occupancy	Proportionate %	Magnitude	Equivalent # of Vehicles
City Residents			
Drive Solo	53.8%	41,695	41,695
2 person Carpool	8.1%	6,278	3,139
3 or more	1.7%	1,317	439
Non-City Residents			
Drive Solo	77.2%	179,490	179,490
2 person Carpool	7.9%	18,368	9,184
3 or more	1.3%	3,023	1,008
Total			**234,955**

From Table 4.6, present demand for parking spaces by employees on any work day is currently estimated at 214,150 while the inventory of available parking spaces that is available to the general public is only 53,223 – approximately 25% of the total demand. However, we will caution against drawing any conclusion from these figures since they grossly undercount the total available parking spots given the methodology used in conducting the inventory. The figure does not include facilities owned by retailers or meant primarily for retail purposes. Among others, this includes the parking lot in front of Wholefoods and the Bakery Square parking garage, both in East Liberty. We also excluded all off-street facilities that are only accessible to permit holders or have limited accessibility.

SECTION
FIVE

5 PROPOSED STRATEGY

This section documents the insights gathered from the needs assessment and environmental scan that will be used in designing the integrated parking application project. The information obtained both from the stakeholder analysis and the environmental scan has been used to frame and provide more substance on the strategy that informed the integrated parking application project. The insights obtained were deployed towards modifying the strategy and actions going forward in a way that reflects the new realities. The objective here is to come up with actions that could be used to address and manage the expectations of stakeholders with regards to the integrated parking application project. The key concerns identified from the environmental scan have been used to examine factors that could either accelerate or impede progress made towards achieving the objectives of the integrated parking application.

What is obvious from our analysis is that a strategy that is solely supply driven is not feasible given input from the stakeholders, the present parking market and the projected demand for parking spaces by 2018. Our approach has been to embrace a menu of initiatives that will impact commuters' demand for parking spaces and also their travel behavior. We have used this to provide broad recommendations that are divided into two subsections. One is product specific and the other, policy related. The policy related subsection speaks to the environment within which the application will be implemented. In framing the strategies, we have taken a broad look at the overall transportation system and address instances where non-parking issues impact on parking availability. In addition, we have taken into consideration synergies that could be exploited – for example, would providing predictive parking information and traffic pattern incentivize commuters to change the way they travel? Detailed information on the subsections and potential strategies being promoted are provided below.

5.1 Product specific Issues

Fine-tuning of the design

The needs assessment from stakeholders has informed the design of the parking application. Once a mock-up of the application is created, it will be demonstrated to key stakeholders to ensure that it meets their expectations. This bi-directional communication is an affirmation of the social interaction and intellectual cogitation mentioned previously in the methodology section. The adaptive strategy process should continue until the stakeholders indicate that the design meets their requirements or there is an acceptance of the design given the associated structural constraints. This precludes stakeholders from falling into a trap of equating what they desire with what is feasible – i.e. assuming an unconstrained boundless horizon. In the same manner, the back and forth interaction prevents the product development team from assuming that what is feasible is desirable. The design process is only effective if it enables the mutual adjustment between the stakeholders' needs and the objectives and constraints of the product design team.

We envisage that there will be at most 6 to 8 individuals who are identified as key stakeholders. The list should be limited to individuals or organizations that have relevance in at least two of the areas identified in the Venn diagram on the right. The diagram was adapted from a similar approach from a study commissioned by the German Agency for Technical Cooperation (12). This could be done through the demonstration of a prototype or a mock-up of the application before this audience. The objective is to ensure that their concerns and expectations were taken into consideration and more importantly, to get an *OK* from the group as regards the design. In instances where some of their needs could not be taken into consideration, the stakeholder must be made aware why this is the case.

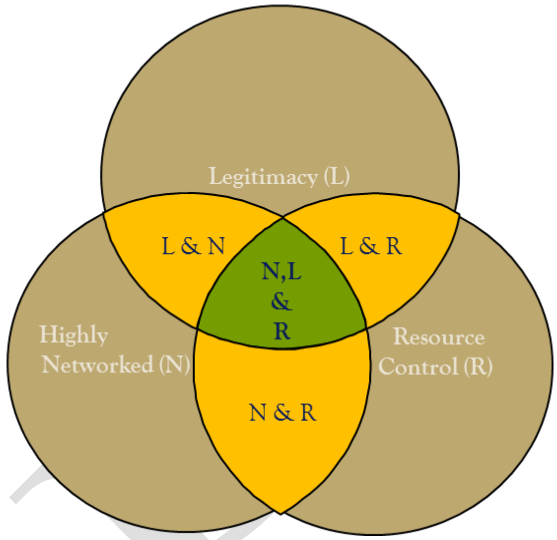


Figure 5.1: Venn diagram of Stakeholders' Influence

We appreciate that getting to a consensus on this may not be an easy endeavor and that often times, some of the discussion goes beyond the technical requirements. To this end, we will recommend that a skilled negotiator with appreciable goodwill and capital within the local transportation environment should facilitate this discussion.

Legacy – piggybacking on ParkPGH

In deliberations with stakeholders, we were reminded several times how effective ParkPGH has been in addressing some of the parking bottlenecks within the Cultural District. This was further reinforced from the document review we did for the environmental scan section. For example, the IBM Smarter Cities Challenge report mentioned the value added by the ParkPGH application and provided suggestions on how its functionality could be enhanced. The expanded scope of the application – from an initial list of eight garages that featured in the pilot to the present number of 19 is also a testament to its popularity and broad acceptance.

We also gathered during the stakeholders' interviews that there are additional desired expansions to ParkPGH, both in its coverage and the functionalities it presents. Marc Fleming of the Pittsburgh Cultural Trust (PCT) mentioned that some of the attributes the project's partners are thinking of include having a system that features even more garages, integrates both on and off-street parking and includes way-finding Variable Message Signs (VMS). He however said that they do not the capacity to pull this off. The IBM Smart Cities challenge report, referenced earlier, also made recommendations that include adding all public and private garages, surface lots and street spaces in the downtown area to the list of parking facilities featured on the application and adding sensor-based detection for improved accuracy of parking availability.

We have taken a cue from these sources and recommended that added functionalities be added to ParkPGH and that this should form the core of the integrated parking application project. Current developments within the city also make this more of a reality. An example is the new electronic parking meters with the associated pay stations that went live in the last quarter of 2012. This should make transitioning into a fully-fledged integrated parking application project more feasible. One option to operationalize this is by using parking spot sensors that could be connected via the web to display available parking spaces. In addition to this feature, payment facilities could be added to ParkPGH. This will allow a commuter to reserve an available parking spot online. She is issued a code which could be punched in when she gets to the gate that allows her access. This will only be needed if the parking facility of interest to the commuter is near full capacity.

The design of ParkPGH lends itself to easily reflect these new attributes. The original design is modular in nature. This feature makes provision for product enhancements and ensures that this retrofitting could be implemented relatively easily. In addition, the product development team spent considerable time addressing operational issues across the different platforms used by the garage owners that featured in the application. Some of these issues emanate from the challenge in trying to integrate data across garage operators that use different software and hardware that are often incompatible. The development team was able to achieve some standardization that guarantee the interoperability of processes and procedures – an attribute that will prove invaluable as added functionalities are added to the application. Finally, its open source platform ensures that transitioning to a fully-fledged integrated parking application could be achieved at a relatively low cost.

Synergistic Opportunities

Some of the insight obtained from the environmental scan and discussions we had with stakeholders revolved around how best to leverage on what presently obtains to improve the effectiveness of the proposed integrated parking application project. A feasible option is relaying the information provided by the integrated parking application project to the public using variable message signs (VMS). This strategy could be implemented at very low cost but with high impact. Using information obtained from the environmental scan that shows that more than 200,000 out of city residents commute to Pittsburgh on any work day, we could target this population using the major transportation arteries as shown in the next page.

Figure 5.2 shows the City of Pittsburgh's workforce thematic map overlaid with the City's major transportation routes. In deciding on where the VMS could be strategically placed, we used information from the radial diagram in Figure 4.4 of the environmental scan section. Close to 60,000 commuters use Interstate 376 to get to work. Route 28 and Interstate 279 account for approximately 70,000 of the commuting population on any work day. This provides some insight on potential routes to use in displaying parking availability information. An example could be a commuter coming from the North Hills[21] via 1-279 or Route 28. Assuming the capacity downtown is already maxed-out, the VMS could display a message saying "*Parking spaces downtown full. Proceed to the North Shore*". Commuters could subsequently drive to the North Shore, park at one of the garages and take the *T* Connector to downtown.

[21] The North Hills refer collectively to Pittsburgh's northern suburbs and is made up of approximately 40 townships and boroughs.

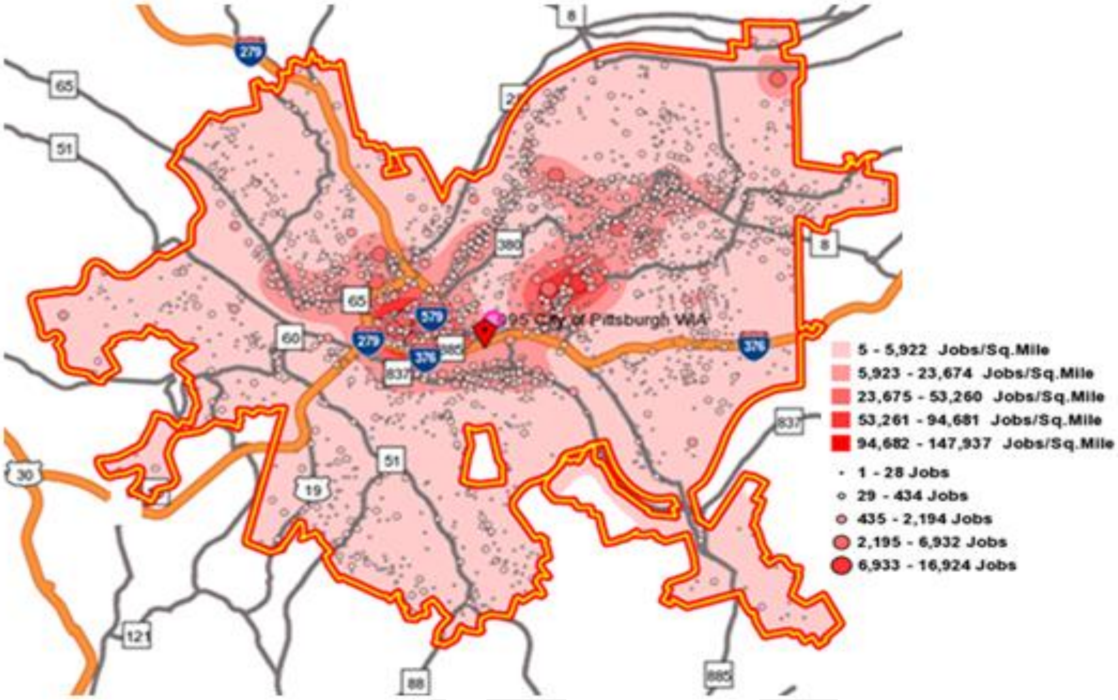


Figure 5.2: Heat Map of Pittsburgh's workforce overlaid with major transportation routes.

This mode of thinking could be extended city-wide using fringe parking facilities that function as Park & Ride outlets. There are discussions in the nascent stage that may better facilitate this – for example, the lojacking of port authority buses by 2014 and extending the T Connector to the South Shore. These developments along with displaying ParkPGH parking information through VMS not only has the potential to address parking situation, it could also go a long way towards reducing the heavy traffic often observed in some parts of the city.

Predictive Parking

This subsection builds on the predictive model of ParkPGH. However, we see the need to treat it separately from the legacy issues given what stakeholders have said with regards to transitioning to a multi modal system. In addition, the insight revealed from the environmental scan showed that it is arguably the most effective way by which any significant reduction in demand for parking spaces could be achieved.

The predictive parking algorithm[22] as presently conceived has two separate components – a long term predictive module and a short term one. The time element has nothing to do with the length of time the parking is required but rather the time horizon before the parking decision is made. Thus, a 3 day look-ahead would be deemed long term while a short term could be a 2 hour horizon. A couple going downtown to watch "*The Lion King*" say next week could use the long term predictive module to calculate the probability of finding a parking space given that a Steeler's game is also scheduled for that same evening. In a similar vein, an individual who is heading downtown from East Liberty in the next hour or two could use the

[22] ParkPGH has a predictive module that is presently not operational.

short term module to make a decision whether to drive or head to the East bus way station to catch a bus.

The promise of the predictive algorithm is that of all the components of the integrated parking application, it has the greatest potential in influencing commuters' travel and parking demand patterns. Integrating parking information with traffic flow pattern has true potential if the parking information provided is not only real time but also predictive. It can encourage commuters to change the way they travel or how they schedule their trips. Apart from providing information on the demand side, garage operators could use the predictive information to better manage their facilities. For example, a predicted higher than normal demand for parking spots could allow a garage operator to artificially increase the facility's capacity by making provision for valet parking.

5.2 Policy Environment

Policy Environment

While the strategy development does not directly address the policy environment, it is crucial to take into consideration some of the concerns voiced by stakeholders and policy related issues that were observed from the environmental scan. We intend using this platform to raise issues we think may limit the effectiveness of the integrated parking application, provide information as to what the possible impacts will be, and where possible, give suggestions as to how they could be ameliorated. This is an affirmation of the two way street we alluded to in the methodology section. Some of the stakeholders we interviewed are active in the policy space and sensitizing them to the consequences of the existing statutes is one way to get them thinking of how they could be modified to make them more effective.

Price/Proximity

Arguably the most recurrent theme raised by the stakeholders we interviewed centered on individuals that park in high density areas for extended period of time. Typically, these are lease holders, employees who take up prime parking spots and residents with access to plum parking locations. This is most noticeable in the downtown and Oakland area and the low vehicle turnover that this parking behavior generates has often being blamed as a key disincentive by customers who need parking space for an hour or two. This situation if not addressed may have a negative impact on the economic vitality of the city. Apart from the negative impact, the persistent perception of not enough parking spaces is also fueled precisely by this parking behavior. The question then is – how do we incentivize people who park for extended periods of time to use available fringe parking facilities and by so doing, free up choice parking spots in the high density area for patrons in need of parking for a limited period of time?

To some degree, we see parking as quasi-public goods[23] where benefits accrue not only to individuals but also to the society if commuters use parking garages in a socially optimum manner. The information provided by ParkPGH is helping to achieve this transition and so is

[23] Some may argue that it is quite a stretch making a case that parking are quasi-public goods. If we were to assume that parking spaces are indeed quasi-public goods, there is the need to go beyond an analysis predicated solely on commuter's buying power or the willingness to pay since it could be shown that a wedge exists between private and social cost or private and social benefit.

better connectivity from the fringe parking facilities to the urban core – for example, the one facilitated by the T-Connector from the North Shore to downtown. These, coupled with a pricing mechanism that induces commuters to park farther away at a reduced cost as shown on the right[24] could go a long way in incentivizing drivers to make parking choices that are not only to their advantage but also that of the society.

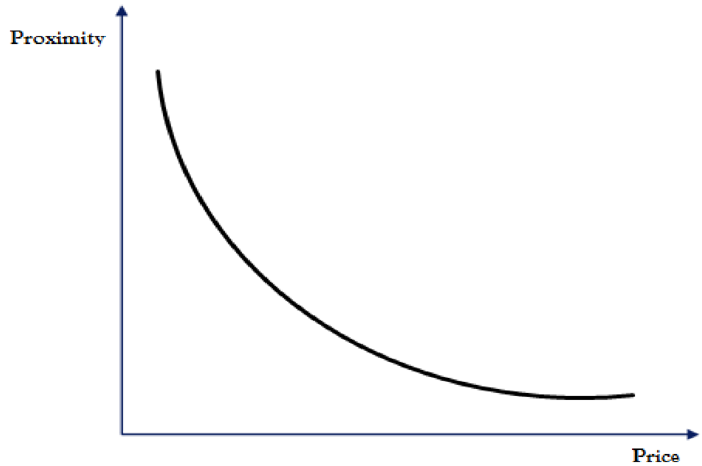


Figure 5.3: Hypothetical Proximity / Price Indifference Curve

In addition, we see the need to point out the distorted messages prices signal when prices are allowed to vary for on-street parking while they are fixed for publicly owned off-street parking facilities even when it could be argued that on-street and off-street parking are near perfect substitutes. Ideally, for the market to function effectively, a flexible pricing mechanism needs to be in place. Thus, there is a need to move not only to a regime of variable pricing but also to a dynamic one. The predictive parking model, a component of the planned integrated parking application will make the dynamic pricing easier to implement through the provision of estimated future parking demand to the garages and lots that are partners in the project. While we do not envisage having a pricing algorithm as an integral part of the application, provision will be made by the application to reflect prices as they change in real time.

Finally, some existing practices ought to be modified and these could be achieved through moral suasion or by sensitizing the general public on how socially inefficient they are. For example, as part of being good corporate citizens, institutions and corporations could choose to decouple parking privileges from the contract they have with upper echelon employees and instead monetize these parking privileges. Not only does this free up the employees from using a specific garage, a development that removes some of the rigidities in the parking market, getting rid of a lease contract similar to an "all you can eat" buffet moderates their demand for parking spaces.

Sundries

One of the challenges is to be able to present the parking sub-system analysis within a broader transportation ecosystem. A policy pronouncement that is local to PAT has effects on parking as does an edict that calls for a fixed proportion of parking spaces for real estate developments. It is also worth examining whether policy measures are siloed, making them sub-optimal. An example of a sub-optimal policy measure is having a provision in place that allows for dynamic pricing for on-street parking but which retains a fixed parking regime for all publicly owned off-

[24] The typical indifference curve shows a locus of points for a bundle of goods across which the customer is indifferent. We have borrowed from this concept to demonstrate the multi-dimensionality of parking by showing that individuals will trade farther distance to their destination for lower parking cost.

street parking assets. Finally, some of these ordinances exist in *de jure* sense but in a *de facto* sense, they are not being implemented.

There are also factors that impact directly on parking. A prime example is street road sensors. These road sensors exist presently in downtown Pittsburgh but they are not activated. The inactivation will preclude the development team from being able to build for example a web connected application that could ascertain which spots are available at any point in time. Having said this, we would like to say that the City is more embracing of these technologies. The lojacking of PAT buses and the display of the information to riders are expected to be effective by 2014 (13). This will allow riders track the buses in real time.

We recognize that some policy issues that may be part of the integrated parking application project go appreciably beyond what could be decided at City Hall. The presumptive mayor has expressed his interest in moving towards a higher vehicle occupancy and truly multimodal transport system. The question is – can some of these initiatives be decided in collaboration with the Allegheny County? For example, could a combination of policy pronouncement and public persuasion help to nudge commuters to higher vehicle occupancy? A specific example could be high occupancy vehicle (HOV) dedicated lanes and tolling of some roads while waving the fee for vehicles with 3 or more occupants. This could be complemented by encouraging *slugging*[25] (14), a commuting practice where impromptu carpooling are formed to gain access to HOV lanes and/or avoid toll cost.

[25] This is a practice on roads with high traffic volume – for example I-95 and 395 between Washington D.C. and Northern Virginia and I-80 between the East Bay and San Francisco.

APPENDIX

A1 Generating population estimates using replicate methods

Estimates of most variable of interest could be obtained from the ACS. However, in some instances, these estimates may not be available or they are categorized in a manner that is not amenable to the research being carried out. In these instances, one could use the US Census PUMS data in order to obtain more flexibility with how the data manipulated. The US Census PUMS data is a sample set that consists of approximately 1% of the total population – about 3.2 million person records[26] for the US in 2011 which is the most recent data available.

Oftentimes, multi-year estimates are available, typically 3 or 5 years. Not only does this allow for population estimates to be generated for smaller geographical areas, it also produces estimates with less margin of error. Consequently, if the variable of interest doesn't change frequently and estimates are being generated for subsets of the population, then one is better served using multi-year estimates. We have elected to do this by using 2009-2011 three year estimate data.

Each of these observations is assigned two types of weighs – one person weight and 80 replicate weights. The person weight is required for the point estimates and both person weight and the replicate weights are needed to calculate the standard error. These weights were used in generating estimates of the type of transportation and the vehicle occupancy of the commuting population. Associated with the estimates generated are sampling errors that provide information on the variability of the estimates and their precision at a given level of confidence. The sampling errors are generated by calculating 80 replicate estimates which are then combined with the primary estimate to calculate the standard error. The margin of error at the 90% confidence level is subsequently generated from the standard error obtained. Point estimates of transportation means and vehicle occupancy are provided in Table A1 for the workforce of 15 cities.

We have employed the Fay's variant of the Balanced Repeated Replication (BRR) method in calculating the standard errors (15). BRR is used in the estimation of sampling variability when a stratified sampling approach is used in collecting the data. Fay's approach, called the Modified Half Sample (MHS) improves on the BRR by addressing the problem of perturbed weights and decreased sample size using an adjustment factor called the Fay coefficient. This coefficient was set to 0.5 for the PUMS data.

Building on the sampling variance, $\hat{V}$ where: $\hat{V} = \frac{\sum_{i=1}^{80}(X_i - X)^2}{N}$

Fay's variance, $\hat{V}_{mhs} = \frac{1}{(1-m)^2}\hat{V} = \frac{1}{(1-m)^2}\frac{\sum_{r=1}^{80}(X_r - X)^2}{N}$ where m is the Fay's coefficient, X_r the replicate estimate and X, the full sample estimate.

[26]Apart from the person records, the PUMS files contain another set of observations based on households called the household records file. The household records file was not used in this study.

Since the PUMS person records file has 80 replicates and $m = 0.5$, the expression above reduces to:

$$\hat{V}_{mhs} = \frac{1}{20}\frac{\sum_{r=1}^{80}(X_r - X)^2}{N}$$

From this point, calculating the standard error is fairly straightforward using a Stata code we wrote to implement the procedure. Tables 4.4 and 4.5 report the margins of error at the 90% confidence level. Table A1 reports the sample estimates without their associated errors.

Table A1: Estimates of the Means of Transportation and Vehicle Occupancy for Selected Cities

Geographical Area	*Means of Transportation*			*Personal Vehicle Occupancy*			*Ratios*	
Cities & Reference Counties[a]	*Personal Car, Truck or Van*	*Others*	*Total*	*Single Occupant Vehicle*	*2 person Commute*	*3 person or more*	*Single divided by all personal vehicles*	*Single Occupants divided by All Commuters*
Atlanta (Fulton & Dekalb)	613803	137326	751129	543350	53245	17208	0.89	0.72
Baltimore (city and county)	536869	118966	655835	468920	55093	12856	0.87	0.71
Buffalo (Erie)	370623	47424	418047	336723	28255	5645	0.91	0.81
Cincinnati (Hamilton)	323645	42507	366152	288900	29393	5352	0.89	0.79
Cleveland (Cuyahoga)	485017	70503	555520	441390	35963	7664	0.91	0.79
Milwaukee[b]	653495	78538	732033	589088	52883	11524	0.90	0.80
Minneapolis (Hennepin)	490767	110565	601332	442107	40346	8314	0.90	0.74
Newark (Essex)	239413	99267	338680	209205	22022	8186	0.87	0.62
Oakland (Alameda)	522355	158534	680889	447521	55294	19540	0.86	0.66
Pittsburgh (Allegheny)	**467504**	**112772**	**580276**	**413384**	**47288**	**6832**	**0.88**	**0.71**
Raleigh (Wake, Durham)	508474	64240	572714	454057	42052	12365	0.89	0.79
Sacramento (Sacramento)	510457	71414	581871	437816	57416	15225	0.86	0.75
St Louis (city and county)	540228	72075	612303	494321	37910	7997	0.92	0.81
Tampa (Hillsborough)	503628	59520	563148	449585	42903	11140	0.89	0.80
Tucson (Pima)	352973	56454	409427	312673	31497	8803	0.89	0.76

Source: Numeritics. Figures based on population estimates generated from US Census PUMS data 2009-2011

[a] *Reference counties are selected based on the geographical area that most city workers are expected to be resident*

[b] *Milwaukee reference counties include Milwaukee, Washington and Waukesha*

A2 Workforce Composition Ratios

In the course of this study, we created ratios that have proved invaluable in assisting the research team to identify the subset of the population to focus on and secondly, examine if there are differences in workforce composition across cities of comparable workforce that featured in the study.

Pittsburgh's relatively high workforce population relative to the resident population provides us with a compelling argument to focus most of the environmental scan research effort on employees' commuting behavioral pattern. A finer segmentation also revealed that 3 out of every 4 city worker is not resident in the city[27]. This revelation, coupled with the significantly different commuting pattern across the two cohorts afforded the research team the opportunity to make an assessment with regards to factors that shape the demand for parking without the need to carry out a comprehensive study.

Table A2 provides the results of the ratio analysis using 15 cities of comparable workforce. Figures for the ratios are shown in the last two columns and they are labeled as to be self-explanatory. Pittsburgh has the highest magnitude for all the cities analyzed for both ratios. Reducing the ratio of non-resident workers relative to city resident workers will make less demand on the available parking spots. It also bears stating that the relatively high ratio also has tax implications which we alluded to as a footnote in the environmental scan section.

Table A2: Workforce Composition and Resident Ratios for Selected Cities

Cities	*Total Employment Figure (a)*	*Total Resident Population (b)*	*Reside in the city but work outside (c)*	*Employed in the city but live outside (d)*	*Total Employed divided by resident population (a/b)*	*Non resident workers divided by city residents employed outside (d/c)*
Atlanta	392195	432427	96578	321177	0.91	3.33
Baltimore	325608	619493	130827	214351	0.53	1.64
Buffalo	143881	261025	53375	100446	0.55	1.88
Cincinnati	211701	296223	67217	162875	0.71	2.42
Cleveland	271633	393806	76699	204931	0.69	2.67
Milwaukee	299751	597867	114702	172087	0.50	1.50
Minneapolis	297849	387753	100194	224946	0.77	2.25
Newark	144020	277540	64468	118508	0.52	1.84
Oakland	197708	395817	108391	151490	0.50	1.40
Pittsburgh	**282841**	**307484**	**55483**	**211185**	**0.92**	**3.81**
Raleigh	331302	416468	92670	247003	0.80	2.67
Sacramento	302979	472178	100933	224853	0.64	2.23
St Louis	232684	318069	73941	174489	0.73	2.36
Tampa	302590	346037	73353	239516	0.87	3.27
Tucson	223755	525796	72696	113120	0.43	1.56

Source: Numeritics. Calculation based on US Census 2011 OnTheMap data

[27] This is almost the exact opposite compared to that observed for the City of New York where non-city residents are only 27% of the working population.

REFERENCES

1. Baxter, G. & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with Computers, 23,* 1, 4-17
2. Preece, J.; Rogers, Y., & Sharp, H. (2002) *Interaction design: Beyond human-computer interaction.* New York: John Wiley & Sons, Inc.
3. (Human-centred design for interactive systems (ISO 9241-210, 2010) Available at http://www.iso.org/iso/catalogue_detail.htm?csnumber=52075
4. IBM report on Smarter Cities Challenge: Available at http://apps.pittsburghpa.gov/mayor/IBM_Smarter_Cities_Report_2013.pdf
5. Fabusuyi T., Hampshire R. & Hill V. (2014). "Evaluation of a Smart Parking System". Forthcoming, *Transportation Research Records*: Journal of the Transportation Research Board of the National Academies.
6. http://www.urbancincy.com/2013/08/cincinnati-approves-elimination-of-center-city-parking-requirements/ Accessed September 18, 2013
7. US Census Public Use Microdata Sample (PUMS) data URL: http://www.census.gov/acs/www/data_documentation/pums_data/
8. US Census Local Employment Household Dynamics (LEHD) OnTheMap URL: http://onthemap.ces.census.gov/
9. US Census Quarterly Workforce Indicators (QWI) URL: http://lehd.ces.census.gov/applications/qwi_online/
10. Circulation and Mobility Vision Project URL: http://www.eastliberty.org/post/east-liberty-circulation-and-mobility-vision Accessed June 4th, 2013.
11. http://www.eastliberty.org/community-planning/plans-and-studies/parking-study Accessed May 28, 2013
12. Mainstreaming Participation: From the Series "*Promoting participatory development in German development cooperation*". GTZ Publication. Copy available online at http://www.fsnnetwork.org/sites/default/files/en-svmp-instrumente-akteuersanalyse.pdf
13. http://www.post-gazette.com/stories/news/transportation/port-authority-system-to-let-riders-track-buses-in-pittsburgh-region-690023/#ixzz2WjU6G9UR
14. Spielberg, F. & Shapiro, P. (2000). "Mating Habits of Slugs: Dynamic Carpool Formation in the I-95/I-395 Corridor of Northern Virginia". *Transportation Research Record* No. 1711, Transportation Research Board of the National Academies, Washington, D.C., pp 31-38.
15. Fay, Robert E. (1995), "VPLX: Variance Estimation for Complex Surveys, Program Documentation," unpublished Bureau of the Census Report.

Evaluation of a Smart Parking System

Tayo Fabusuyi
Lead Economist, Numeritics
5907 Penn Avenue, Suite 313
Pittsburgh, PA 15206

Robert C. Hampshire
Assistant Professor of Operations Research and Public Policy
H. John Heinz III College
School of Public Policy and Management
School of Information Systems and Management
Carnegie Mellon University
4800 Forbes Ave.
Pittsburgh, PA 15213

Victoria Hill
Research Scientist, Numeritics
5907 Penn Avenue, Suite 313
Pittsburgh, PA 15206

Word Count: 5200 + 500 (2 Figures) + 1250 (5 Tables) = 6,950
Date: November 12, 2012

Abstract

This paper documents the methodological approach and findings of an evaluation process for a smart parking application that provides real time information on parking availability. The initiative is in response to the increased demand for parking spaces within the Pittsburgh Cultural District and the desire to improve patrons' parking experiences. Primary data, obtained through semi structured interview, in-person and online surveys of patrons were utilized for the stakeholders' analysis, baseline data, process evaluation and outcome evaluation phases. Secondary data that utilized count data obtained from website use logs was employed for the output evaluation phase. The contributions of the evaluation framework are the insights it provides on how the key challenges created by the unique environment within which the system was deployed were addressed and how the framework could be employed in tackling response shift bias through the use of a binary system approach that uniquely identifies distinct cohorts of respondents. The report is especially timely given the prohibitively expensive cost of employing a supply side approach in addressing cities' parking problems, the ease of replicating the evaluation framework and product design and the wealth of information it provides to the body of knowledge in the evaluation of technological products.

1 Introduction and Project Objectives

ParkPGH is a smart parking system that uses historical parking and event data in a prediction model to provide real-time information on the availability of parking in eight parking facilities within the Pittsburgh Cultural District. The Cultural District is home to the arts and entertainment scene supported by the Pittsburgh Cultural Trust (PCT), a nonprofit arts organization established in 1984 to lead the cultural and economic development of downtown Pittsburgh primarily through the use of the arts. Since its inception, the PCT has witnessed significant increases in attendance and patronage within the District. This development has placed considerable strain on the existing amenities within the District, particularly parking facilities, a situation further compounded by the scale of activities on the North Shore[1] and the added demand for parking from sporting fans.

To address this problem, PCT, with funding from the Benter Foundation, initiated ParkPGH, a smart parking, technology based, pilot program within downtown Pittsburgh. The program will enhance the existing off street parking facilities within the District by providing real time information using a host of information delivery methods that includes an iPhone application, traditional and mobile website, text messaging and an interactive voice response system. The primary goals of the program are to reduce search time and search time variability when finding a parking space within the Cultural District and to make the District a more desirable destination for patrons by reducing the anxiety and uncertainties related to parking issues. Other goals include reduction in late-coming incidence to PCT performances, a decrease in greenhouse gas emissions and congestion reduction through less cycling while looking for a parking spot, and to attract new patrons who were previously deterred by the uncertainty of parking availability.

Currently, the pilot program monitors eight parking garages totaling 5000 parking spaces, representing approximately 20% of the total parking supply in downtown Pittsburgh and over 90% of the parking supply in the cultural district. This large share of parking spaces within the Cultural District provides a unique opportunity to evaluate the program's impact. The evaluation approach consisted of both a formative and a summative component. On the formative side, the evaluation addressed usability, accessibility and accuracy of the information provided by the pilot program. The summative component focused on ascertaining progress made in achieving stated goals and in estimating the program's value added.

The study is timely given the prohibitively expensive cost of employing a supply side approach in addressing cities' parking problems, the ease of replicating the evaluation framework and product design and the wealth of information it provides to the body of knowledge in the evaluation of intelligent transportation solutions. While we have emphasized the common themes that are generalizable irrespective of the situation, every effort has been made to reflect the context of the environment in which the product was deployed. To that end, the evaluation framework employed has been informed primarily by the target population and the unique environment that captures parking in downtown Pittsburgh.

The rest of the paper is organized as follows. The project's description is addressed in the next section. The third section presents the evaluation framework and the data sources employed for the evaluation. Pre and post deployment measures are addressed in the fourth section while section five provides estimates of the project's impacts on congestion reduction, the time value of money and reduced expenditure on gasoline. The concluding section provides insight on the caveats associated with our findings and gives suggestions on areas where the evaluation study could be potentially improved.

[1] Pittsburgh's geographical layout, with a "Golden Triangle" downtown bounded by three rivers, is unique. The "North Shore" refers to the area across one river from downtown that contains the football and baseball stadiums, along with a variety of hotels and restaurants. It is possible to park downtown and walk across a bridge to the North Shore.

2 Project Description

A series of IT-enabled initiatives exist that utilize a demand side approach in addressing parking problems. These initiatives are collectively referred to as smart parking solutions and they are broadly classified into two categories - *parking guidance systems (PGS), and real-time/prediction information* (Hampshire et al, 2011). The PGS systems employ variable message signs and are typically coupled with transit and park & ride lots with an example of actual implementation in Cologne, Germany (Orski, 2003). The latter category examines the display of information on parking spots using either real-time or prediction information via a wireless medium that links several vehicles (Caliskan et al, 2007; Teng et al, 2008).

ParkPGH[2] belongs to the latter category. At the core of the ParkPGH app is a system development and integration module that collects real time parking information from the included garages by tapping into the gate counts for each garage. This was made possible through the use of a web interface and infrastructure that collects, validates, and stores parking information in real time. The resultant information is updated every minute and delivered through channels that include websites, iPhone app, SMS text, voice and a mobile version of the website that provides the same information as the traditional website but is

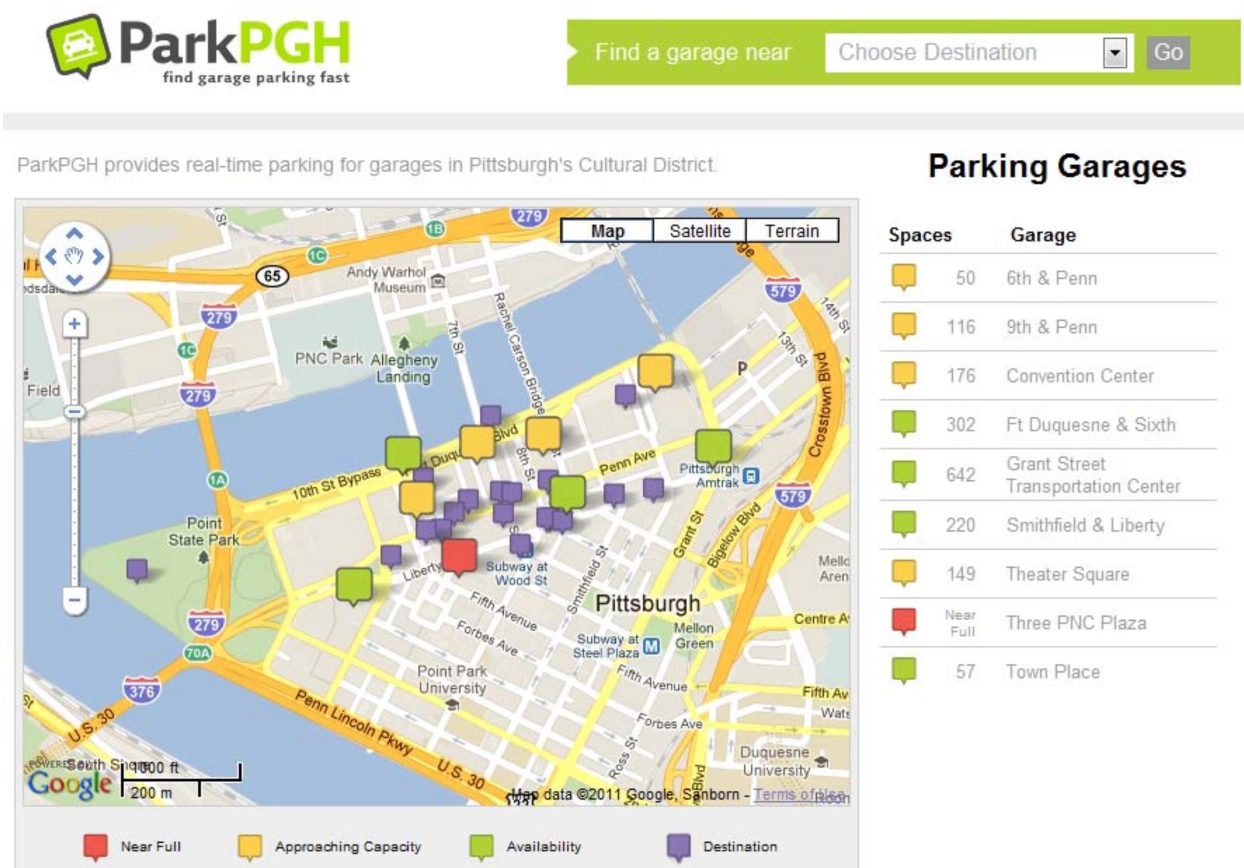


Figure 1: ParkPGH representation of Pittsburgh's downtown with available parking spaces

optimized for mobile devices such as Blackberries and Android phones. The "traffic sign" colors used in the

[2] The ParkPGH application has both real time and predictive modules although this evaluation only covers the real time component.

app are utilized in providing information to patrons looking for parking spaces. The green, yellow and red color coding is complemented with a numerical figure that shows the available number of parking spots, except in cases where the garage is deemed full or close to full. A snapshot of the website showing destinations within the Cultural District, garages and the available spaces is provided below.

The iPhone app and the mobile website feature a scrollable view, listing each available parking facility and its parking space availability. Clicking on a garage reveals more information, including the facility address, map and pricing. In addition to parking garage information, popular destinations will also be displayed so that visitors can locate their targeted destination and find the closest available parking. The app or the mobile website also allows users to subscribe to parking alerts. For example, a user could elect to receive a text message notification if a specific parking garage fills up before a chosen time on a certain day. A situation in which these alerts would be useful is if a person is attending a 7 p.m. show and wants to be alerted if the lot they had planned to park in fills up before 6:30 p.m. The alert will also suggest nearby garages with available parking.

A series of initiatives was also launched to promote ParkPGH. Specific marketing activities include using ParkPGH as the parking information source for the Convention Center events, displaying the app on posters in and around the Cultural District, placing advertisement in regional papers and magazines and organizing a number of press events. Other activities used to get the word out about smart parking application are social media campaigns, website promotions, jumbotron video ad, email blasts and ticket inserts. The effectiveness of these initiatives was not part of the evaluation process.

3 Evaluation Approach

An appreciable volume of literature exists on smart parking applications. However, very little documented evaluation exists of these initiatives. The few documented evaluations in existence primarily target parking guidance information systems or smart parking systems that are coupled with park and ride lot use (Rodier et al, 2005). Others address much broader initiatives, for example, the National Evaluation Plan for San Francisco Urban Partnership Agreement and the accompanying report on post-launch implementation (SF*park*: Putting Theory into Practice, August 2011).

We have borrowed a cue from the evaluation guidelines specified in the National Evaluation Plan and tailored it to better speak to the ParkPGH initiative. The ParkPGH evaluation framework consisted of two phases, a pre-deployment phase that includes a stakeholders' analysis and the collection of baseline data and a post–deployment phase that addresses the process and outcome evaluation pieces. Semi structured interviews were utilized for the stakeholders' analysis while surveys, both in-person and online, were administered to the beneficiaries of the smart parking application. Other data used for the evaluation include usage data from Google Analytics and secondary data from document review.

The pre-deployment or ex ante evaluation addresses both the stakeholder analysis and the collection of baseline data. This phase of the evaluation includes identifying the stakeholders and the deficit to be addressed by the program intervention with the deficit being framed as the difference between the status quo – the present state of parking within the Cultural District and the desired state. We subsequently collected baseline data to establish the status of parking before the deployment of ParkPGH.

The post-deployment or ex-post evaluation addresses both the formative and the summative evaluation. The formative evaluation is process driven and provides real time information as ParkPGH is being rolled out.

The real time information has been invaluable in providing the development team crucial insight on how receptive the public is to the pilot program and alerts them to areas where users are experiencing difficulties. The summative evaluation focuses primarily on program outcomes and captures the state of parking within the Cultural District after ParkPGH deployment based on indicators that proxy the key objectives identified by stakeholders. In addition, we have provided estimates of program impact and information on cost benefit analysis (CBA).

The evaluation framework was designed to be robust enough to address some of the inherent pitfalls when evaluating a program of this nature. Some of these include:

- *Correction for the oversampling of early comers surveyed during PCT events:* The most constraining issue with the use of in-person surveys had to do with an oversampling of early-comers to events, as those patrons arriving early were the ones with enough time to complete an in-person survey. This was addressed in two ways. The first was by using an online survey, which included a broad sampling of patrons which encompassed both early-comers and late-comers. These online surveys were administered to patrons using the PCT email list the day after the event. We were also able to selectively identify and survey those patrons who arrived close to the curtain call using time stamped information from their event tickets.

- *Increasing the number of respondents for the Pre-Deployment phase*: The Smart Parking application went live during the time baseline data was being collected. To increase the number of observations used for the baseline data, we identified the control group for the post-deployment phase; those individuals who did not know about the existence of the smart parking technology or who were yet to make use of it and treated this cohort as if they belonged to the pre-deployment phase.

- *Addressing response-shift bias:* The evaluation framework allows for the examination of the quality of self-reported measures provided by respondents in instances where multiple surveys are administered over a period of time. This response shift bias situation may arise when individuals have rated themselves at one time from one perspective and then change their responses later because these perspectives have changed.

It is imperative to address the possible presence of response shift bias given that the assumption of an invariant measurement scale both before and after the program intervention may not hold (Howard, 1980). The typical approach in ascertaining the effect of a program is to administer identical questionnaires both before and after program implementation. However, for self-reported measures, an inaccurate impact measure may be obtained if the frame of measurement on which the pretest questionnaire is answered is altered when responding to the posttest survey.

We addressed this by utilizing a binary numbering system to identify subsets of the respondent population, for example, 01 (respondent completed only the post deployment survey) and 11 (respondent completed both pre and post deployment surveys). We could now subsequently investigate the response shift bias alluded to earlier. For example, are there systemic differences in the data provided by individuals who completed the outcome survey given that they did (or did not) complete the baseline questionnaire? We investigate this by looking at the respondents for the posttest questionnaire, classifying into two cohorts depending on whether they responded or not to the pretest survey. For each question of interest, we subsequently compare $\frac{\sum_{j=1}^{j} Q_i}{j} | z = 0$ and $\frac{\sum_{k=1}^{k} Q_i}{k} | z = 1$ to ascertain if the difference between them is statistically significant where Q_i represents the ith question, j and k represent the respondent population and z assumes a value of 1 if the pretest survey was completed and 0 otherwise[3].

4 Pre and Post Deployment Measures

The pre and post deployment evaluation measures provide information on both the efficiency with which ParkPGH is operating and its effectiveness in achieving program objectives. Over and above this, we have used this information to shed light on program management issues and provide insights on how modifications could be made to program design.

4a Pre Deployment Measures

Prior to gathering baseline data, a Stakeholders' Analysis was conducted to determine precisely who the target audiences were, what issues and concerns existed surrounding parking within the Cultural District, and in consultation with stakeholders, what the ideal state should be. The process revealed that the patrons of the PCT, businesses within the Cultural District and garage owners are the key stakeholders and that an appreciable number of these individuals are dissatisfied with the current parking situation. Key program objectives include reducing parking search time and search time variability, decreasing the incidence of late-coming as a result of difficulties with finding a parking spot and improving peoples' perceptions about parking downtown. It is also expected that a reduction in the uncertainty associated with finding a parking space will attract new patrons to the Cultural District. Information on the stakeholders including their expectations and objectives and program measures that address these objectives are provided in Table 1.

Table 1: Stakeholder Analysis and Measures

Stakeholder	Expectations & Objectives	Measures
PCT/PCT Patrons	Decrease in late coming incidence to events	Percentage of patrons arriving after curtain
	Reduction in parking search time	Difference in pre/post average search time.
	Reduction in search time variability	Mean parking search time deviation
	Reduced parking stress for patrons	Perception measures through surveys
Garage Owners & Management	Improved management of lease holders	Predicted demand estimates
	Increased flexibility in handling contingencies.	Predicted demand
Pittsburgh Downtown Partnership (PDP)	More positive perception on parking	Perception measures through surveys
	Reduced cycling time	Average parking search time outcome measure.
	Decreased greenhouse gas emissions	Estimated value of congestion reduction.

[3] While a comparison of means showed little difference, we could not conclusively say that these differences are not statistically significant given the small sample size and the need to control for population differences across the cohorts compared.

Findings from the stakeholders' analysis are presented in Table 1. The table identifies the key stakeholders, itemizes their expectations and objectives of the project and provides indicators that could be used in measuring progress made towards these objectives. The PCT intends to reduce the incidence of late coming to events and reduce the stress associated with parking for its patrons. Predictive information provided by ParkPGH will allow garage owners to proactively manage their facilities. For example, if a higher than average demand is predicted for a specific period, garage management could artificially increase their capacity by making provision for valet parking. In addition, a more favorable perception of parking within the Cultural District may encourage individuals, who were previously deterred from coming downtown because of the parking situation, to patronize businesses within the District.

A needs assessment that builds on the stakeholders' expectations and objectives was subsequently conducted. Data for this phase was collected through a combination of in-person and online surveys administered to patrons attending Pittsburgh Cultural Trust events. The baseline data obtained with respect to key objectives are presented in Table 2.

Table 2: Baseline Data on Key Program Objectives

Program Objectives	Data Obtained
Parking search time	7.3min
Search time variability	5.4min
Late coming incidence	27.0%
Perception about parking (% *indicates those surveyed without a positive response*)	
Parking satisfaction	25.7%
Ease of finding a parking space	22.4%
Overall parking experience	22.7%

In all, a total of 736[4] individuals were surveyed about their perceptions on parking within the Cultural District in the time period between September 18th, 2010 and January 23rd, 2011. The survey instruments employed utilized the use of a 1-5 Likert measure for the scaled responses. This scale was subsequently converted to a 1 to 3 scale – positive, neutral and negative. The survey also includes responses with options, binary responses and continuous variable questions. The surveys were administered based on events scheduled by the Pittsburgh Cultural Trust (PCT) and were either administered in-person or online using the email address of PCT patrons who attended a performance.

Parking search time is measured by the mean search time while *Search time variability* is measured by the standard deviation from the mean. A low standard deviation number indicates less variability while a high standard deviation number shows that the data points are more dispersed around the mean. The search

[4] This number consists of both online and in-person surveys carried out over a 4 month period. Of the total number of individuals surveyed 501responded to the online survey while 235 were surveyed in person. Differences in responses to the questions asked in the survey were not statistically significant across these two cohorts except for a couple of questions that are related to program outcomes where higher than the average in-person survey responses were observed for the online cohort. Non-response bias was observed among the in-person cohorts because individuals who showed up close to curtain time were not interested in participating in the survey and the survey team ended up oversampling the early comers, consequently, leading to downward bias estimates for search time and search time variability for the in-person cohort.

time variability, measured by the standard deviation is 5.4minutes. This means that approximately 70% of all respondents found a parking spot between 1.9 and 12.7 minutes (Mean ± 1.0 standard deviation).

More than one out of every four respondents said they have been late for a Cultural District event because they had difficulties finding a parking spot. A similar number also reported not having a positive experience with overall parking when coming for a Cultural District event. In addition, the needs assessment phase revealed that patrons are reluctant to use fringe parking lots partially because of security issues and because of the long walk in dress attire during the winter season – approximately 70% revealed their preference for closer proximity as compared to lower price.

4b Post Deployment Measures

In order to improve upon and ascertain the value added by ParkPGH, a series of indicators were tracked. Count data was used to track output measures that include the weekly usage volume for each of the delivery channels used to provide information by ParkPGH. This includes iPhone app, mobile and traditional website usage, number of text messages sent on request, number of unique views, number of automated phone responses, bounce rate and average duration of page views. A sample of the measures tracked is shown below.

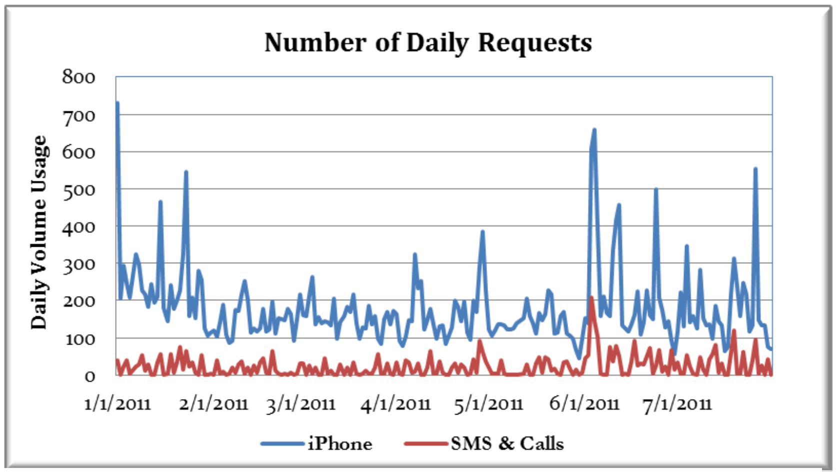


Figure 2: Daily requests by selected delivery channels

Figure 2 shows the number of daily requests for selected delivery channels between January 1st 2011 and July 31st, 2011. The usage volume is typically higher during the weekdays compared to weekends except when events are scheduled. The noticeable spike in usage on the weekend of June 3rd to the 5th is attributed to the Pittsburgh JazzLive Festival, a weekend of music that includes outdoor stages, visual art shows, International musicians and a JazzLive crawl.

The usage pattern was driven, in part, by a wide range of marketing activities carried out to inform and educate PCT patrons about ParkPGH. Marketing activities targeted to PCT patrons include ticket inserts, email blasts to patron lists, playbill advertisements, website promotions and social media campaigns. Other activities address a broader population by utilizing posters in and around the Cultural District, advertising in regional magazines and jumbotron video advertisement. However, the evaluation of the effectiveness of these activities was not undertaken.

Process measures were also utilized for formative evaluation purposes. Information obtained from these measures was used to make modifications to the smart parking project. Ease of use, difficulties with design and accuracy of the information provided are some of the process related measures tracked. A negative response on the online survey to any of these measures prompts an open-ended question that allowed the respondent to provide detailed information as to the nature of the problem being encountered. Such information was subsequently relayed to the development team. Table 3 shows the data obtained for process related measures for a total sample size of 43 respondents.

Table 3: Process related measures (%)

PROCESS MEASURES	%
Usability (Ease of Use)	
% of respondents with positive response	77.1
% of respondents that are indifferent	20.0
% of respondents with negative response	2.9
Usability (Difficulties with Design)	
% of respondents that experienced difficulties with product design	8.8
Information Accuracy	
% of respondents that said information provided was not accurate	6.8

While only 3% of respondents reported having difficulties using ParkPGH, approximately 1 out of every 12 reported experiencing difficulties with the design or with the accuracy of the information provided. Some of the problems users experienced include difficulties telling a landmark from a parking structure, recorded messages not being clear, the cursor hovering over the icon, and sending a text request too early.

An appreciable degree of effort was expended on addressing the information accuracy issue, particularly in situations where garages are close to full capacity. Some of the challenges in providing accurate information stem from the fragmented ownership and diverse management structure of the garages that are featured in the pilot phase of the smart parking application. When the project was initially conceptualized, it was thought that there was a uniform method of determining the number of currently available parking spots in the garages, along with a way of determining when the garage could be identified as being "full." However, each parking garage has its own "culture" of determining how and when to identify the garage as being "full." Variables that factor into that decision include the number of leased spots to hold open, use of valet parking, the threshold level at which the "full" sign goes up and garages that distinguish between hard and soft full.

This lack of standardization has made it challenging to provide accurate information on parking availability across garages when garage utilization is close to maximum capacity. This issue was addressed in part by providing a web portal for garage managers. The platform allows the documentation of lease management strategies and process issues that shape the idiosyncratic features exhibited by some garages. The information is shared with the software development team with the objective that subsequent modifications to the smart parking algorithm will reflect these garage specific traits. In addition, we have suppressed the information on the number of parking spaces available when the garage is deemed full or close to maximum capacity. The possible options by which information is relayed to the public were pilot tested to ascertain the ideal level of detail especially when garages are close to full capacity.

Outcome measures that document the impact of ParkPGH are provided in Table 4. Approximately one out of every two respondents reported that the application has reduced the time it takes them to find a parking space. The magnitude of the reduction in search time ranges from as little as a minute to more than 6 minutes with individuals reporting a 4-6 minute reduction in search time being in the majority.

Table 4: Outcome related measures

DOCUMENTED OUTCOME	%
ParkPGH has made finding parking spaces easier	
% of respondents with positive response	57.2
Specific reduction in search time	
% of respondents reporting a reduction in search time	48.6
% of respondents with 1-3min reduction	17.1
% of respondents with 4-6min reduction	22.9
% of respondents with more than 6 min reduction in search time	8.6

5 Estimated Impact & Cost Benefit Analysis

ParkPGH's estimated impact was calculated over a seven month period (1/1/2011 – 7/31/2011) using evaluation findings and count data from Google Analytics. 271,512 garage enquiries were generated[5] over the seven month period. Of this figure, 63.4% are unique views. This information, coupled with the mean reduction in search time from Table 4 translates to a total of 5,746.6 hours saved.

From the hours saved, we have estimated ParkPGH's impact as the cumulated savings from the time value of money and the reduced gas expenditure. Key assumptions used in calculating the impact include an average fuel economy of 20 miles per gallon, a $3.50 cost for a gallon of gas and a downtown cruising speed of 10miles per hour. We have also assumed that the survey results are representative of the population. The calculated estimates are provided in Table 5

Table 5: ParkPGH Estimated Impact

Impact Type	*Form of Measure*	*$/Unit*	*# of Unit*	*Savings ($)*
Time Value	Hour	20.44[6]	5746.6	117,460.5
Gas Expenditure	Gallon	3.50	2873.3	10,056.56
Cumulative Savings				**127,517.06**

The annual impact is estimated at $218,600.67 and the annual potential impact at planned full scale deployment is estimated at $1,093,003.35. These figures are premised on a linearity to scale assumption. Secondly, it bears stating that we have not employed an adjustment factor for the number obtained for the unique garage inquiries. The rationale is that figures from the documented outcomes from the surveys were used to estimate the value added by the parking application and we have assumed that the individuals surveyed are representative of the population of ParkPGH users. Thus, it is expected that individuals who ended up not making the trip or were just checking the site out for novelty reasons will not be within the cohort of respondents who reported a reduction in parking search time.

[5] Statistics also exist for the bounce rate and average duration of page views. However, we have chosen not to adjust the effective number of requests by these figures given that virtually all the information a driver needs to find a parking spot is accessible on the first page of the app.

[6] Mean hourly wage for Pittsburgh, PA. Figure obtained from the US Department of Labor, Bureau of Labor Statistics, May 2010 Occupational Employment and Wage Estimates for Pittsburgh, PA

In addition to the estimated impact, a Benefit Cost analysis was calculated using both the NPV and the Benefit Cost ratio (BCR) approach. Cost components taken into consideration include capital costs, operation and replacement costs. The analysis was performed with a 5% discount rate and a 5 year time horizon using $\frac{\sum_{t=0}^{4}(B_t - C_t)}{(1+r)^t}$ for the NPV and $\frac{PV_B}{PV_C}$ for the BCR where PV is the present value, r is the discount rate, t, the horizon in years, B the benefit and C, the cost. The analysis revealed a NPV of $549,372 and a 2.34 BCR, an indication that for every dollar spent on the ParkPGH project, the society gains approximately $2.34 in benefits.

6 Conclusion

The evaluation of ParkPGH, a smart parking application contributes to the body of documented work on the evaluation of technological innovation for transportation. The application was developed to provide real time information on the availability of off-street parking spots within the Pittsburgh Cultural District using a host of information delivery methods. The primary objectives of the program are to reduce parking search time and search time variability, decrease the incidence of late-coming as a result of difficulties with finding a parking spot, and to improve patrons' perceptions about parking downtown.

To ascertain the degree to which these objectives were achieved, we created an evaluation framework that documents the approach by which data is collected and information solicited at various decision points in the assessment process. The assessment includes an outcome and a process evaluation piece, with the outcome piece identifying progress made towards ParkPGH program goals, and the process evaluation becoming part of a feedback mechanism that provides information on usability and accuracy of the smart parking tool to program developers.

Findings from the evaluation of the ParkPGH pilot program indicate that approximately one out of every two respondents reported that the application has reduced the time it takes them to find a parking space. The magnitude of the reduction in search time ranges from as little as a minute to more than 6 minutes with the majority of individuals reporting a 4-6 minute reduction in search time. On the process side, while only 3% of respondents reported having difficulties using ParkPGH, approximately 8% experienced difficulties with the design or with the accuracy of the information provided. In addition, a NPV in excess of $500,000, measured in 2011 constant prices, was estimated for the project over a 5 year horizon. When expressed in BCR, the society gains roughly $2.34 for each dollar spent on ParkPGH. These are conservative estimates given that the business component of the impact analysis was not taken into consideration. Increase in sales tax receipts could be used to proxy this component but it was problematic attributing the observed increase in tax receipts to the ParkPGH project.

We could not however report on the reduction in search time variability and patron perception post deployment due to lack of data. The inability to provide outcome measures on some variables is not the only shortcoming assocated with the data paucity issue. For example, it was not possible to establish conclusively whether there is response-shift bias in the self-reported reports. Finally, it is important to note that the figures obtained for the post deployment measures were obtained from a fairly small sample size that may not be representative of the population of interest.

Acknowledgement

We would like to thank Marc Fleming and John Mumper of the Pittsburgh Cultural Trust for guidance and Merrill Stabile, Jim Funovits and Don Levkus from Alco Parking for providing us with the parking data set, events calendars and many valuable suggestions. The Pittsburgh Parking Authority and the Pittsburgh Downtown Partnership were also instrumental in the success of ParkPGH. Thanks are also due to Katsunobu Sasanuma, our coauthor in an earlier paper that addresses the predictive algorithm of the application. We would also like to extend our gratitude to Hajra Iftikhar, Christopher Loncke and Collins Siu for assisting with data collection. Finally, we would like to acknowledge Deeplocal Inc. for building the ParkPGH application. This work was supported by the Benter Foundation and Traffic 21, a Carnegie Mellon University initiative.

References

Caliskan, M., et al. (2007), "Predicting Parking Lot Occupancy in Vehicular Ad Hoc Networks." Vehicular Technology Conference, VTC2007-Spring. IEEE 65th. pp. .277-281.

Hampshire, R.C., Fabusuyi, T., Hill, V. and Sasanuma, K., "Predictive Modelling for Smart Parking: Case of ParkPGH," 18th World Congress on International Conference of the Intelligent Transportation Systems, Orlando, FL, 2011.

Howard, G. S. (1980). Response-shift Bias: A problem in evaluating interventions with pre/post self-reports. *Evaluation Review*, 4(1), 93-106

Rodier, C. J., Shaheen, S. A., & Smirti, M. Transit Based Smart Parking in the US: Behavioral Analysis of San Francisco Bay Area Field Test. *Transportation Research Record: Journal of the Transportation Research Board, No. 1927*, Transportation Research Board of the National Academies, Washington, D.C., 2005

San Francisco Urban Partnership Agreement National Evaluation Plan: Prepared for the US Department of Transportation by Batelle Memorial Inst. Dec 2009 www.upa.dot.gov/docs/fhwajpo10022/sanfranupa.pdf

Schrank, D., & Lomax, T. The 2005 Urban Mobility Report. Texas Transportation Institute, College Station, TX May 2005

SF*park*: "Putting Theory into Practice". Post-launch implementation summary and lessons learned. August 2011 http://sfpark.org/wp-content/uploads/2011/09/sfpark_aug2011projsummary_print-2.pdf

Teng, H., Qi, Y. and Martinelli, D. R. (2008), "Parking difficulty and parking information system technologies and costs." *Journal of Advanced Transportation*, Vol. 42, pp. 151–178

US Department of Labor, Bureau of Labor Statistics, May 2010 Occupational Employment and Wage Estimates for Pittsburgh, PA http://www.bls.gov/oes/current/oes_38300.htm#00-0000

IS THE CURB 80% FULL OR 20% EMPTY? ASSESSING THE IMPACTS OF SAN FRANCISCO'S PARKING PRICING EXPERIMENT

Draft submitted for consideration by *Transportation Research Part A*, October 2013

Adam Millard-Ball
University of California, Santa Cruz
Santa Cruz, California 95064
United States

Rachel R. Weinberger
Nelson\Nygaard Consulting Associates
New York, NY 10001
United States

Robert C. Hampshire
Carnegie Mellon University
Pittsburgh, Pennsylvania 15217
United States

ABSTRACT

The city of San Francisco is undertaking a large-scale controlled parking pricing experiment. San Francisco has adopted a performance goal of 60% to 80% occupancy for its metered parking. The goal represents an heuristic performance measure intended to reduce double parking and cruising for parking, and improve the driver experience; it follows a wave of academic and policy literature that calls for adjusting on-street parking prices to achieve similar occupancy targets. In this paper, we evaluate the relationship between occupancy rules and metrics of direct policy interest, such as the probability of finding a parking space, the amount of cruising, and show how cruising and arrival rates can be simulated or estimated from hourly occupancy data. Further, we evaluate the impacts of the first two years of the San Francisco program, and conclude that rate changes have helped achieve the City's occupancy goal and reduced cruising by 50%.

1. Introduction

Parking management has been a vexing problem for cities since the invention of the automobile. One concern is excess travel, congestion, air pollution and greenhouse gas (GHG) emissions that are caused by drivers searching for available parking – an activity colloquially known as *cruising*. Studies of cruising date to 1927 (Shoup 2006a) and some researchers have estimated that upwards of 30%, and maybe as much as 50%, of traffic on a given downtown street is comprised of people searching for a parking spot (Shoup 2006b; Shoup 2008; Arnott & Rowse 1999). Shoup estimated that cruising in one small area of Los Angeles produced 3,600 miles of excess travel each day – equivalent to two round trips to the Moon each year (Shoup 2005).

One common response by cities has been to require developers to provide "sufficient" off-street spaces to accommodate expected demand for free parking and to provide municipal garages to make up for shortages at the curb. Many cities introduced off-street parking requirements for new development by the mid-1960s, and such policies have largely prevented cruising in low-density, suburban and newly developed areas. But the wisdom of such parking requirements has recently come into question, not least for cost and environmental reasons. In a bid to foster urban density, and walkability and more efficient transit, some cities such as San Francisco, Seattle and Minneapolis have begun to eliminate parking requirements, particularly downtown and in other urban centers.

Moving away from a policy of copious, free off-street parking places a premium on curb management. If off-street parking is not available, or is provided at a higher cost than on-street alternatives, drivers may rationally choose to cruise (Shoup 2006a; Arnott & Inci 2006). The need for on-street management has long been recognized. In 1935, *Popular Mechanics* reported that the City Council of Oklahoma City introduced parking meters, the first city to do so, in order to enable customers to a commercial area to find a space more easily (Anon 1935); and a 1956 book by the United States Bureau of Public Roads recommends maintaining a curb occupancy rate of no more than 85%-90% in order to mitigate cruising (Bureau of Public Roads 1956). During the 1970s and 1980s many cities lost sight of this need. Unable to foster the political will to effectively manage their curbs these cities suffered double parking; parking in loading zones, bus stops and in front of fire hydrants; and increased cruising. However, there has been a recent wave of interest in price-based curb management to mitigate these problems. Cities such as San Francisco, Seattle, Pasadena, Budapest, Mexico, D.F. and Seoul have set parking occupancy performance standards and adjusted pricing to meet the performance goals.

San Francisco has piloted and carefully documented an extensive and innovative parking management program (SF*park*). We use a new data set from SF*park* to address two related questions. First, we examine the theoretical and empirical relationships between parking performance standards – typically expressed as keeping average occupancy within a certain range – and the outcomes of policy interest, such as the driver's experience and the amount of cruising. Second, we provide a preliminary evaluation of the effectiveness of SF*park*. While the body of knowledge in this area is growing, until now there has been little opportunity to model and analyze an empirical case as complex as San Francisco. SF*park* comprises a variety of initiatives that are detailed below. We do not attempt to separate the effects of the individual components of the SF*park* project; rather we examine travel behavior impacts of the project as a whole.

The contributions of the paper are theoretical, methodological and empirical. On the theoretical side, we show how different measures of parking performance, such as occupancy, relate to the driver experience and cruising. On the methodological side, we develop techniques to estimate cruising, arrival rates and the probability that a block is full from aggregated occupancy data. We then employ these theoretical and methodological tools to an empirical analysis of a large-scale controlled dynamic pricing experiment, SF*park*. While one might expect that increased prices would reduce occupancy and cruising, the magnitude of any impacts is not obvious ex ante – particularly since price adjustments are small and are not immediately visible to drivers.

The following section reviews existing work on cruising and measuring the performance of parking systems, and then shows how this work can be informed by insights from the large literature on queueing theory. We then introduce the empirical setting of San Francisco, and describe the SF*park* program and our sources of data. Subsequent sections discuss the simulation model of cruising that we calibrate using data from SF*park*, and present the model results in terms of cruising and other measures of parking performance. We conclude by discussing policy extensions and directions for future research.

2. Understanding Parking Performance

Shoup (2006a) identifies 16 empirical cruising studies conducted between 1927 and 2001. In more recent years, there have been numerous studies of cruising added to this collection. Empirical studies rely on some kind of driver survey (Shoup 2006b), videotaping (King 2010), or driving and searching by car (Shoup 2006a). This last technique has been criticized as adding to cruising, thus changing the fundamental terrain of the study. Some have tried to address that criticism by using bicycles. Driver surveys generally stop people at intersections or when they have come out of their cars to ask about the purpose of their travel (people stopped during their journey are asked if they are seeking parking) or their experience finding a parking place (people who have parked). Studies that rely on video – or other visual techniques – may be the most robust. They count vehicles passing an open space and infer that the inverse of one plus the number of vehicles to pass an open space is equal to the proportion of traffic that is looking for parking.

The other class of cruising studies is theoretical; this work is well represented in the economics literature. Most analyses conclude that cruising is due to misallocation of resources and should be eliminated (Arnott & Inci 2006; Button 2006). An extension of Arnott & Inci (2006) is due to Arnott & Rowse (1999) who look specifically at spatial competition between curb parking and garages. One study suggests that street parking should be priced equivalent to the marginal cost of providing an additional off-street space (Calthrop et al. 2000).

In contrast to a marginal cost pricing approach, Shoup (2006a) recommends that on-street prices be set to achieve an average occupancy level of 85%, with an explicit rationale of eliminating cruising. Though Anderson and de Palma (2004) question the premise that cruising should be entirely eliminated, the Shoup rule-of-thumb requires that price vary both throughout the day and across different blocks, in order to achieve the occupancy goal. The rule-of-thumb has gained wide policy traction and, as noted above, occupancy targets have been introduced in places including Budapest, Seattle and Mexico, D.F. A similar approach with a slightly lower occupancy target has been adopted as part of SF*park*. A recent empirical analysis of the San Francisco case by Pierce and Shoup (2013) shows an elastic demand for parking on blocks where meter prices have been adjusted.

In spite of widespread acceptance of the 85% or similar occupancy standard, very few studies have sought to analyze the heuristic. The existing literature – primarily based on theory, limited empirical observations and simulation models – suggests that the total amount of cruising would decrease as prices adjust to achieve the target occupancy. However, it is also possible that rate changes have merely displaced cruising drivers to other, perhaps non-metered, blocks, leaving total cruising constant, or even have the unintended effect of increasing trip-making. An increase in trip-making and attendant vehicle travel would occur if higher prices lead to parking spaces being occupied by a larger number of short-stay trips, instead of fewer trips by long-stay commuters. Indeed, one stream of work concludes that, in the presence of strategic drivers, parking occupancy can increase when the per unit time price of parking increases, see Glazer & Niskanen (1992).

Two studies using simulation models do look at the threshold and in particular focus on the important non-linearities in occupancy and cruising (Gallo et al. 2011; Levy et al. 2012). In the latter study, an agent-based model is employed. The authors identify changes in the system dynamics at about 85% but find a much greater impact above 92% (Levy et al. 2012). This paper differs from the previous work in that we develop a robust method by which to understand a fairly complex system and we are able to apply our method empirically, using a fairly large dataset.

Average occupancy is a convenient measure, and intuitive to understand. As suggested by the two simulation studies noted above, however, average occupancy does not directly translate into two key measures of policy interest – how easy it is for drivers to find parking (the driver experience), and how much cruising occurs.

In this paper, we first argue that average occupancy is not the policy relevant variable as driver behavior is not guided by occupancy rate on a block. Rather, it is guided by price and availability; hence the driver is only interested in whether or not there is available parking, and at what price. As long as there is an available space, it matters little if the block is 5% or 95% full. Similarly, no cruising occurs if there is available space, again, regardless of whether average occupancy is at 5% or 95%. Certainly, parking demand is stochastic and a block is more likely to be full at higher average occupancies; the point here is that the probability of a block being full is the measure that is relevant for policy. It is important to note, there is a nonlinear relationship between the average occupancy and the probability of finding a place to park. We focus, therefore, on driver experience instead of the parking space's experience.

This view is supported by fundamental results in queueing theory (see Kleinrock 1976). The queueing literature establishes that the probability of an arriving customer finding a system full is not the same as the time-averaged number of unavailable resources (i.e., average occupancy). For example, an increase in average occupancy from 30% to 40% likely has no impact on the probability of finding a space, in sharp contrast to an increase from 90% to 100%. This implies that the marginal change in the probability of finding a block full as a function of average utilization grows at an increasing rate. Formally, the relationship between average occupancy and the probability of a full block is convex.

Second, the nonlinear relationship between average occupancy and the probability of a block being full will vary depending on the period over which occupancy is averaged. Consider, for example, a block with 85% average occupancy. The longer the averaging period, the more likely is this average to include instances of 100% occupancy. At the extreme, if a one-minute average is taken of 60 second-level observations, an 85% average usually means that the block is never full. Given this intuition and the convexity of the relationship, by Jensen's inequality (Rudin 1987), we would expect the probability of a full block under the two-week average metric (i.e., as the average converges to expected occupancy) to be higher than under the hourly average metric (even when the average occupancy evaluates to the same value). Empirical evidence on the impact of time averaging is discussed later in the paper – in particular, see Figure 4. This issue is important because it highlights the impact of the time scale of setting occupancy targets on cruising.

Third, more people will be trying to park at high-demand times. Thus more people are exposed to crowded conditions even if crowding is experienced for less time. The problem is best illustrated by the case where a block is empty for half the time, fills up very rapidly, and remains full, during which time drivers continue to arrive but are forced to seek parking elsewhere. Objectively, this block has a time-averaged occupancy rate of ~50%, yet only one user experiences it as 50% full. The vast majority of parkers, or would-be parkers, arrive after the block is full and experience it at 100% occupancy. While the occupancy target may thus be met, the user experience may still leave something to be desired.

Queueing theory provides established results specifying the connection between time averages and user averages, and the conditions under which the two averages are equal (Wolff 1982; see Melamed & Whitt 1990). To formalize the experience of the *typical driver*, assume that drivers arrive randomly to park at a block according to a non-stationary Poisson process, $\{N(t) | t > 0\}$ with an arrival rate function, λ(t), which is a function of the time of day. The number of arriving drivers up to time T is denoted by the random variable $N(T)$, and denote the random arrival time of the i^{th} driver by T_i. Let X_t be a Bernoulli random variable denoting the parking occupancy of the block at time t. In this stylized setting, a block at time t can be either full, $X_t=1$, or not full, $X_t=0$. The driver average (shown below on the left) is the policy relevant variable, the time average (shown below on the right) is the commonly used heuristic. Formally, these can be stated:

$$E\left[\frac{1}{N(T)}\sum_{i=1}^{N(T)} 1\{X_{T_i}=1\} \middle| N(T)>0\right]$$

and

$$\frac{1}{T}E\left[\int_0^T 1\{X_s=1\}\,ds\right]$$

respectively. These are equal only very particular conditions and we expect the time-average and customer-average perspective of the system to be different. If the demand anticipates and responds to the occupancy level of the system, then these two averages may diverge (Wolff 1982). The expected parking occupancy, as experienced by the *typical driver* is computed by weighting the occupancy by the arrival rate (Massey 2002).

$$E\left[\frac{1}{N(T)}\sum_{i=1}^{N(T)}1\{X_{T_i}=1\}\middle|N(T)>0\right]=\frac{E\left[\int_0^T 1\{X_s=1\}\lambda(s)\,ds\right]}{\int_0^T \lambda(s)\,ds}. \tag{1}$$

The expected value is interpreted as the weighted fraction of arriving drivers that find the block full.

The empirical model developed later in this paper addresses all three of these issues. We use queueing theory as the basis to derive an empirical relationship between average occupancy and two related quantities of policy interest – the probability that a driver finds a block full, and the number of blocks cruised. We analyze how the length of the averaging period – hourly or biweekly – affects the form of this relationship. And we demonstrate how occupancy data can be used to estimate the arrival rate of drivers looking for parking. By weighting the occupancy data by arrival rates, we focus on the driver average, rather than the time average.

2. Empirical Setting and Data

2.1 Overview of SF*park*

The empirical setting for our analysis is San Francisco, which is home to a large-scale smart parking initiative – SF*park* – developed to improve the management of on- and off-street parking.[1] A unique feature of SF*park* is that it includes both pilot (treatment) and control areas. While SF*park* is administered by the San Francisco Municipal Transportation Agency (SFMTA), the United States Department of Transportation (USDOT) has been an important partner. USDOT has helped finance state-of-the-art technology with new parking meters and in-street sensors that communicate data regularly to a data management system. The system includes two new ways to accept payment, credit card and pay-by-phone; these are in addition to the previous payment options of cash and parking cards. The mantra of SF*park* has been to improve the parker experience and that philosophy undergirds many of their decisions.

One of the key elements of SF*park* is the use of pricing is to reduce the number of drivers cruising for an on-street parking space. This is evidenced by the program's slogan, "Circle Less, Live More." Decreasing the number of cruising drivers is directly connected to the primary public policy goals of interest: reduced traffic congestion and pollution. Several other public policy goals follow from reduced cruising, including safer streets for bikers and pedestrians, and more reliable public transit schedule adherence.

[1] The information in this section is derived from the policy and evaluation reports on the SF*park* website (www.sfpark.org), and personal communications with staff at the San Francisco Municipal Transportation Agency.

Parking prices under SF*park* are adjusted regularly in an attempt to bring average occupancy within the target range of 60% to 80%. This range is slightly lower than Shoup's (2005) recommendation of an 85% occupancy target; the rationale of SF*park* is that an occupancy rate of 60-80% averaged over a two-week evaluation period considers variance within the averaging period, which may include moments where rates exceed 85% and may even reach 100%. When average occupancy in the evaluation period[2] on a given block in a given time band (e.g. weekdays 7am to noon) exceeds 80%, the hourly cost to park is increased by 25 cents. When average occupancy is below 60%, the rate is reduced by 25 cents (50 cents if it is below 30%). Rates are constrained to a maximum of $6.00 per hour, and a minimum of 25 cents per hour.

Three hundred and forty-one on-street blocks (i.e., pairs of opposing block faces or street segments) were included in the pilot and eligible for rate adjustments, in addition to one surface lot and 14 parking garages (which are not considered in this paper). There are three time bands: (meter opening time to noon; noon to 3pm; and 3pm to close), over two day types (weekday and weekend), allowing for six possible price regimes.[3] These different block, day-type and time band combinations create more than 2,000 possible on-street price adjustments at each rate change on the 341 pilot blocks.

During the first two years of SF*park* operations, the period evaluated in this paper, there were ten rate changes. On 5% of the SF*park* blocks the meter rate was never adjusted indicating that average occupancy was in the target range. In 37% of cases the meter prices were adjusted upward or stayed the same at each adjustment. These segments experienced average occupancy above the target level during at least one rate change period. In 37% of cases the meter price was adjusted downwards or stayed the same, indicating segments that were under the target occupancy during at least one rate change period. As of the 10th rate change in April 2013, nine blocks had reached the $6 per hour cap, and 165 were at the 25 cent per hour minimum. Finally, it is worth noting that 20% of the segments were adjusted up at least once and down at least once. These fluctuating segments may merit additional attention in future research.

[2] The length and nature of the evaluation period has been refined during the SF*park* pilot. Initially, two weeks of data were used to compute a separate average by time band, giving an average of 10 days of data for weekdays and 2-4 days of data for weekends (depending on whether meters operate on Sundays in a given area). More recently, Mondays and Fridays have been excluded from the data, meaning that the weekday average uses six days of data. Holidays and special events are also excluded.

[3] An additional timeband was introduced for evening parking in March 2013 in one neighborhood. This is not considered in the analysis here.

2.2 Data Sources

The data used for this study comprise variations on the in-road parking sensor data collected by SFMTA. Some of the analysis is based on hourly average occupancy rates on each block. These hourly data, provided by SFMTA, span the period March 1, 2011 to April 14, 2013. This represents a 5-month baseline period followed by 10 rate changes. In addition, for a subset of the two-year period, we have captured instantaneous occupancy data from the SFMTA website's application programming interface (API).

2.2.1 SFMTA Hourly Data

The hourly data contains information for metered on-street spaces on 408 blocks, plus one off-street lot which we do not consider in this paper. Of the 408 blocks, 256 are pilot blocks, and a further 55 blocks form a study control group designated by SFMTA, where sensors were installed but meter prices held fixed throughout the period.

Sensor data are available for 97 additional blocks, which we do not include in the analysis unless stated. Some of these additional blocks were not considered for rate changes because they fall under the jurisdiction of the Port of San Francisco rather than SFMTA; the Port pursues its own on-street pricing policies. Others were not considered for rate changes because sensor installation was not yet complete, or because smart meters (which allow rate changes to be transmitted wirelessly to the meters, avoiding the need for meter-by-meter manual adjustments) had not yet been installed. This group of blocks without smart meters are almost all located in the downtown area where metered spaces are restricted to commercial loading for most of the day. Figure 3 shows the geographic distribution of these three categories of block.

Each data point specifies the date, the hour, the number of metered and commercial spaces on the block, and the parking rate in effect. Most important for this analysis, the SFMTA hourly data set also includes parking occupancy averaged over the hour. Each data point combines parking occupancy of both sides of the street, which makes most sense for one-way streets and represents a minor data limitation for our analysis with respect to two-way streets (discussed in more detail below). The entire data set comprises 7,064,098 data points over approximately a two-year period. For the results reported here, we only consider the 2,422,901 data points during metered hours, or (in the case of the figures) a more limited subset of 1,682,208. This limited subset only consists of blocks with a continuous record of occupancy data and rate adjustments over the two-year period, and excludes blocks where sensors or smart meters were installed at a later date, sensors were removed for repaving, or where similar issues lead to gaps in data.

2.2.2 Web API Snapshots

The second data set was collected by developing a web application that interacts with the SF*park* API, made available by SFMTA to mobile phone and web application designers as well as any other interested party. The data collected from the API provide snapshots of parking availability and capacity for each side of the street (i.e., block faces) which we aggregate to both sides of the street (i.e., blocks) in order to match the hourly data. Here, we use data for 340 blocks[4], collected at approximately 5-minute intervals.

The two data sets contain overlapping periods of observations from January 1, 2012 to February 14, 2012. The API data set comprises 4,664,469 block-level data points during this period, which reduces to 1,730,770 when we limit the data to observations during metered hours. The API snapshot data set was joined to replicates of the hourly data set using the unique block IDs and the date and time. The two data sets were further checked and cross-validated with each other for consistency. During this validation process, 3.4% of observations from the API snapshot data were discarded due to inconsistencies in hourly average occupancy. In most cases, these inconsistencies simply reflect sampling error given that the API provides about 12 snapshots per hour while the hourly data averages the second-by-second occupancy data from the sensors.

3. Model and Estimation of Parking Availability

Our empirical analysis entails three main stages. First, using the API data at five-minute intervals, we determine the empirical relationship between the probability of a block being full and its average occupancy. This relationship is of intrinsic interest given that the probability of being full is the measure of direct policy relevance, while performance measures and data collection have typically focused on average occupancy. The probability that an arriving driver finds a block full is also needed for our simulations. Second, using the hourly data, we estimate an arrival rate for each one-hour interval on each block, in order to weight our results to reflect the driver experience. Third, we simulate the amount of cruising, and compare these estimates to manual surveys conducted by SFMTA. [5]

In all cases, the underlying model for a block is a stationary Markovian multiserver queue (Kleinrock 1976), which assumes n identical resources, which are parking spaces, and that drivers searching for parking arrive on a block at random via a Poisson process with rate λ. If there is a parking space available, then a driver parks in accordance to first-come, first-served. Once parked, each driver's parking

[4] While there are 408 blocks in the SFMTA hourly data set, we only captured information on 340 through the API. The API does not provide information for the 55 control blocks. On the remaining missing blocks, street repaving meant that no data was available during the period of data collection, or sensors were installed at a later date.

[5] In principle, the probability that a block is full could be obtained directly from the sensor data. However, only hourly average occupancy data are retained by SFMTA, and we only have 5-minute API data for a subset of blocks and dates. Similarly, arrival rates are not computed by SFMTA, and in any case would not include the latent arrivals that are estimated by our method.

duration is random with an exponential distribution of mean μ that is independent of the other drivers' parking durations. The model further assumes that cruising drivers search until they are able to park without giving up. Under this model, in steady state the probability that an arriving driver finds no available parking spaces is derived using the Erlang C formula whose functional form is below

$$\gamma_n(\rho) \equiv \frac{(n\rho)^n}{n!} \cdot \frac{1}{1-\rho} \cdot P\{N=0\}, \tag{2}$$

where

$$P\{N=0\} = \left(\sum_{k=0}^{n-1} \frac{(n\rho)^k}{k!} + \frac{1}{1-\rho} \frac{(n\rho)^n}{n!} \right)^{-1} \tag{3}$$

is the probability that no cars are parked. The steady state average number of occupied parking spaces is:

$$\rho = \frac{\lambda}{\mu n}. \tag{4}$$

Thus, the Erlang C formula expresses the relationship between the average occupancy and the probability that a driver finds an available parking space. This model provides a theoretical foundation that enables our empirical strategy. While we have assumed the first-come, first-serve service discipline, the mean number in the system, mean waiting time and the Erlang C formula remain valid for service in random order (e.g. if a newly arrived driver "jumps the queue" and beats other cruising drivers to an open spot).

In our empirical estimations, the arrival rates λ_{it} vary over each of N blocks $i = 1 \ldots N$ and T time periods $t = 1 \ldots T$. In general, each time period t represents a one-hour period on a weekday, Saturday or Sunday/holiday. If each block is a stationary Markovian multiserver queue, then the parked cars departing a block also follows a Poisson process with rate γ_{it}. The independence of the departure process from the average parking time in this model is due to a foundational queueing theory result called Burke's theorem (Burke 1968).

3.1 Empirical Estimation of Parking Availability

The relationship between the probability of a block being full (Pr[full]) and hourly average occupancy is calibrated from the joined hourly occupancy and five-minute API data. Pr[full] is calculated for each hourly period as the proportion of API observations where the block is full.

The Erlang C formula given in Eq. (2) provides a deterministic relationship between the "true" average occupancy ρ, the number of spaces on each block n, and Pr[full]. While hourly average occupancy $\hat{\rho}$ is observed, this is not the same as ρ. Rather, ρ is a function of the true arrival rate, length of stay and size of block, while $\hat{\rho}$ is the observed outcome following a random process of arrivals. Since Eq. (2) is nonlinear, we cannot simply substitute $\hat{\rho}$ for ρ; the bias is analogous to that in measurement error models (Cameron & Trivedi 2005). Instead, we estimate the following regression equation,

$$\log\left(percent\_full_j\right) = n_j \log\left(n_j\hat{\rho}_j\right) - \log\left(n_j!\right) + \log\left(\frac{1}{1-\hat{\rho}_j}\right) - \log\left(\sum_{k=0}^{n_j-1}\frac{\left(n_j\hat{\rho}_j\right)^k}{k!} + \frac{\left(n_j\hat{\rho}_j\right)^{n_j}}{n_j!}\cdot\left(\frac{1}{1-\hat{\rho}_j}\right)\right) \quad (5)$$
$$+\beta_0 + \beta_1 n_j + \beta_2 \log n_j + \beta_3 n_j\hat{\rho}_j + \varepsilon_j$$

where for each data point *j*: *n* is the number of spaces on the block; $\hat{\rho}$ is the observed occupancy on the block averaged over that hour; percent full is the percentage of API observations on the block during that hour where no space is available; ε is a mean zero error term; and β_0, β_1, β_2, β_3 are coefficients estimated via iteratively reweighted least squares. The first four terms in Eq. (5) comprise the deterministic component of the logged Erlang C formula. The remaining terms provide a flexible parametric component that captures both the effects of measurement error and other departures from the assumptions of the Markovian multiserver queue model.

Table 1 shows the coefficients of the regression model.[6] Figure 1 (left panel) shows the fit of the regression model predictions against the actual data. As can be seen, the fit is very close across multiple block sizes – a paramount consideration given that the purpose of this regression is entirely predictive. Figure 1 (right panel) shows the smoothed predictions for various block sizes.

The relationship between block size (number of spaces) and Pr[full] can also be seen in Figure 1. For any given hourly average occupancy, Pr[full] decreases as the number of spaces increases. This makes intuitive sense and suggests that a uniform occupancy target, across all block sizes, may be inappropriate

[6] Alternative models with a subset of the four coefficients were also estimated, but the model in Eq. (5) / Table 1 was selected based on the lowest AIC value, a common model selection criterion. The addition of block fixed effects may give a better fit, but would eliminate the ability to generate predictions for out-of-sample blocks (i.e. blocks in control areas and other blocks missing from the API data). As it is, the model generates very close predictions.

from a policy perspective. On a block with only one space, the hourly average occupancy is the same as Pr[full] – the relationship is a 45-degree line. For very large blocks, a parker has a good chance of finding a space even at an occupancy level of 90% or more.

The parameters estimated in the regression model are applied to the full dataset to estimate Pr[full] for each data point in the hourly occupancy data set – including data points which do not overlap with the API data. In other words, Pr[full] is estimated as a function of the number of spaces on a block and the hourly average occupancy.

Table 1 **Predictive Model to Estimate Probability that Block is Full**

	Estimate	**Standard Error**
α (intercept)	0.125	0.00287
β_1 (number of spaces)	-1.095	0.00291
β_2 (log number of spaces)	-0.0180	0.00281
β_3 (no. of spaces x hourly average occupancy)	1.094	0.00292
n=135,133		

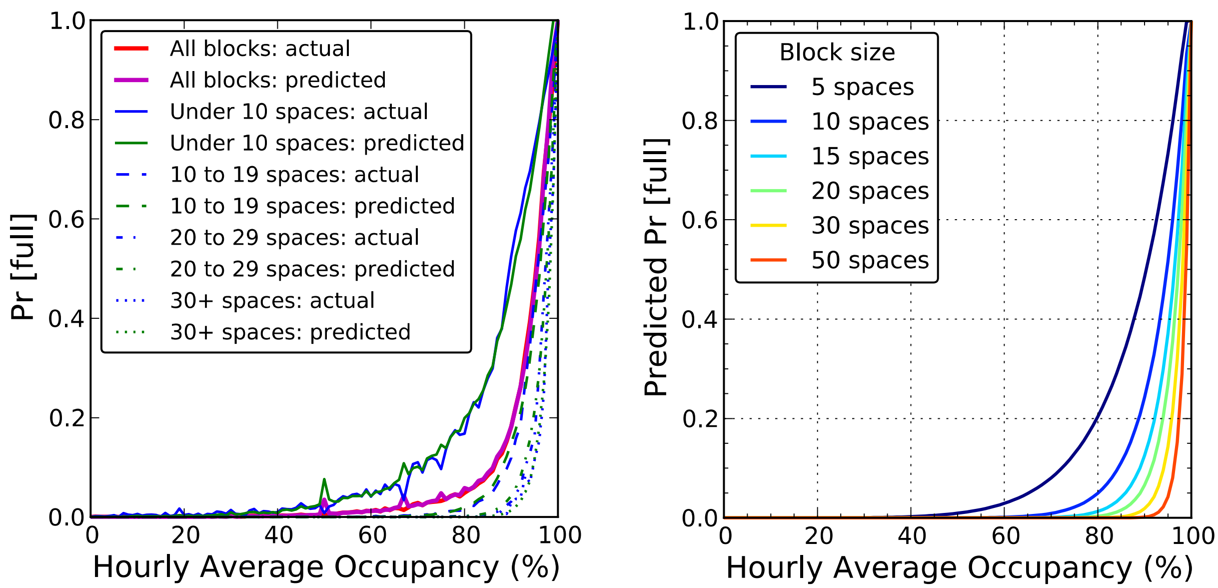


Figure 1 **Predicted Probability of Block Being Full.**

Left panel: actual vs predicted probability. Right panel: predictions for different block sizes

3.2 Estimation of Arrival Rates

We estimate arrival rates in order to weight the simulation results by the level of demand on a block, and thus generate results that are more representative of the driver experience. Estimating arrival rates, rather than taking them directly from the data, is necessary for two reasons. First, the data are censored – if a block is 100% full, then further arrivals (i.e., latent, and unserved, demand) are not observed. Second, the granularity of the available data causes a naïve estimate to miss many instances of parking turnover. Suppose, for example, the API data show an occupancy of six vehicles on a block, rising to seven vehicles in the subsequent snapshot five minutes later. One vehicle could have arrived. Or two vehicles could have arrived and one departed. Or three could have arrived and two departed, and so on.

The assumption of a Poisson process for arrivals and departures in the model in Eq. (2) enables the underlying arrival and departure rates to be recovered as the parameters of a Skellam or Poisson Difference distribution. Formally, if $X \sim \text{Poisson}(\lambda)$ and $Y \sim \text{Poisson}(\gamma)$, then $X - Y \sim \text{Skellam}(\lambda, \gamma)$. In this case, we do observe the quantity $X - Y$ as the change in occupancy between each five-minute snapshot. Both parameters are identified by assuming that arrival and departure rates are constant on each block within each hour-long period.

The Skellam distribution has several well-known properties (Skellam 1948) and the parameters can be estimated by the method of moments or maximum likelihood (Alzaid & Omair 2010). In the present context, the censoring (i.e., that arrivals are not observed once the block is full) necessitates a modified approach. We therefore maximize the log likelihood function

$$\log L(\lambda, \gamma; c_i, m_i) = \sum_{i=1}^{N} \log\left[f_{SK}(c_i; \lambda, \gamma) + \sum_{j=m_i}^{\infty} \sum_{k=1}^{\infty} f_P(j+k; \lambda)\, f_P(j-c_i; \gamma)\, g(j+k, c_i, m_i) \right] \quad (6)$$

where f_{SK} and f_P respectively denote the Skellam and Poisson probability mass distribution functions, given the arrival rate λ and departure rate γ; c_i denotes the observed change in occupancy between each pair of 5-minute observations i; and m_i denotes the maximum potential change (i.e., the number of available spaces at the start of the 5-minute period.)

The first term in Eq. (6) represents the likelihood provided by the Skellam distribution, which by definition sums probabilities over all possible combinations of uncensored arrivals j and departures $j - c_i$ that would yield the observed change in occupancy c_i. The remaining terms represent the likelihood summed over all possible combinations of arrivals $j \geq c_i$ and censored arrivals $k \geq 1$. For each possible combination j, k, the likelihood is the product of the probabilities of observing the number of arrivals $j + k$ and departures $j - c_i$, each of which is given by a Poisson distribution.

The term g denotes the probability that the combination of arrivals and departures is feasible. For example, take the case of a block with a net occupancy change of zero, one available space, one uncensored arrival and one censored arrival, i.e. $c_i = 0$, $m_i = 1$, $j = 1$ and $k = 1$. There are two arrivals and one departure, but they can only occur in the order (a, a, d). With the orders (d, a, a) or (a, d, a), the second arrival will not be censored. We estimate g using a Monte Carlo simulation over 1,000 random permutations of each combination of c, m, j and k. This approach approximates the complex closed form likelihood function of the transient distribution of the underlying multi-server queue (see Kleinrock 1976).

Computationally, the maximum likelihood is estimated iteratively, using the method of moments for the uncensored Skellam distribution (Alzaid & Omair 2010) to provide the starting values. The arrival and departure rates are estimated separately for 72 one-hour intervals on each block, corresponding to each hour of the day on weekdays, Saturdays and Sundays/holidays.

Figure 2 plots the estimated arrival weights as a function of average occupancy on each block. For comparison, two alternative methods of estimating the arrival weights are illustrated. At low occupancies, estimates based on the uncensored Skellam distribution are similar to those from the censored distribution. However, at occupancy levels above about 85%, the two sets of estimates diverge, and the censored estimates are more plausible (there is no drop in arrival rates at high occupancies). Using observed arrivals only (e.g., a change in occupancy from 6 to 8 over a 5-minute period represents two observed arrivals) results in artificially low arrival rates, particularly at high occupancies, as most arrivals are not observed. Because arrivals are unobserved it appears that the arrival rate simply drops off substantially once a block is full, or near full. Obviously there is no intuition for this, indeed the observed drop in arrivals should suggest that drivers continue to arrive but cannot be accommodated, thus they contribute to the cruising problem that the program attempts to address.

Figure 3 shows the distribution geographically, plotting the blocks with widths proportional to the arrival rate. (Control blocks, for which no API data are available, are shown with a uniform width.) Interestingly, there are no clear geographic patterns, other than low arrival rates on some side streets and others with just a handful of metered spaces.

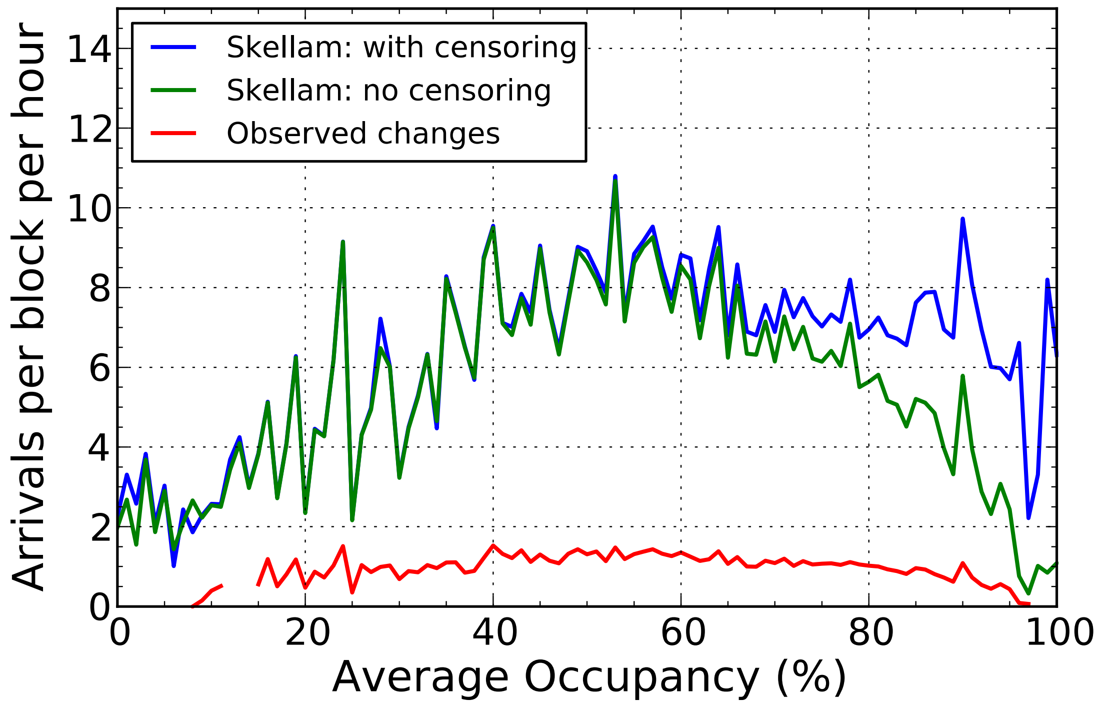


Figure 2 **Comparison of Alternative Arrival Weight Estimators**

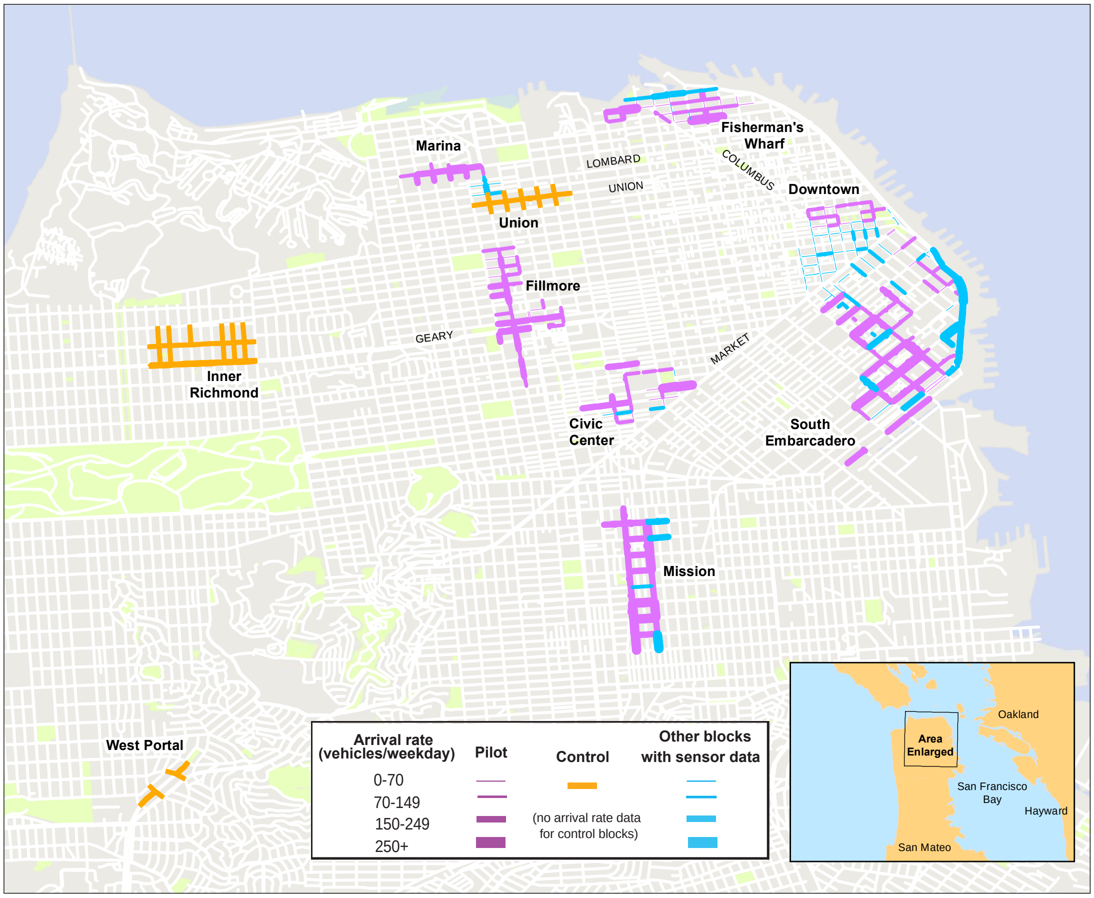


Figure 3 **Estimated Arrival Rates by Block (vehicles per weekday)**

4. Cruising Simulation

For each hourly observation in the SFMTA dataset, a single cruising simulation is run.[7] A parker 'arrives' at each block within each hourly period, and finds a space on that block with probability 1 – Pr[full]. If a space is found, then the number of blocks cruised is recorded as zero. Otherwise, the parker randomly selects an intersecting block,[8] and finds a space on that block with 1 – Pr[full]. Thus, the parker proceeds via a random walk through the neighborhood until either a space is found, or the cap of 30 blocks cruised is reached (and by assumption, the parker gives up or parks off-street). Note that blocks (including the

[7] Multiple simulations could be run and the average number of blocks cruised taken. However, we do not report results for individual hours on individual blocks, and so the law of large numbers will apply at the level of all blocks within a given time period. Our approach also preserves the full range of the distribution.

[8] Some blocks on the fringes of a pilot or control area have few intersecting blocks with sensor data. In these instances, the block's nearest neighbors (e.g. parallel blocks) are added to ensure that at least four blocks are available to be chosen at random as the parker cruises. Also note that the randomly selected block is constrained to be within 400m (~1/2 mile) of the original block, ensuring that the parker cannot cruise too far from his or her presumed destination.

original block) can be visited multiple times. We assume a first-come, first-served system; relaxing this assumption would not affect mean cruising times, but would slightly lengthen the tail of the distribution.[9]

This approach has several advantages over alternative methods of assessing cruising. Most importantly, it allows cruising to be estimated for every hour on every block, rather than the small sample possible with manual methods. It also avoids potential selection bias whereby cruising surveys may focus on busy blocks at busy times. The downsides are primarily as follows:

1. Blocks are chosen at random from the set of blocks that intersect the parker's current location. Refinements to this process could take account of the direction of travel, one-way streets and other restrictions, but we do not consider these here.
2. Intra-hour correlations between neighboring blocks are not considered. The simulation only considers blocks within the same hourly observation period (e.g. 10-11AM on June 22, 2011). However, it is likely that Pr[full] is spatially correlated within each hour. For example, if at 10:10AM a particular block is full, the neighboring block is more likely to be full at that precise time than would be expected from the occupancy averaged over the hour.
3. Only streets with sensor data and general metered parking are included. Thus, cruising on residential side streets that are not equipped with sensors, or on other blocks with no general metered parking in that hour are not accounted for.
4. The simulation assumes that a parker can take advantage of available spaces on either side of the street. On a one-way street, this is realistic (except on wide streets at times of heavy traffic volume). On two-way streets, this may require illegal U-turns, except on streets with perpendicular parking. In practice, many motorists do make U-turns to secure a vacant space on the opposite side of the street, particularly if available parking is scarce. However, the assumption will underestimate cruising from more law-abiding drivers.

Points 2 and 4 and, to the extent that residential streets with free 2-hour parking have higher occupancy rates, point 3 are likely to mean that our estimates of cruising under count and are, therefore, a lower bound on cruising.

[9] A related issue is that it takes some time for drivers to cruise along a block, and that a vacant space may be taken by another driver in the meantime. However, we interpret Pr[full] as the steady state probability, and thus it is equally likely that a space is vacated ahead of the driver.

5. Results

5.1 Evaluating SF*park* Average Occupancy Targets

Figure 4 plots the relationship between average occupancy and two related metrics: the probability that a block is full (blue lines), and the average number of blocks cruised per parking attempt (red lines). The first metric is calculated from the Erlang C-based regression model. The second metric is calculated from the cruising simulations. The average number of blocks cruised is a function of Pr[full], but also depends on the spatial correlation of occupancy, i.e. the probability of finding a space on neighboring blocks if the desired block is full.

There are two points of particular note from the chart. First, both the probability that a block is full and cruising have highly nonlinear relationships with average occupancy. Below 95% occupancy, there is almost no cruising – even if no space is available on a particular block, a driver is likely to find space on the next block visited. Above 95% occupancy, however, the expected cruising distance increases dramatically. The probability of a block being full also increases more rapidly at higher average occupancies. Moving from 85% to 90% average occupancy has much more impact on cruising than moving from 80% to 85%.

Second, it matters how average occupancy is computed. For any given average occupancy, further aggregation (solid lines) results in a higher probability that a block is full and implies more cruising than a lower aggregation would indicate (dotted lines). This occurs because of the nonlinear (convex) shape of the curves in Figure 4; the reasons were discussed above in the section *Understanding Parking Performance*. Intuitively, a longer averaging period will include more observations with higher-than-average occupancies where both cruising and Pr[full] are much higher, as well as lower-than-average occupancies where cruising and Pr[full] are more similar to those at the mean. For example, an hourly average occupancy of 85% might not include any instances when the block was full, meaning that cruising will be zero. In contrast, a two-week average occupancy of 85% will include many instances when the block was full (and thus cruising occurs), as well as many when the block was almost empty.

A direct implication of this second finding is that average occupancy targets should not be set without reference to the period over which the average is calculated. If a two-week period of averaging is used, as in the case of SF*park*, then a lower occupancy target may be appropriate to ensure availability and achieve a given level of cruising. If a day or two of data are used (perhaps as in a small town with fewer data collection resources and fewer parking spaces), then a higher occupancy target may be appropriate. Another implication is that the variance in occupancy matters as well as the mean. The higher the variance, the greater the probability of full will be for any given mean occupancy.

We do not attempt to calculate the optimum occupancy level in this paper. However, any such calculation would need to balance the costs of either increasing supply or reducing demand to reduce average occupancy against the benefits of time savings for drivers looking for parking, along with air pollution and congestion externalities saved. Moreover, the nonlinearities shown in Figure 4 indicate that the real gains come from reducing demand on the blocks with the very highest demand (more than 95% average occupancy), rather than those with more moderate occupancy levels.

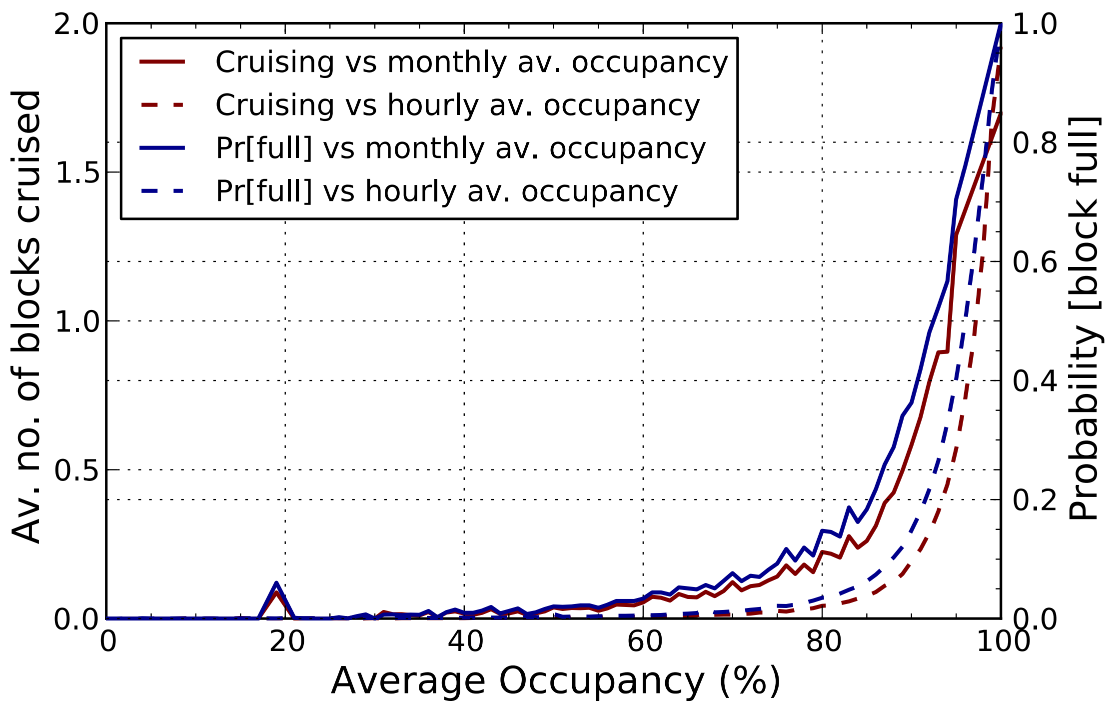


Figure 4. A comparison between hourly average and monthly average occupancy

5.2 Changes Over Time in Occupancy and Cruising

We evaluate changes over time in occupancy and cruising through both a descriptive analysis (Figures 5 and 6; Table 2) and a regression analysis (Table 3). In both cases, we compare changes in pilot areas (where rates have been adjusted) to those in control areas (where sensor data exists but no rate changes have been made). This analysis is intended to illustrate the application of the metrics developed earlier in this paper, and to provide initial evidence for the overall impacts of SF*park*.

5.2.1 Descriptive Results

Figure 5 plots the changes in the distribution of hourly average occupancy for four periods: the baseline – i.e. March to July 2011, which was before the advent of any rate changes, and three subsequent periods. There has been little visually discernible change in the distribution of occupancy over time. Despite significant rate changes on some blocks, both upwards and downwards, hourly average occupancy has hardly budged. Indeed, there is a slight increase in the number of blocks at very high occupancies, including 100%. However, the control areas have experienced an even greater increase in this regard, suggesting that citywide trends of increasing occupancy – perhaps due to economic growth – may be important.

The plot of the distribution also shows that parking availability is generally good within the SF*park* study area. Very few blocks are fully occupied, and the majority of the system operates at less than 80% occupancy. These data are shown in Table 2 where it is easy to see that the control areas have more blocks with average occupancies of 81% to 90% while the pilot areas are more likely to have blocks in the 96% to 100% occupancy range.

Figure 6 shows the changes in four metrics – hourly average occupancy, the probability that a block is full and average blocks cruised (left axis) and average rate per hour (right axis) – for weekdays from March 2011 through April 2013. As in the previous plots, observations are weighted by the arrival rates, so that blocks that have more arrivals and more latent demand are weighted more highly. Results for the pilot areas are shown with solid lines, and the control areas with dashed lines.

As would be expected given that there has been little change in the distribution of hourly average occupancy, there are few clear trends evident from the charts. Parking rates (pink lines) have come down in the morning period, and increased in other periods. However, these rate changes have had little discernible impact on cruising, hourly average occupancy or the probability that a given block is full. Average hourly occupancy and the probability that a block is full have remained almost constant or increased slightly since May 2011.

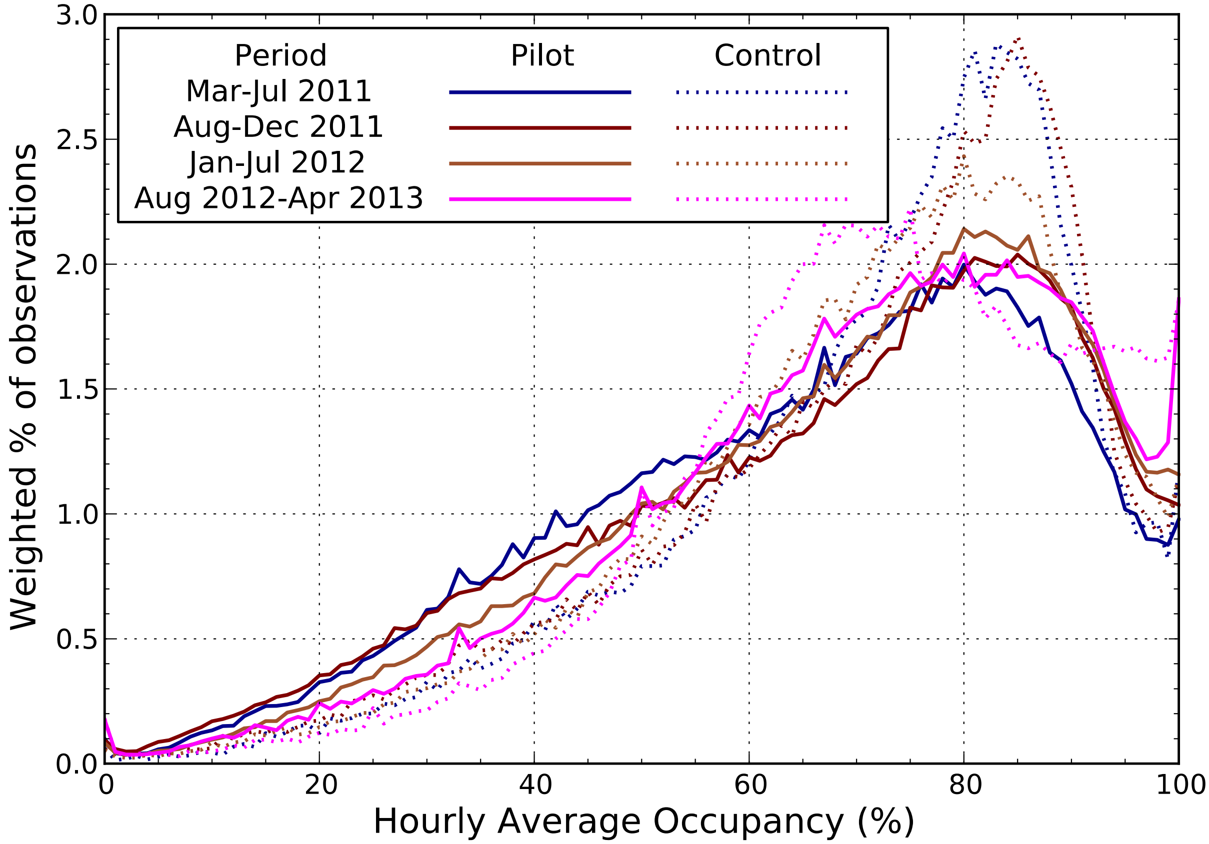


Figure 5 **Changes over time in distribution of hourly average occupancy (weekdays, metered hours)**

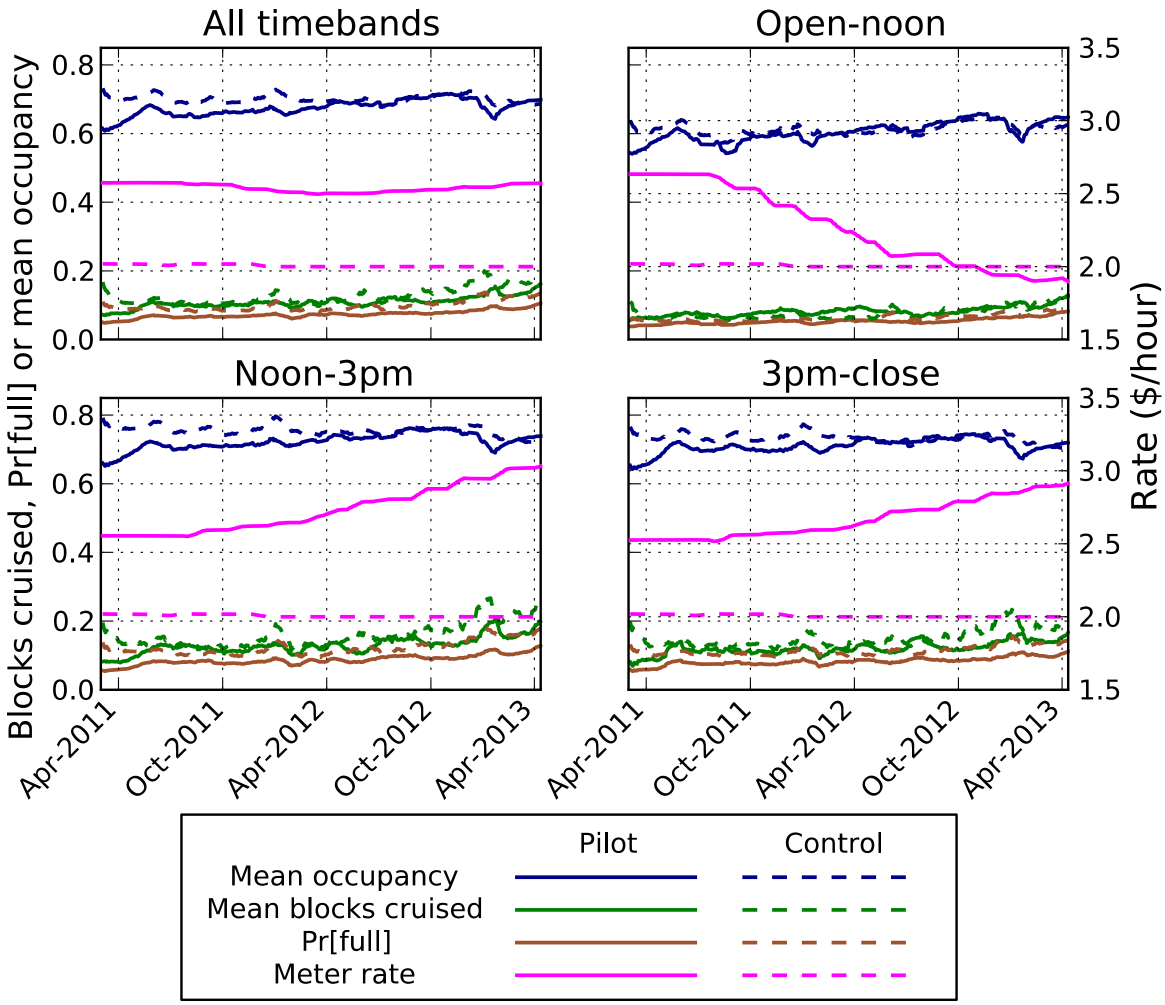


Figure 6 **Changes in occupancy, cruising and meter rates over time**

Control	Baseline (Mar–Jul ’11)	Period 1 (Aug-Oct ’11)	Period 2 (Oct-Dec ’11)	Period 3 (Dec ‘11-Feb ’12)	Period 4 (Feb-Mar ‘12)	Period 5 (Mar-May ’12)	Period 6 (May-Aug ’12)	Period 7 (Aug-Oct ’12)	Period 8 (Oct ’12-Jan ’13)	Period 9 (Jan-Mar ’13)	Period 10 (Mar ’13 – Apr ’13)
	Rate Period										
0 to 59%	23.1%	25.6%	24.9%	23.4%	24.9%	24.7%	25.6%	21.4%	23.6%	26.7%	27.2%
60 to 80%	38.9%	37.0%	35.6%	35.8%	38.0%	40.0%	42.9%	43.8%	40.8%	40.9%	40.1%
81 to 85%	14.1%	13.5%	13.4%	13.8%	13.7%	12.4%	9.0%	9.9%	9.2%	7.9%	7.8%
86 to 90%	12.0%	12.1%	13.2%	13.2%	11.6%	11.0%	8.2%	8.9%	8.4%	7.8%	7.3%
91 to 95%	6.9%	7.1%	7.6%	8.3%	6.6%	7.0%	7.9%	8.4%	8.7%	8.1%	8.1%
96 to 99%	3.7%	3.5%	4.2%	4.2%	4.1%	3.9%	5.0%	6.0%	7.5%	6.5%	6.8%
100%	1.2%	1.2%	1.1%	1.2%	1.1%	1.0%	1.4%	1.6%	1.8%	2.0%	2.7%
Pilot											
0 to 59%	36.8%	35.6%	33.1%	34.0%	32.1%	29.2%	29.5%	25.4%	31.6%	30.2%	28.9%
60 to 80%	34.8%	32.3%	33.2%	33.6%	33.2%	34.4%	36.3%	37.3%	35.7%	37.7%	36.6%
81 to 85%	9.5%	9.8%	10.4%	10.5%	10.4%	11.1%	10.1%	11.2%	9.5%	8.9%	9.0%
86 to 90%	8.3%	9.3%	9.9%	9.6%	10.3%	10.6%	9.6%	10.7%	8.9%	8.7%	9.3%
91 to 95%	6.1%	7.4%	7.9%	7.2%	7.8%	8.3%	8.2%	8.8%	7.3%	7.5%	8.2%
96 to 99%	3.6%	4.4%	4.6%	4.1%	4.8%	5.1%	5.2%	5.2%	4.8%	4.8%	5.5%
100%	1.0%	1.1%	1.0%	1.0%	1.3%	1.2%	1.2%	1.3%	2.2%	2.1%	2.5%

Notes: SFMTA target range shown in green. Weighted occupancies used for pilot areas. Early rate adjustments were slightly staggered across different neighborhoods (generally over a single week), and so dates are approximate.

Table 2 **Distribution of occupancies (all days, metered hours only)**

5.3 Regression Analysis

To formally test the impacts of the first ten rate adjustments, we use two dependent variables in the regression analysis. The first is the number of percentage points by which occupancy falls outside the 60-80% range. (Almost identical results are obtained using a model where the dependent variable is the absolute difference from 70% occupancy, the center of the target range.) The different models include neighborhood- or block-level fixed effects to account for unobserved characteristics of each neighborhood or block, such as the number of nearby destinations, and to control for time variation using some combination of fixed effects for date, month, day of week and time of day. The key identifying assumption is that citywide trends affect pilot and control groups in the same way. One of the models is a negative binomial specification, which is suitable given the large number of zeros in the dependent variables (recall that a zero represents an observation within the target 60-80% range).[10]

The key independent variable of interest is the number of rate changes. As shown in Table 3, the results indicate a small but (in most cases) statistically significant impact of each rate change on occupancy, with these individually small impacts adding up to larger cumulative effects over the first two years. On average, each rate change brings a block 0.1 to 0.2 percentage points closer to the 60-80% range, and thus the average impact is 1-2 percentage points after ten rate changes.

The impacts on cruising are smaller, and in some of the models are not statistically significant at conventional levels. However, these signs are still encouraging, and suggest that each rate change reduces the average search distance for parking by 0.007 to 0.017 blocks – or 0.07 to 0.17 blocks after the tenth rate change. Given that the mean number of blocks cruised is 0.13, this represents a reduction in cruising of more than 50% after two years of SF*park*, compared to the situation without the SF*park* program.

A more flexible regression specification uses dummy variables for each rate change, which relaxes the assumption of the models in Table 3 that impacts are linear in the number of rate changes. Each dummy variable is zero in control areas and in pilot areas indicates whether an observation falls within a given rate adjustment period. The marginal effects of these dummy variables are plotted in Figure 7. The qualitative conclusions remain unchanged; small impacts after each rate change, which in cumulative terms amount to substantive changes after ten rate changes.

The positive results from the regression models come in spite of the fact that availability does not appear to have improved in the SF*park* pilot areas (Table 2 and Figure 5). The interpretation here is that the first

[10] Due to difficulties in achieving convergence, neighborhood- rather than block-level fixed effects are used in the negative binomial model for occupancy. This may explain why the estimates are somewhat lower than the OLS models, and suggests that the OLS model results are to be preferred.

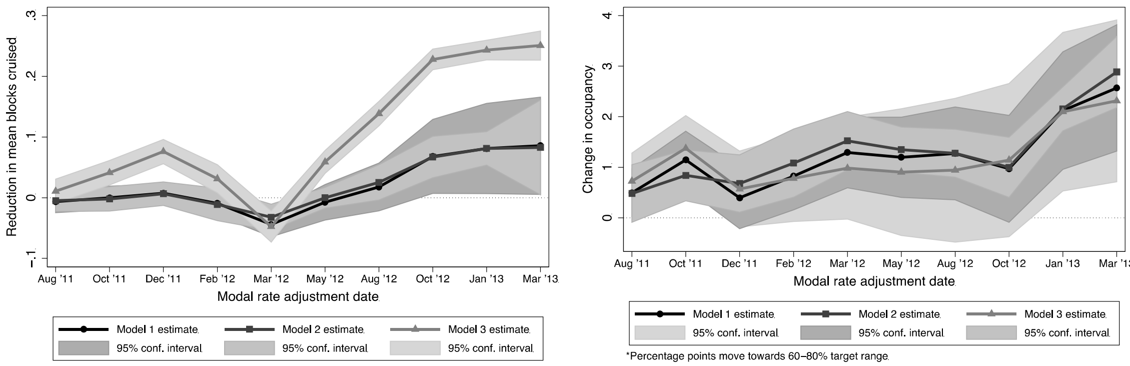
two years of SF*park* were characterized by a rebounding local economy, which is likely to have increased parking demand throughout the city. Even if parking availability and cruising worsened in the pilot areas, they worsened more in the control areas. Thus, our results can be interpreted as the impact of SF*park* relative to a counterfactual situation where SF*park* was not implemented, rather than to the impacts relative to the pre-implementation period.

One concern in the analysis might be that the control areas are fundamentally different to the pilot areas, making them a questionable point of comparison. The pilot areas include the central business district (Downtown, South Embarcadero and Civic Center) as well as the tourist-oriented Fisherman's Wharf. Dropping these four areas from the analysis ensures that both the remaining pilot areas and all control areas are characterized by neighborhood commercial development surrounded by primarily residential areas, and does reduce the magnitude of the estimates of impacts occupancy to about a quarter of those in Table 3. The results for cruising remain similar. Moreover, not all estimates are statistically significant at conventional levels. However, while the conclusions are less definitive, the evidence still points to a substantive impact of SF*park* in the first two years.

Table 3 Regression models to identify impacts of rate adjustments

Dependent Variable	**Occupancy (distance from target range)[1]**			**Blocks cruised**		
Model	**1**	**2**	**3**	**4**	**5**	**6**
Specification	OLS	OLS	Negative binomial	OLS	OLS	Negative binomial
Number of rate changes	-0.2059 (0.0632)	-0.2133 (0.0193)	-0.0888[2] (0.1023)	-0.0068 (0.0037)	-0.0070 (0.0011)	-0.0164[2] (0.0008)
Capacity (spaces per block)[3]			-0.0144 (0.0025)			
Fixed effects:	Block, month, day of week, hour	Block, date, hour	Neighbor-hood, month, day of week, hour	Block, month, day of week, hour	Block, date, hour	Block, month, day of week, hour
Standard errors	Clustered by block	Clustered by date	Clustered by block	Clustered by block	Clustered by date	Observed information matrix
N	1,953,150	1,953,150	1,953,150	1,953,037	1,953,037	1,942,109

(1) Dependent variable: Percentage points by which observation falls outside [60%,80%] interval for occupancies
(2) Marginal effect of each rate change, rather than coefficient, is shown
(3) In other models, capacity is captured in the block fixed effects
Standard errors in parentheses



Note: Marginal effects rather than coefficients are shown. Y-axis is inverted compared to Table 3.

Figure 7 Impacts of rate changes over time on cruising (left) and occupancy (right)

5.4 The Spatial and Temporal Patterns of Cruising

Given that reducing cruising is one of the central goals of SF*park*, it is useful to analyze the current patterns of cruising in more detail. Table 4 shows the overall distribution of cruising. Recall that the simulations assume that parkers can take advantage of vacant spaces on either side of the street. If parkers are restricted to one side of the street (thus cutting the effective capacity of each block in half), the mean number of blocks cruised increases by about 50% in both pilot and control areas. Note that because of the nonlinear relationship between occupancy and cruising, the number of blocks cruised will usually be a more volatile metric than average occupancy, as it is highly dependent on the number of blocks that are full at a given time and their spatial correlation.

The data in Table 4 suggest that cruising is limited during metered hours,[11] with a weighted mean of 0.13 blocks cruised (equivalent to 13 meters, or just a few seconds) for each driver arriving and looking for parking. It is important to stress that this represents a lower bound on cruising for several reasons. First, as noted above, cruising would be nearly doubled if parkers could only take advantage of vacant spaces on one side of the street. Second, even if a vacant space is available, it may not be taken by a parker –

[11] The overall level of cruising during non-metered hours is very similar. However, as shown later in the paper (see Figure 6), this conceals a large amount of cruising immediately after meters cease to operate, coupled with much lower levels of cruising in the early hours of the morning.

perhaps due to an impending tow-away restriction or a 30-minute time limit. Third, our simulation assumes that drivers follow a random path and are unimpeded by one-way streets and turn restrictions. However, the overall message in qualitative terms is that cruising is perhaps primarily a perception problem, or is localized on under-priced or unmetered streets or at unmetered times. Indeed, SF*park* has begun to address these issues through improved driver information, through installing new meters and through extending hours of operation.

Table 4 also shows the comparison to SFMTA's manual cruising surveys. The manual survey data are gathered by data collectors following a prescribed route by bicycle or car, and recording the location of the first vacant metered parking space they find. The manual surveys find considerably more cruising than our simulations, and in particular, many more searches that result in long searches for parking. The reasons for the differences are likely to be as follows:

1. Weighting by the arrival rate substantially reduces the amount of cruising. This is because the probability of a block being full is much lower on longer blocks, and these longer blocks have higher arrival rates. For comparison, the unweighted mean number of blocks cruised is 0.20.
2. The manual surveyors only search for parking on the right-hand side of the street on two-way streets, while our simulations allow for illegal U-turns. As noted above, restricting the search to one-side of the street would increase the simulated mean number of blocks cruised by about 50%.
3. Our simulations do not account for intra-hour correlations across blocks. For example, if the first block is full at a particular time, the next block is more likely to be full, even if hourly average occupancies are moderate.
4. The manual surveys take into account temporary restrictions such as construction, which the sensor data may not account for.

Overall, the comparison to the manual surveys suggests that the simulations in pilot areas provide a reasonable but lower-bound estimate of the amount of cruising. It is unclear why cruising is much higher in the manual surveys in the control areas, but the non-random nature of the manual surveys, where the prescribed survey route begins on the same block and follows the same prescribed route each time, is likely to play a role. In the most frequently sampled control area (Inner Richmond), the starting block has high average occupancy and a small number of metered spaces.

Table 4 **Distribution of Cruising**

	Weighted % of simulations		% of SFMTA manual surveys	
Blocks Cruised	**Pilot Areas**	**Control Areas**	**Pilot Areas**	**Control Areas**
0 (parking found on initial block)	91.9%	88.8%	78%	55%
1	5.7%	8.4%	12%	19%
2	1.4%	1.8%	5%	9%
3	0.5%	0.6%	2%	5%
4	0.2%	0.2%	2%	4%
5	0.1%	0.1%	0%	1%
6 or more	0.2%	0.1%	2%	6%
Mean blocks cruised	0.13	0.16	0.54	1.61

Note: Data are for metered hours only

It is also instructive to examine the pattern of cruising and other metrics over the course of the day. The previous sections reported results for metered hours only, but Figure 8 shows an extended simulation for all hours of the day. (When meters are not operational, the simulation assumes that parkers take the first available space, whether or not it is metered.) The figure plots the data for each pilot and control district separately, due to the different temporal patterns and meter operating hours across districts. The shaded areas represent typical meter operating hours.

In all districts except downtown and the tourist-oriented Fisherman’s Wharf, both the probability that a block is full and the amount of cruising spike immediately after metered hours end. Price-sensitive parkers may be delaying their arrival until free parking is available, or perhaps searching for free parking on residential blocks earlier in the day when meters are in operation. The implication is that cruising is of greater concern outside metered hours, and possibly on non-metered blocks.

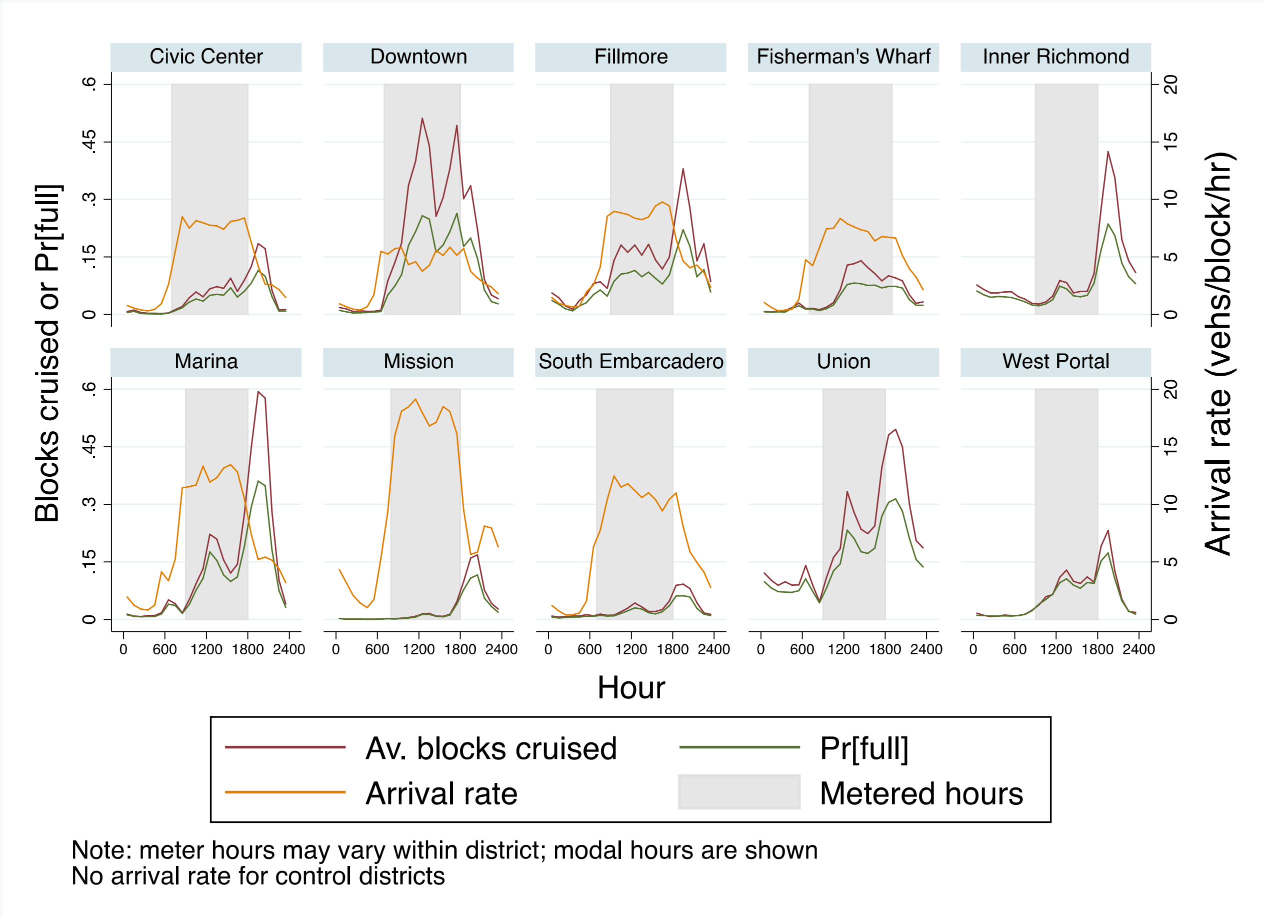


Figure 8 **Cruising and Pr[full] by district and time of day (weekdays only)**

Finally, it is worth noting another important implication of the non-linearities in occupancy, probability of a block being full and the related cruising. We showed in Table 2 and in the figures that the distribution of occupancies has changed very little. In the first year of SF*park*, a very small number of streets were highly problematic and likely contributed disproportionately to cruising in San Francisco. While a small percentage of the sample, at less than 2%, the incidence of fully occupied blocks may seem trivial. At the same time, it is close to 94,000 times over the course of the first year that blocks had an average occupancy of 100%. The map in Figure 9 shows the locations of the 40 blocks that accounted for 50% (47,000 hours) of the hours where occupancy exceeds 96%, and, in turn, very likely a similar share of cruising.

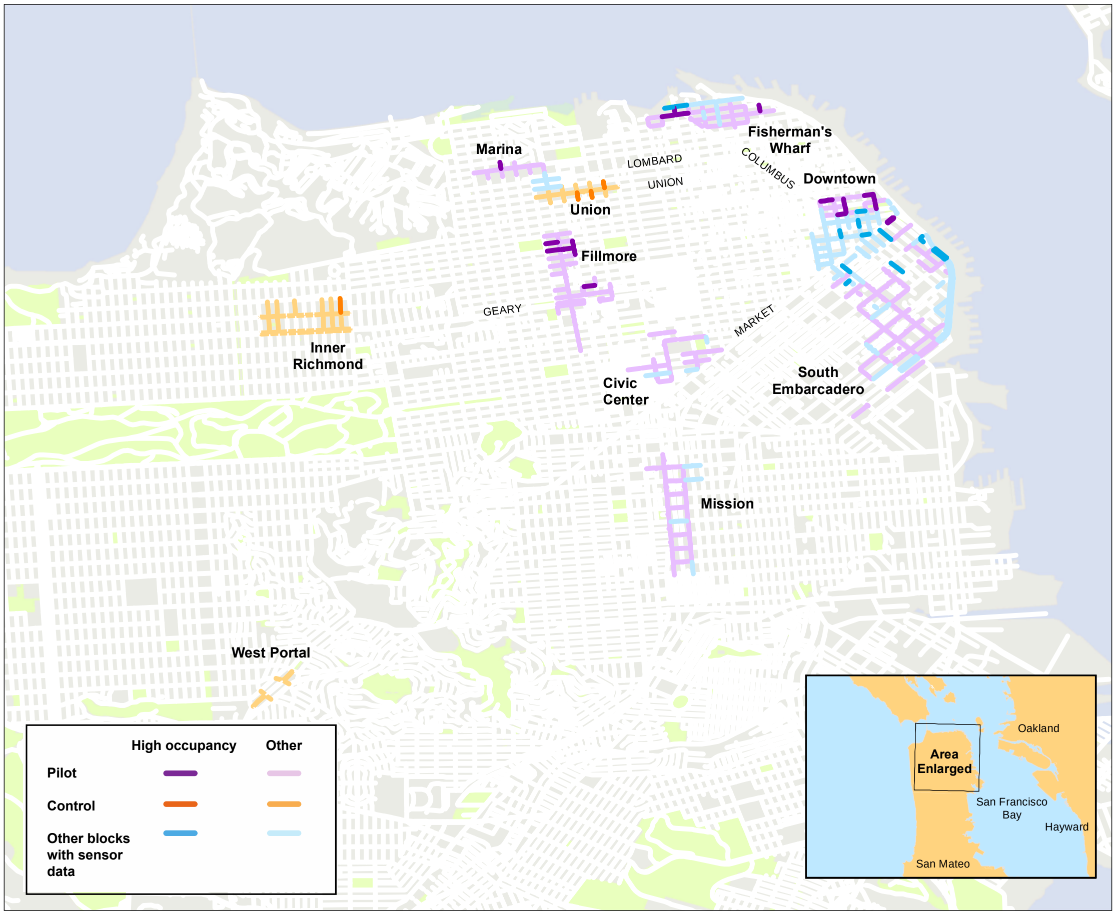


Figure 9 Distribution of high-occupancy blocks
(blocks that account for 50% of hours with occupancy greater than 96%)

6. Discussion of Results and Conclusion

In 2011, San Francisco embarked on the most ambitious parking management experiment in the United States, if not the world. In this paper, we estimate that the program is slowly achieving its goal of moving occupancy into its target range of 60-80%. We also estimate that *SFpark* has reduced cruising for parking by about 50%, although these results are less certain. The impacts of each rate change are individually small, but after the ten rate changes evaluated in this paper, the changes are shown to be cumulatively substantive. Gradual impacts over time also suggest that it has taken time for rates to come up to market-changing levels and for parkers to adjust to rate changes, learning where to find blocks with cheaper and more abundant parking.

It should also be noted that these impacts come against a background of other policy changes implemented under SF*park* – relaxing time limits, providing more information to users and improving other aspects of the parker experience – and a rebounding economy. These changes would normally be expected to increase demand and reduce availability, making the positive results in this paper even more notable. Moreover, the results also come in spite of likely latent demand on some blocks that are persistently full, or more-than-full due to the presence of double or other forms of illegal parking.

The strength of our approach allows the SFMTA to assess cruising throughout the metered system rather than remaining restricted to manual surveys, which, at best, only spot-check cruising. The approach is also generalizable to other cities with similar data and the conclusions are generalizable more broadly. There are also some shortcomings to consider. Due to the censoring of arrival observations once a block is full, we can only estimate additional arrivals. While our estimate is theoretically robust, it is based on five-minute observations and could be refined with finer grain data.

In addition to the policy-relevant impacts, the SF*park* experiment is already providing a large volume of useful data that allows the merits of different performance metrics to be tested, and the relationships between different metrics to be examined. It is important to bear in mind that average occupancy is not the metric of interest when determining impacts on congestion and air pollution. In this paper, we show how this data can be used to estimate the relationships between average occupancy; the probability that a driver can find a parking space; the amount of cruising; and actual and latent parking demand in terms of the number of arrivals to a block.

As we discuss, 85% occupancy has been widely promoted in the literature as an optimum performance standard. Our analysis, consistent with that of others, shows this to be a reasonable threshold considering that average occupancies below that threshold track well with probability that a driver will find a parking space and probability of finding a space on streets with occupancies above that threshold go quickly to zero (Figure 3). More succinctly, with continuous occupancies below 95% there is virtually no cruising. However, the precise impacts of the performance standard will vary depending on the size of the block and the length of the period over which occupancy is averaged. The fewer spaces on the block and the longer the period of averaging, the lower the occupancy standard needed to achieve a given availability to the parker and a given level of cruising.

A simple rule of thumb such as 80% or 85% is useful in data-poor settings (i.e., almost everywhere except San Francisco at present). But the analysis based on SF*park* data allows policy makers, even in data-poor settings to make more nuanced decisions with respect to performance standards and rate setting. A performance standard that varies by block, or is based on the probability of the block being full rather than average occupancy, may be a more policy-relevant basis for changing rates.

Future research should certainly consider the impacts of performance-based parking management initiatives over a longer time frame, as the parking system moves towards a new equilibrium. However, there are several wider issues of interest that are beyond the scope of this paper. SF*park* and similar programs in other cities provide a rich source of data to analyze the spatial pattern of parking changes and the interactions between on- and off-street parking. Determining price elasticities and changes in consumer surplus are also potential avenues for investigation, along with SF*park*'s impacts on wider issues of policy interest such as vehicle travel, retail revenue, transit operating speeds and traffic safety.

Finally, we have not investigated the bigger question of parking availability on trip making. As cities see lower cruising due to better curb management it is also conceivable that there is more turnover which could imply more trip making. More trip making could mean more efficient use of the road network but could also imply different impacts on congestion (perhaps on different parts of the system) and greater emissions associated with greater VKT. On the other hand, the greatest impacts of a program such as SF*park* on vehicle travel may be the hardest to measure. If performance-based pricing can succeed in improving not only parking availability but in creating the perception that parking is easy to find, then potential long-term benefits lie in defusing political pressure for additional off-street parking, and increasing the competitive advantage of urban neighborhoods.

Acknowledgements

We are grateful to SFMTA staff, particularly Jay Primus, Leslie Bienenfeld, Stephanie Nelson and Alex Demisch for providing access to SF*park* data, and for numerous clarifications on the data and price adjustment methodology. We also thank SFMTA staff for helpful comments on earlier drafts. The conclusions do not necessarily reflect the views of SFMTA. We are grateful to Emma McDonnell at UC Santa Cruz for producing the maps. This work is partially supported by the National Science Foundation under Grant No. CMMI #1055832.

References

Alzaid, A.A. & Omair, M.A., 2010. On the Poisson Difference Distribution. Inference and Applications. *Bulletin of the Malaysian Mathematical Sciences Society*, 8(33), pp.17–45.

Anderson, S.P. & de Palma, A., 2004. The economics of pricing parking. *Journal of Urban Economics*, 55(1), pp.1–20.

Anon, 1935. Coin-in-Slot Parking Meter Brings Revenue to City. *Popular Mechanics*, p.519.

Arnott, R. & Inci, E., 2006. An integrated model of downtown parking and traffic congestion. *Journal of Urban Economics*, 60(3), pp.418–442.

Arnott, R. & Rowse, J., 1999. Modeling Parking. *Journal of Urban Economics*, 45(1), pp.97–124.

Bureau of Public Roads, 1956. *Parking Problems in Cities*, Washington, D.C.

Burke, P.J., 1968. The Output Process of a Stationary M/M/s Queueing System. *The Annals of Mathematical Statistics*, 39(4), pp.1144–1152.

Button, K., 2006. The political economy of parking charges in “first” and “second-best” worlds. *Transport Policy*, 13(6), pp.470–478.

Calthrop, E., Proost, S. & Van Dender, K., 2000. Parking Policies and Road Pricing. *Urban Studies*, 37(1), pp.63–76.

Cameron, A.C. & Trivedi, P.K., 2005. *Microeconometrics: methods and applications*, Cambridge: Cambridge University Press.

Gallo, M., D’Acierno, L. & Montella, B., 2011. A multilayer model to simulate cruising for parking in urban areas. *Transport Policy*, 18(5), pp.735–744.

Glazer, A. & Niskanen, E., 1992. Parking fees and congestion. *Regional Science and Urban Economics*, 22(1), pp.123–132.

King, D., 2010. Estimating Environnmental and Congestion Effects from Cruising for Parking. In *Paper presented at Transportation Research Board Annual Meeting*. Washington, D.C.

Kleinrock, L., 1976. *Queueing Systems*, Wiley.

Levy, N., Martens, K. & Benenson, I., 2012. Exploring cruising using agent-based and analytical models of parking. *Transportmetrica*, pp.1–25.

Massey, W.A., 2002. The Analysis of Queues with Time-Varying Rates for Telecommunication Models. *Telecommunication Systems*, 21(2-4), pp.173–204.

Melamed, B. & Whitt, W., 1990. On Arrivals That See Time Averages. *Operations Research*, 38(1), pp.156–172.

Pierce, G. & Shoup, D., 2013. Getting the Prices Right. *Journal of the American Planning Association*, 79(1), pp.67–81.

Rudin, W., 1987. *Real and Complex Analysis*, McGraw Hill.

Shoup, D.C., 2006a. Cruising for parking. *Transport Policy*, 13(6), pp.479–486.

Shoup, D.C., 2006b. *Curbing Cars: Shopping, Parking and Pedestrian Space in SoHo*, New York.

Shoup, D.C., 2008. *Driven to Excess: What under-priced curbside parking costs the Upper West Side*, New York.

Shoup, D.C., 2005. *The high cost of free parking*, Washington, DC: Planners Press.

Skellam, J.G., 1948. A probability distribution derived from the binomial distribution by regarding the probability of success as variable between the sets of trials. *Journal of the Royal Statistical Society. Series B (Methodological)*, 10(2), pp.257–261.

Wolff, R.W., 1982. Poisson Arrivals See Time Averages. *Operations Research*, 30(2), pp.223–231.

On the Modeling of Parking with Dynamic Arrival Rates: Incorporating Information

Daniel Jordon

September 3, 2013

We would like to assess the performance of a system where drivers get information from other drivers about available parking. The full model will include a spacial dimension for the location of queues, a time dimension that includes traffic congestion, as well as an information passing regime of either in vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I). The purpose of this document is to elaborate on both the individual components of this model and steps that will be undertaken to construct and analyze this model. Throughout this document I will refer to people parking as *agents*.

1 Basic Modeling with information

The first order of business is setting up the simulation of Markovian server queues where either the queue or exiting agents pass on information about the number of vacancies to potential agents. I expect potential agents will respond to this information by being more willing to enter the queue as the number of 'vacancies' increases (for infinite server queues potential agents respond to the number of agents within the queue). To capture this effect a network of queues will be used where the rate of the arrivals is dependent on the both time and the state, that is, we will be using $(M_{x,t}/M_t/\infty)^n$ or $(M_{x,t}/M_t/m)^n$.

In addition to getting the simulation we hope to establish steady-state results for such a network.

2 Networks of Queues

We will use a network of queues to model traffic in a given area. We follow an approach that is similar to the ones used in [1], [7], and [3]. Nodes will represent either destinations within a city, intersections or other important parts of the transportation infrastructure, or on-street parking and garages. Upon entering the network, agents will select their desired *destination* node according to some distribution d. Agents follow a path to their destination (say for example, the shortest path) and when they arrive they make a decision as to which of the adjacent *garage* nodes to go to next. For agents participating in the information exchange they always choose the garage with largest expected availability. Non-participating agents will determined their parking garage randomly[1].

[1]There are a few other modeling choices to make when it comes parking. For example, we could decide to have participating agents choose the garage that maximizes some utility function that depends on distance to the destination node, availability, and costs, while non-participating agents choose based only on proximity and costs. The draw back with this (more realistic) approach is estimating the utility function that people have when it comes to parking preferences.

2.1 Incorporating information

Information propagation is a key component in this model. The arriving agents come in two different types: agents who are participating in the information exchange and agents who are not. When an agent departs a node he takes the most recent information that the node has, and in particular, he takes with him the *exact* number of users at that node. The agent also notes the time of his departure, so this information losses its value as time passes. Each node depends on information carrying agents to bring information about the other nodes in the network. When an agent arrives at a node the node takes the most recent information about the network that the agent has. This way, the node will keep track of the most recent piece of information that any of the arriving agents have about the status of the network (such as total number of users or the mean sojourn time at a given node).

When a drivers communicates they will typically have old information about parking availability throughout the network. Agents will have to choose how to incorporate new information in such a way that yields an optimal guess about the current state. Some of the key issues is how potential agents should incorporate 'new' information. Information will always be 'old' in the sense that the information you observe happened sometime in the past, and may not accurately reflect the current state of the network. We propose the following simple update rule for when drivers receive information: if the time stamp of the information is newer than your information, the new information replaces your information. Under this setup we aim to answer the following questions:

- Does the information sharing lead to a more socially optimal outcome? More specifically, does the information sharing regime outlined above, with a simple updating procedure, yield less road congestion?
- At what level of vehicle participation in the V2V information exchange does the system behave differently? Are there any tipping points where the level or participation in information sharing causes the system to behave differently?
- How sensitive are the results to changing service rates of garages or infrastructure?
- How sensitive are the results to error in observation? If drivers depart from a given node with inaccurate information, should drivers use a different updating rule?

3 The Mathematical Model

The network is composed of several different types of queues, where each type represents a different part of the transportation infrastructure. Nodes that represent the road network will be modeled using $M_t/M/1$ queues (or $M_t/M/k$ queues with processor sharing), garage nodes will be modeled with $M_t/M_t/k/k$ queues, and destination nodes will be modeled with $M_t/M/k$ queues[2]. Few nodes will receive arrivals from outside the network, but those that do will have a time dependent arrival rate to capture time of day effects in transportation.

Once an agent chooses his destination they have a set route on how to get there. When an agent arrives at their destination they choose where to park by selecting one of the adjacent garage nodes. After departing from their parking spot they then choose a new destination selected from some distribution d. Under this setup, it appears that such a system is a classed Jackson network where agents change their type after they reach a destination. One of the main

[2] On-street parking is modeled as just another garage in this model. To distinguish it from an actual garage we can change its distance to destination nodes, or its costs relative to a garage node.

differences between our model and a classed Jackson network (or a Kelly Network, see [5] or [4]) is the mechanism for which agents change their class. Here, agents change their class based on information the queue already has. Since information is passed by the agents themselves the arrival of new information is a Poisson process. Some of the other differences between our model here and a classical classed Jackson network is the inclusion of loss queues and time varying arrival rates.

3.1 Mathematical Formulations of single server queue

For the classed queue server $M/M/1$. Let $Q(t)$ be the usual queue-length stochastic process with state space $\mathbb{N}_0$, the non-negative integers. The arrivals form a Poisson process with rate λ and receive service for an amount of time that is exponentially distributed with rate μ. If we set $p_n(t) = \mathbb{P}\{Q(t) = n\}$, then the p_n's solve

$$\dot{p}_0(t) = \mu p_1(t) - \lambda p_0(t), \tag{1}$$

and when $n \geq 1$,

$$\dot{p}_n(t) = \mu p_{n+1}(t) + \lambda p_{n+1}(t) - (\lambda + \mu) p_n(t) \tag{2}$$

where $\dot{p}_n = \frac{d}{dt} p_n$. This we are searching for a sequence of positive functions $\{p_n\}$ that satisfy the above equations.

Formulation using generators

Here we detail an analogous way to define the problem which, to our knowledge, was first developed in [6]. Let $\ell_1(\mathbb{N}_0)$ denote the space of absolutely summable sequences endowed with the usual norm, which we denote by $|\cdot|_1$. and for each $n \in \mathbb{N}_0$ let $e_n : \mathbb{N}_0 \mapsto \mathbb{R}$ be the indicator given by

$$e_n(m) = \begin{cases} 1, & m = n \\ 0, & m \neq n. \end{cases}$$

Each e_n can be thought of as a sequence in $\ell_1(\mathbb{N}_0)$ where the k-th entry is zero except when $k = n$. With this in mind, it is clear that the set $\{e_n\}$ forms a basis for $\ell_1(\mathbb{N}_0)$. Let $\mathbf{R}$ and $\mathbf{L}$ denote the right-shift and left-shift operators on $\ell_1(\mathbb{N}_0)$ respectively, where for each $n \in \mathbb{N}_0$,

$$e_n\mathbf{R} = e_{n+1}, \qquad e_n\mathbf{L} = e_{n-1},$$

except we have $e_0\mathbf{L} = 0$. The operator $\mathbf{R}$ corresponds to the arrival of an agent to the queue, while $\mathbf{L}$ corresponds to the departure of an agent from queue. We define $\mathbf{A}$ as the operator

$$\mathbf{A} = \lambda\mathbf{R} + \mu\mathbf{L} - \lambda\mathbf{I} - \mu\mathbf{LR}$$

where $\mathbf{I}$ is the identity operator. We define $\mathbf{p}(t)$ to be the function

$$\mathbf{p}(t) = \sum_{n \in \mathbb{N}_0} p_n(t) e_n,$$

(or similarly as $\mathbf{p}(t) = [p_0(t), p_1(t), p_2(t), \ldots]$) then we can succinctly write (1) and (2) as

$$\dot{\mathbf{p}}(t) = \mathbf{p}(t)\mathbf{A} \tag{3}$$

which is the forward Kolmogorov equation for an $M/M/1$ queue. That is, given an initial vector $\mathbf{p}_0 \in \ell_1(\mathbb{N}_0)$ we look for a function $\mathbf{p}$ such that for each $t \in \mathbb{R}_+$, (3) is satisfied and $|\mathbf{p}(t)|_1 = |\mathbf{p}_0|_1$.

3.2 Mathematical Formulation of a classed-queue

We now apply a similar construction used for the $M/M/1$ queue to one with classes. We consider only FIFO discipline. Let $\mathcal{C}$ be a *finite* set of classes. Representative elements of $\mathcal{C}$ will be denoted by α or β. An agent of class α forms a Poisson process with rate λ_α and μ_α is their exponential service rate. Since we need to be aware of who is being served, we must keep track of the configuration of the queueing lines. Let E denote the state space of all possible queueing line configurations. We can express each non-empty line $\sigma \in E$ as an ordered collection (or string) of elements from $\mathcal{C}$, that is, $\sigma = (\alpha_1, \ldots, \alpha_n)$ for some integer $n \in \mathbb{N}$ where each $\alpha_i \in \mathcal{C}$.

Formally, E is the free non-abelian semigroup with identity generated by $\mathcal{C}$. Let $\bullet$ denote the semigroup operation of E. Then each $\sigma \in E$ can be written as $\sigma = \alpha_1 \bullet \cdots \bullet \alpha_n$ where each $\alpha_i \in \mathcal{C}$. The element $\alpha_1 \bullet \cdots \bullet \alpha_n$ captures the state of having n agents in line with the i-th agent being of the α_i class. If $\sigma = \alpha_1 \bullet \cdots \bullet \alpha_n$ is in E, we define $|\sigma| = n$ and we will let σ_k denote α_k if $k \leq n$ and be 0 otherwise. In light of the following proposition (proven in the appendix), we can view $\ell_1(E)$ as the space $\bigoplus_{n=0}^{\infty} \ell_1(\mathcal{C})^{\otimes n}$, the *tensor algebra of* $\ell_1(\mathcal{C})$.

Proposition. *Let $\mathcal{C}$ be a finite set, and let $S_\mathcal{C}$ be the free non-abelian semigroup with identity generated by $\mathcal{C}$. Then $\ell_1(S_\mathcal{C})$ is isomorphic to the tensor algebra of $\ell_1(\mathcal{C})$.*

We now define a family $\{\mathbf{R}_\alpha\}_{\alpha\in\mathcal{C}}$ of right-shift operator as follows

$$\left(\bigotimes_{k=1}^{n} e_{\alpha_k}\right)\mathbf{R}_\alpha = \left(\bigotimes_{k=1}^{n} e_{\alpha_k}\right) \otimes e_\alpha.$$

Similarly, we define a family of left-shift operators $\{\mathbf{L}_\alpha\}_{\alpha\in\mathcal{C}}$ as

$$\left(\bigotimes_{k=1}^{n} e_{\alpha_k}\right)\mathbf{L}_\alpha = e_\alpha(\alpha_1') \bigotimes_{k=2}^{n} e_{\alpha_k}.$$

Thus $\mathbf{R}_\alpha : \ell_1(\mathcal{C})^{\otimes n} \mapsto \ell_1(\mathcal{C})^{\otimes n+1}$ and $\mathbf{L}_\alpha : \ell_1(\mathcal{C})^{\otimes n} \mapsto \ell_1(\mathcal{C})^{\otimes n-1}$, $\mathbf{R}_\alpha$ corresponds to an arrival of an agent of class α, and $\mathbf{L}_\alpha$ corresponds to the departure to an agent of class α. We introduce a modification operators $\mathbf{M}^{\mathrm{b}}_{\alpha\beta}$ and $\mathbf{M}^{\mathrm{e}}_{\alpha\beta}$; roughly, they change the class of an agent from an α-class agent to a β-class agent. The operator $\mathbf{M}^{\mathrm{b}}_{\alpha\beta}$ modifies agents located at the *beginning* of the queue (if possible), while $\mathbf{M}^{\mathrm{e}}_{\alpha\beta}$ modifies agents located at the *end* of the queue (if possible). Formally, they are defined as

$$\left(\bigotimes_{k=1}^{n} e_{\alpha_k}\right)\mathbf{M}^{\mathrm{b}}_{\alpha\beta} = e_\alpha(\alpha_1') e_\beta \otimes \left(\bigotimes_{k=2}^{n} e_{\alpha_k}\right), \qquad \left(\bigotimes_{k=1}^{n} e_{\alpha_k}\right)\mathbf{M}^{\mathrm{e}}_{\alpha\beta} = e_\alpha(\alpha_n')\left(\bigotimes_{k=1}^{n-1} e_{\alpha_k}\right) \otimes e_\beta.$$

We set $\mathbf{M}_\alpha = \mathbf{M}^{\mathrm{b}}_{\alpha\alpha} = \mathbf{M}^{\mathrm{e}}_{\alpha\alpha}$ to be the analog of the operator $\mathbf{LR}$ used in the $M/M/1$ queue. Lastly, we define two families of functions, $\{s^{\mathrm{b}}_{\alpha\beta}\}$ and $\{s^{\mathrm{e}}_{\alpha\beta}\}$, that specify whether an agent will change classes as he is entering or leaving the queue, respectively. We refer to these functions as the *switching functions*. Since we want the current state of the queue to influence whether we change classes, we have $s_{\alpha\beta} : E \mapsto [0, 1]$. We can now construct the generator $\mathbf{A}$ for the $M^C/M^C/1$ queue:

$$\mathbf{A} = \sum_{\alpha\in\mathcal{C}} \left[\lambda_\alpha \mathbf{R}_\alpha \sum_{\beta\in\mathcal{C}} s^{\mathrm{e}}_{\alpha\beta}\mathbf{M}^{\mathrm{e}}_{\alpha\beta} + \mu_\alpha \sum_{\beta\in\mathcal{C}} s^{\mathrm{b}}_{\alpha\beta}\mathbf{M}^{\mathrm{b}}_{\alpha\beta}\mathbf{L}_\beta - \lambda_\alpha \mathbf{I} - \mu_\alpha \mathbf{M}_\alpha\right] \tag{4}$$

3.2.1 Using a classed queue to transfer information

This system will emulate the transmission of information in a queueing network. To see this, consider the following setup. Allow the set $\mathcal{C}$ to be of infinite size for the sake of argument. An agent's class will be the time stamp of the information he has. This way, an agent's class conveys how new their information is. Suppose that whenever someone comes into contact with someone who has newer information than themselves, they change their type to reflect this. We can handle such a system easily under the current framework. The set $\mathcal{C}$ has a strict total ordering, and if we use the following switching functions:

$$s^{\mathrm{e}}_{\alpha\beta}(\sigma) = s^{\mathrm{b}}_{\alpha\beta}(\sigma) = s^{\mathrm{b}}_{\alpha\beta}(\alpha_1 \otimes \cdots \otimes \alpha_n) = \begin{cases} 1, & \beta = \max_{1\le k\le n} \alpha_k, \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

arriving agents always switch to the 'best' class that they see in the queue. Whenever an agent leaves the queue they change their class again to the 'best' class. This allows agents to bring information with them to their new queue. When an agent with new information arrives at a queue, agents currently in the queue that depart before him will receive this information, and will change their class to reflect this fact using (5) and (4).

3.3 The stochastic process for information updating

In this section we will write down the stochastic process for the $M_t/M_t/m$ queue with the information exchange mechanism detailed above. There are a few salient points that should be highlighted. We want to emulate an information exchange that has *all* users in the queue adopt the 'best' information available. We want to be able to calculate the steady state distribution of the joint process for the information and the number of people in the queue, where again, *everyone is of a particular information class.* Put this way, we can think of the state-space a little differently. Instead focusing on all queue configurations of the different classes we describe the queue as an element of $\mathbb{N}_0 \times \mathcal{C}$, where $\mathcal{C}$ describes the type of information everyone in the queue has. In this setup, the state space specifies the length of the queue and *the class of everyone that is in the queue.* An equivalent way to observe the state space is to look at the length of the queue and the class of the most recent arrival *after he has updated is information.* This is the approach that we take here.

There are a few things to note in this setup 1) The arrivals for each class of information forms a Poisson process; and 2) Being of a particular class does not affect your service rate (although it is not difficult to model that process). Throughout we will draw on some of the results for Poisson random measures here (for a refresher on Poisson random measures see Appendix §B).

Information exchange for the $M/M/1$ queue

Let $\mathcal{C}$ denote the set of classes. We assume $\mathcal{C}$ is ordered (but it can be countably infinite in size). Due to the ordering of $\mathcal{C}$, we lose no generality by assuming $\mathcal{C} = \{1, 2, \ldots\}$. The arrival of class k agents form a Poisson process with rate λ_k, and we assume all classes have the same service rate μ. Let

$$\lambda \coloneqq \sum_{k\in\mathcal{C}} \lambda_k, \qquad \text{and} \qquad p_k \coloneqq \frac{\lambda_k}{\lambda}.$$

and assume $\lambda < \infty$. Let $\{S_n\}_{n\in\mathbb{N}}$ form a Poisson random measure with mean measure $\lambda\mathrm{Leb}$ on $\mathbb{R}_+$, and let $\{Y_n\}_{n\in\mathbb{N}}$ be an independency of exponentially distributed random variables with scale parameter μ, that is, $\mathbb{P}\{Y_n > t\} = e^{-\mu t}$ for all $n \in \mathbb{N}$. Set $D_0 = 0$ and define

$$D_n \coloneqq [D_{n-1} - S_n]^+ + S_n + Y_n, \tag{6}$$

where $[\cdot]^+ = \max\{\cdot, 0\}$. This process is the departure time of the n-th arrival for the queue under a FIFO discipline of an $M/M/1$ queue. Finally, we let $\{C_n\}_{n\in\mathbb{N}}$ be an independency of random variables with distribution m given by $m\{k\} = p_k$. The random variable C_n specifies the class of the n-th arrival.

We now write down a process that captures the exchange of information using classes. The n-th arrival comes marked with a class, C_n, which describes their information (how new their information is, the type of information, etc.). When they arrive at a queue, they update their class (read: information) by taking into account the other classes already in the queue. The rule for updating information will be simple, they take the best information available. With this rule the best information available is the class of agent currently at the end of the line. Their updated class (read: updated information) will be denoted by F_n and is defined as follows. Set $F_1 = C_1$, and take

$$F_n \coloneqq \max\{F_{n-1}1_{\{S_n \le D_{n-1}\}}, C_n\}, \tag{7}$$

that is, an newest arrival's class is the same class as the previous agent's class if the previous agent is in the queue and his class is better, otherwise the newest arrival keeps his class.

Information exchange for the $M_t/M_t/m$ queue

The above construction can be generalized to account for time varying arrival rates, queues with m servers, and time varying class probabilities. Let $\lambda(t)$ denote the *arrival rate of agents at time t*. We assume $\lambda(t)$ is measurable on $\mathbb{R}_+$. Let Λ denote the measure

$$\Lambda(A) = \int_A ds\, \lambda(s), \qquad A \in \mathcal{B}_{\mathbb{R}_+},$$

and let $\{X_n\}$ form a Poisson random measure with mean measure Λ. Set $D_i = X_i + Y_i$ for $i = 1, \dots, m$, and define $D_{(k),n}$ to be the k-th ordered statistic for the set $\{D_1, \dots, D_n\}$. For each $n > m$ we define the random variable D_n as follows

$$D_n \coloneqq [D_{(n-m),n-1} - X_n]^+ + X_n + Y_n. \tag{8}$$

Then D_n is the departure time for the n-th arrival for an $M_t/M_t/m$ queue. Let $\{C_t\}_{t\in\mathbb{R}_+}$ be the class process, that is, C_t describes the probability of a certain class arriving at time t. We define the process $\{B_n\}$ as

$$B_n(\omega) \coloneqq C_{X_n(\omega)}(\omega), \qquad \omega \in \Omega, \tag{9}$$

thus, each B_n is a random variable for the class of the n-th arrival. The updated class process $\{F_n\}_{n\in\mathbb{N}}$ is defined by the following: Set $F_1 = B_1$, $F_i = \max\{F_{i-1}1_{\{X_i \le D_{(1),i}\}}, B_i\}$ for $i = 2, \dots, m$ and take

$$F_n \coloneqq \max\{F_{n-1}1_{\{X_n \le D_{(n-1),n-1}\}}, B_n\}. \tag{10}$$

The interpretation is the same as is was in the $M/M/1$ queue, if the n-th agent arrives to a nonempty queue (that is, if $X_n \le D_{(n-1),n-1}$), his class is changed to the class of the agent before him if it is better, otherwise he keeps his class. For the $M/M/1$ we did not need to use ordered statistics in our definition of D_n. If $m = 1$ the definition of D_n given in (8) becomes the one given in (6).

Remark 3.1. Keep in mind that we use the updated class of the latest arrival to describe the state of the entire queue. Thus, if X_n is the most recent arrival then F_n describes the state of the queue. For this reason it is unnecessary to update the class of everyone else in the queue. So the updated class of the $(n-1)$-st agent is independent of whether the n-th agent arrives before the queue empties, that is, F_{n-1} is independent of $1_{\{X_n \le D_{(n-1),n-1}\}}$.

Remark 3.2. Notice that there is nothing special about the arrival process $\{X_n\}$ forming a Poisson random measure in the definition of $\{F_n\}$. All that is necessary is that the arrival process come *marked* with the process $\{B_n\}$. Another thing to note is that each B_n is independent of whether n-th arrival arrives before the queue empties, so B_n is independent of $1_{\{X_n \le D_{(n-1),n-1}\}}$.

Lastly, we let Q_t describe the number of people in the queue at time t. Using the random variables defined above we get

$$Q_t = \sum_{n=1}^{\infty} 1_{[0,t]\times(t,\infty)} \circ (X_n, D_n), \tag{11}$$

that is, Q_t counts the number of agents that arrived in $[0,t]$ and departed in (t,∞). The next theorem shows that the process $\{F_n\}$ converges in distribution. We assume $\{X_n\}$ forms a Poisson random measure, the departure process $\{D_n\}$ has the form of (8), $\{Q_t\}$ has the form (11), $\{B_n\}$ has the form (9), and of course, $\{F_n\}$ has the form defined in (10).

Theorem 3.3. *Let $\{X_n\}$ be an arrival process, $\{D_n\}$ be the departure process, $\{Q_t\}$ be the queuing process, and $\{B_n\}$ be random variables taking values in a finite ordered set $\mathcal{C}$. If $\{B_n\}$ and $\{Q_t\}$ both converge in distribution then $\{F_n\}$ converges in distribution and*

$$\mathbb{P}\{F \ge k\} := \lim_{n\to\infty} \mathbb{P}\{F_n \ge k\} = \frac{\mathbb{P}\{B \ge k\}}{1 - \mathbb{P}\{B < k\}\mathbb{P}\{Q \ge 1\}} \tag{12}$$

where $\mathbb{P}\{Q = 0\} := \lim_{t\to\infty} \mathbb{P}\{Q_t = 0\}$.

Proof. For any $n \ge 1$ we have the following characterization of the set $\{F_n \ge k\} \subset \Omega$,

$$\{F_n \ge k\} = \{B_n \ge k\} \cup \big(\{B_n < k\} \cap \{X_n \le D_{(n-1),n-1}\} \cap \{F_{n-1} \ge k\}\big).$$

We note two things about the random variables in the above expression. First, since the class of the $(n-1)$-th agent is independent of all subsequent arrivals, F_{n-1} and $1_{\{X_n < D_{(n-1),n-1}\}}$ are independent. Second, each B_n is independent of $1_{\{X_n < D_{(n-1),n-1}\}}$ and F_{n-1}. Thus,

$$\mathbb{P}\{F_n \ge k\} = \mathbb{P}\{B_n \ge k\} + \mathbb{P}\{B_n < k\}\mathbb{P}\{F_{n-1} \ge k\}\mathbb{P}\{X_n \le D_{(n-1),n-1}\}. \tag{13}$$

Now, the event $\{X_n \le D_{(n-1),n-1}\}$ says the n-th agent arrives to a nonempty queue, $\mathbb{P}\{X_n \le D_{(n-1),n-1}\}$ converges to the long run probability of finding a nonempty queue as $n \to \infty$, thus,

$$\lim_{n\to\infty} \mathbb{P}\{X_n \le D_{(n-1),n-1}\} = \mathbb{P}\{Q \ge 1\}.$$

Since $\{B_n\}$ converges in distribution, all events in (13) converge as $n \to \infty$, except perhaps the terms involving F_n. Set $f_n = \mathbb{P}\{F_n \ge k\}$, $b = \lim \mathbb{P}\{B_n \ge k\}$, and $a = \lim \mathbb{P}\{B_n < k\}\mathbb{P}\{X_n \le D_{(n-1),n-1}\}$. Let $\epsilon > 0$ be sufficiently small such that $|a \pm \epsilon| < 1$. Then for n sufficiently large we can manipulate (13) to get

$$(b-\epsilon)\sum_{j=0}^{r}(a-\epsilon)^r + (a-\epsilon)^{r+1} f_{n-1-r} \le f_n \le (b+\epsilon)\sum_{j=0}^{r}(a+\epsilon)^r + (a-\epsilon)^{r+1} f_{n-1-r}.$$

Then as $n \to \infty$ we can take $\epsilon \to 0$ and $r \to \infty$ to squeeze $\{f_n\}$ into convergence. Taking the limit in (13) and solving then yields the desired result. $\square$

We have the following corollary for the case when $\{B_n\}$ are i.i.d. random variables.

Corollary 3.4. *Let $\{X_n\}$ be an arrival process, $\{D_n\}$ be the departure process, $\{Q_t\}$ be the queuing process, and $\{B_n\}$ be i.i.d. multinomial random variables. If $\{Q_t\}$ converges in distribution then $\{F_n\}$ converges in distribution with distribution function given by* (12).

Under the information protocol that we described, everyone in the queue has the same class. Thus, we can accurately characterize this particular $M_t^C/M_t^C/m$ queue as random variable taking values in the space $\mathbb{N}_0 \times \mathcal{C}$, where the state $(n,k) \in \mathbb{N}_0 \times \mathcal{C}$ tells us that the queue has n agents in it and everyone is of the class k. We define the state process $\{\hat{Q}_t\}$ as the random variable

$$\hat{Q}_t = (Q_t, F_\eta) = \left(\sum_{n=1}^{\infty} 1_{[0,t]\times(t,\infty)} \circ (X_n, D_n),\ F_\eta \right), \tag{14}$$

where $\eta = \eta(t) = \sup\{n \in \mathbb{N} : X_n \in [0,t]\}$. We show that the process $\{\hat{Q}_t\}$ converges in distribution whenever $\{F_n\}$ converges in distribution, which depends on convergence of the $M_t/M_t/m$ process $\{Q_t\}$ defined in (11). The proof mimics the proof of convergence for $\{F_n\}$ and we present it here for convenience.

Theorem 3.5. *Let $\{X_n\}$ be an arrival process, $\{D_n\}$ be the departure process, $\{B_n\}$ be the class process, and $\{\hat{Q}_t\}$ be the process* (14)*. If $\{B_n\}$ and $\{Q_t\}$ both converge in distribution then $\{\hat{Q}_n\}$ converges in distribution and*

$$\lim_{t\to\infty} \mathbb{P}\{\hat{Q}_t \geq j \text{ and } F_\eta \geq k\} = \begin{cases} \mathbb{P}\{Q \geq j\}\big(\mathbb{P}\{B \geq k\} + \mathbb{P}\{B < k\}\mathbb{P}\{F \geq k\}\big) & j \geq 2 \\ \mathbb{P}\{Q \geq j\}\mathbb{P}\{F \geq k\} & j < 2, \end{cases}$$

where $\mathbb{P}\{F \geq k\} \coloneqq \lim_{t\to\infty} \mathbb{P}\{F_n \geq k\}$ is given by (12) *and $\mathbb{P}\{Q \geq j\} \coloneqq \lim_{t\to\infty} \mathbb{P}\{Q_t \geq j\}$.*

Proof. We first fix $n \geq 1$, $j \geq 2$, any $k \in \mathcal{C}$ and calculate:

$$\mathbb{P}\{Q_t \geq j, F_\eta \geq k\} = \mathbb{P}\{F_\eta \geq k | Q_t \geq j\}\mathbb{P}\{Q_t \geq j\}. \tag{15}$$

Recall that, by definition, the η-th customer is the most recent arrival before t. Then, if we know that $Q_t \geq 2$ we know that η-th agent arrived to a nonempty queue. Thus, on the set $\{Q_t \geq j\}$ we have $F_\eta = \max\{F_{\eta-1}, B_\eta\}$. Note that the updated class of the $(\eta-1)$-th agent is independent of all subsequent arrivals, thus $F_{\eta-1}$ and Q_t are independent. Second, each B_η is independent of Q_t and $F_{\eta-1}$. Thus,

$$\mathbb{P}\{F_\eta \geq k | Q_t \geq j\} = \mathbb{P}\{\max\{F_{\eta-1}, B_\eta\} \geq k\} = \mathbb{P}\{B_\eta \geq k\} + \mathbb{P}\{B_\eta < k\}\mathbb{P}\{F_{\eta-1} \geq k\}. \tag{16}$$

Since $\eta \to \infty$ as $t \to \infty$ and both $\{B_n\}$ and $\{Q_t\}$ converge in distribution, all events in (16) converge as $t \to \infty$, except perhaps the terms involving F_η. But, $\{F_n\}$ converges in distribution by Theorem 3.3. Thus, using (15) and (16) we have for $j \geq 2$,

$$\lim_{t\to\infty} \mathbb{P}\{Q_t \geq j, F_\eta \geq k\} = \mathbb{P}\{Q \geq j\}\big(\mathbb{P}\{B \geq k\} + \mathbb{P}\{B < k\}\mathbb{P}\{F \geq k\}\big).$$

Now we handle the case when $j = 0, 1$. In both cases, the knowledge that the $Q_t \geq j$ tells us nothing about the state of the queue for the η-th arrival. This implies the random variables F_η and Q_t are independent. Thus, for $j = 0, 1$ we have

$$\lim_{t\to\infty} \mathbb{P}\{Q_t \geq j, F_\eta \geq k\} = \mathbb{P}\{Q \geq j\}\mathbb{P}\{F \geq k\}.$$

completing the proof. ∎

We now want to calculate conditional expectations of F_n. Fortunately, the recursion

$$F_n \coloneqq \max\{F_{n-1}1_{\{X_n \leq D_{(n-1),n-1}\}}, B_n\}$$

makes it easy to calculate certain conditional expectations. In particular, it easy to find the distribution of F_{n+1} given one the current state F_n. Recall that $B_n = C_{X_n}$ where $\{C_t\}$ was some process taking values in the class set $\mathcal{C}$. If we assume $\{C_t\}$ is an independency then we have

$$\mathbb{P}\{F_{n+1} > a | F_n = a\} = \mathbb{P}\{B_{n+1} > a\} = \mathbb{P}\{C_{X_{n+1}} > a\} = \mathbb{P}\{C_0 > a\}.$$

For a generic class process $\{C_t\}$ we have

$$\begin{aligned}
\mathbb{P}\{F_{n+1} > a | F_n = a\} &= \lim_{t\to\infty} \mathbb{P}\{C_{X_{n+1}} > a \text{ and } X_{n+1} \leq t\} \\
&= \lim_{t\to\infty} \mathbb{P}\{C_{X_{n+1}} > a | X_{n+1} \leq t\}\mathbb{P}\{X_{n+1} \leq t\} \\
&= \lim_{t\to\infty} \sum_{k=0}^{n} \frac{c(t)^k}{k!} e^{-c(t)} \int_0^t ds\, \mathbb{P}\{C_s > a\}
\end{aligned}$$

where $c(t) = \Lambda([0,t])$.

3.4 A Network of Queues Transmitting Information

We will use a classed network of $M_t^C/M_t^C/1$ queues to model such a system, and will use the notation $(M_t^C/M_t^C/1)^N$ to denote such a network. We want agents to carry with them some information about the current state of the network. In particular, we want agents to carry the load at a queue when they departed, and a time stamp so that observers know how old this information is. The purpose of using classed networks is to use the presence of a particular class to convey this information. As mentioned above, we can easily model a queue that passes information if we assume that there are infinitely many different classes, since we would have a class for all possible configurations of queue lengths and time stamps.

For practical purposes, it is 'easy' to design a class set C that is finite but still conveys all possible configurations of queue lengths and time stamps. As for queue lengths, we know that the queue length can never 'really' be infinite (there are only finitely many atoms in the universe). As for the time stamps, one could simply choose T sufficiently large and count break up $[0, T]$ into buckets of size ΔT. Information given at time $t > T$ would be given the class corresponding to t mod T. But even this set is too large, and we can do better.

3.5 Stress Testing the Information Sharing Regime

A

Proposition A.1. *Let C be a finite set, and let S_C be the free non-abelian semigroup with identity generated by C. Then $\ell_1(S_C)$ is isomorphic to the tensor algebra of $\ell_1(C)$.*

Proof. Let $\bullet$ denote the semigroup operation of S_C. Then every non-identity element $\sigma \in S_C$ can be written as $\sigma = \sigma_1 \bullet \cdots \bullet \sigma_n$ for some $n \in \mathbb{N}_0$ where each $\sigma_i \in C$. If $\sigma = \sigma_1 \bullet \cdots \bullet \sigma_n$ is in S_C, we define $|\sigma| = n$ and we will let o denote the identity element of S_C. Note that we can think of each element of S_C as having the form $\sigma_1 \bullet \cdots \bullet \sigma_n \bullet o \bullet \cdots$. Let $V_n = \{\sigma \in S_C : |\sigma| = n\}$. We specify a basis for $\ell_1(V_1) = \ell_1(C)$ as follows

$$e_{\sigma_i}(\sigma_j) = \begin{cases} 1, & \sigma_i = \sigma_j \\ 0, & \text{otherwise,} \end{cases}$$

and using these we can write a basis for $\ell_1(V_n)$ as follows

$$e_\sigma(\sigma') = \prod e_{\sigma_k}(\sigma'_k) = \begin{cases} 1, & \sigma = \sigma' \\ 0, & \text{otherwise.} \end{cases} \tag{17}$$

We can use the basis defined for $\ell_1(V_n)$ in (17) to show that $\ell_1(V_n)$ is isomorphic to $\ell_1(C)^{\otimes n} = \bigotimes_{k=1}^n \ell_1(C)$. The mapping given by

$$e_{\sigma_1 \bullet \cdots \bullet \sigma_n}(\sigma'_1 \bullet \cdots \bullet \sigma'_n) \mapsto e_{\sigma_1}(\sigma'_1) \otimes \cdots \otimes e_{\sigma_n}(\sigma'_n)$$

where $\otimes$ is the tensor product operator, is a homomorphism from $\ell_1(V_n)$ to $\ell_1(C)^{\otimes n}$. Since elements of the form $e_{\sigma_1} \otimes \cdots \otimes e_{\sigma_n}$ form a basis for $\ell_1(C)^{\otimes n}$, this mapping is an isomorphism. Thus

$$\bigoplus_{n=0}^{\infty} \ell_1(V_n) \simeq \bigoplus_{n=0}^{\infty} \ell_1(C)^{\otimes n},$$

and since $\ell_1(S_C) = \bigoplus_{n=0}^{\infty} \ell_1(V_n)$ we are done. $\square$

B The Queues and Poisson Random Measures

In this section we will construct a stochastic process $\{Q_t\}_{t\geq 0}$ that describes the number of people in an $M/M/1$ queue. We will do this using a Poisson random measure, which will construct as well. First, we will formally define a Poisson random measure, starting with the definition of a random measure.

Definition B.1. A mapping $M : \Omega \times \mathcal{E} \mapsto \bar{\mathbb{R}}_+$ is called a *random measure* if $\omega \mapsto M(\omega, A)$ is a random variable for each A in $\mathcal{E}$ and if $A \mapsto M(\omega, A)$ is a measure on $(E, \mathcal{E})$ for each ω in Ω. The following defines a positive random variable for each $f \in \mathcal{E}_+$:

$$Mf(\omega) = \int_E M(\omega, dx) f(x), \quad \omega \in \Omega.$$

Also, the measure μ defined by

$$\mu(A) = \mathbb{E}\, M(A) = \int_\Omega \mathbb{P}(d\omega) M(\omega, A), \quad A \in \mathcal{E},$$

is called the *mean of* M. Lastly, $\mathbb{E}\, Mf = \mu f$ for $f \in \mathcal{E}$.

Definition B.2. Let $(E, \mathcal{E})$ be a measurable space and let ν be a measure on it. A random measure N is said to be *Poisson with mean* ν if

1. For every A in $\mathcal{E}$, the random variable $N(A)$ has the Poisson distribution with mean $\nu(A)$.
2. Whenever $A_1, \ldots, A_n$ are in $\mathcal{E}$ and disjoint, the random variables $N(A_1), \ldots, N(A_n)$ are independent, where $n \geq 2$.

B.1 Construction of a standard Poisson random measure

We now construct a 'standard' Poisson random measure N on $\mathbb{R}_+$ with mean λLeb, that is, N will be a random measure on the space $(\mathbb{R}_+, \mathcal{B}_{\mathbb{R}_+})$ where $\mathcal{B}_{\mathbb{R}_+}$ is the σ-algebra of Borel sets of $\mathbb{R}_+$. Let $\{T_n\}_{n\in\mathbb{N}}$ be an independency of exponentially distributed random variables with scale parameter λ, that is, we have $\mathbb{P}\{T_n > t\} = e^{-\lambda t}$ for each $n \in \mathbb{N}$. Set $X_n \coloneqq T_1 + \cdots + T_n$ and define N as follows

$$N(\omega, A) \coloneqq \sum_{n=1}^{\infty} 1_A \circ X_n(\omega), \qquad \omega \in \Omega,\ A \in \mathcal{E}. \tag{18}$$

Random measures defined this way are said to be *formed by the process* $X = \{X_n\}$. We can easily check that N is a random measure, but this is not the interesting part.

We now prove that N is a Poisson random measure. First, we can see that $N(A)$ and $N(B)$ are independent whenever A and B are by the independence of $\{T_n\}$. We now check that $N([0,t])$ has the Poisson distribution mean $\lambda\text{Leb}([0,t]) = \lambda t$ for each $t > 0$. We have

$$\mathbb{P}\{N([0,t]) \le n\} = \mathbb{P}\left\{\sum_{n=1}^{\infty} 1_{[0,t]} \circ X_n \le n\right\} = \mathbb{P}\{X_{n+1} > t\} = 1 - \mathbb{P}\{X_{n+1} \le t\}. \tag{19}$$

Now, in order to make further progress we need to know the distribution of X_{n+1} for some arbitrary n. Luckily, we can show that X_{n+1} has the gamma distribution with shape index $n+1$ and scale parameter λ. To see this, assume Y has the gamma distribution with shape index a and scale parameter λ. Then

$$\begin{aligned} \mathbb{E}\, e^{-rY} &= \int_{\mathbb{R}_+} dx\, \frac{\lambda^a x^{a-1} e^{-\lambda x}}{\Gamma(a)} e^{-rx} \\ &= \frac{\lambda^a}{(\lambda+r)^a} \int_{\mathbb{R}_+} dx\, \frac{(\lambda+r)^a x^{a-1} e^{-(\lambda+r)x}}{\Gamma(a)} = \left(\frac{\lambda}{\lambda+r}\right)^a. \end{aligned} \tag{20}$$

Since, the exponential distribution with scale parameter λ is also the gamma distribution with shape index 1 and scale parameter λ we can use (20). Using the independence of $\{T_n\}$ with (20) we can calculate the Laplace transform of $X_{n+1} = T_1 + \cdots + T_{n+1}$ to get

$$\mathbb{E}\, e^{-rX_{n+1}} = \prod_{k=1}^{n+1} \mathbb{E}\, e^{-rT_k} = \prod_{k=1}^{n+1} \left(\frac{\lambda}{\lambda+r}\right) = \left(\frac{\lambda}{\lambda+r}\right)^{n+1}.$$

Thus, S_{n+1} has the gamma distribution with shape index $n+1$ and scale parameter λ[3]. With this knowledge we can continuing from (19), which yields

$$\mathbb{P}\{N([0,t]) \le n\} = 1 - \mathbb{P}\{X_{n+1} \le t\} = \sum_{k=0}^{n} \frac{(\lambda t)^k}{k!} e^{-\lambda t}.$$

To finish, we need to calculate the distribution of $N((s,t])$ for all $s < t$, $s, t \in \mathbb{R}_+$. We observe that if $s < t$ then $N([0,t]) = N((s,t]) + N([0,s])$. Using the independence property of N we have the following relation for the generation functions

$$\mathbb{E}\, z^{N([0,t])} = \mathbb{E}\, z^{N((s,t])+N([0,s])} = \mathbb{E}\, z^{N((s,t])} \mathbb{E}\, z^{N([0,s])}.$$

Since the generating function for a Poisson random variable with mean c is $e^{c(z-1)}$, we have $\mathbb{E}\, z^{N([0,t])} = e^{\lambda t(z-1)}$ and $\mathbb{E}\, z^{N([0,s])} = e^{\lambda s(z-1)}$. This yields $\mathbb{E}\, z^{N((s,t])} = e^{\lambda(t-s)(z-1)}$, completing the proof of the claim that N is a Poisson random measure with mean measure λLeb.

[3] The gamma distribution with shape index n and scale parameter λ is also known as the Erlang-n distribution (with scale parameter λ).

B.2 Construction of a Poisson random measure

We can construct a Poisson random measure with *arbitrary* mean measure ν on $(\mathbb{R}_+, \mathcal{B}_{\mathbb{R}_+})$ by modifying the construction of a 'standard' Poisson random measure given in §B.1. Of course, we do not mean intend on the following construction going through for an 'arbitrary' measure ν, just those that have finite cumulative distribution functions. That is, we require the function $c(t) := \nu[0,t]$ be finite for all $t \in \mathbb{R}_+$. We see that c is increasing on $\mathbb{R}_+$. Let c^{-1} denote the functional inverse of c:

$$c^{-1}(u) := \inf\{t \in \mathbb{R}_+ : c(t) > u\}.$$

Let $\{T_n\}_{n\in\mathbb{N}}$ be an independency of standard exponentially distributed random variables (their scale parameter is 1) and define $X_n := c^{-1} \circ (T_1 + \cdots + T_n)$. For convenience we define $Y_n := T_1 + \cdots + T_{n+1}$. Using $\{X_n\}$ we form the following random measure

$$N(\omega, A) := \sum_{n=1}^{\infty} 1_A \circ X_n(\omega), \qquad \omega \in \Omega,\ A \in \mathcal{E}. \tag{21}$$

We now check that $N([0,t])$ is a Poisson random variable with mean $\nu[0,t]$. To this end we calculate

$$\mathbb{P}\{N([0,t]) \le n\} = \mathbb{P}\left\{\sum_{n=1}^{\infty} 1_{[0,t]} \circ X_n \le n\right\} = \mathbb{P}\{X_{n+1} > t\} = \mathbb{P}\{c^{-1} \circ Y_n > t\} \tag{22}$$

$$= \mathbb{P}\{Y_{n+1} > c(t)\} = 1 - \mathbb{P}\{Y_{n+1} \le c(t)\}, \tag{23}$$

where we used the fact that $c(c^{-1}(t)) \ge t$. By the same analysis given in §B.1, we know that Y_n has the gamma distribution with shape index $n+1$ and scale parameter 1. Thus

$$\mathbb{P}\{N([0,t]) \le n\} = 1 - \mathbb{P}\{Y_{n+1} \le c(t)\} = \sum_{k=0}^{n} \frac{c(t)^k}{k!} e^{-c(t)},$$

allowing us to conclude that $N([0,t])$ is Poisson with mean $c(t) = \nu[0,t]$. The rest of the proof that N is a Poisson random measure is the same as the one given in §B.1.

For simulation, this construction is not the most efficient method. Even when the function c^{-1} is easy to calculate there is a faster way to construct $\{X_n\}$. If we assume ν is absolutely continuous then c is differentiable almost everywhere, and we let $\lambda(t)$ denote its derivative. Let λ be such that $\lambda(t) \le \lambda$ and let $\{B_t\}$ be an independency of Bernoulli random variables with mean $\lambda(t)/\lambda$. Let $Q(t, \cdot)$ denote the distribution of B_t, and let $\{Y_n\}$ form a standard Poisson random measure with mean $\lambda\mathrm{Leb}$. Then by Theorem B.5 we know that $\{(Y_n, B_{Y_n})\}$ forms a Poisson random measure M on $\mathbb{R}_+ \times \{0,1\}$ with mean measure $\mu = \lambda\mathrm{Leb} \times Q$, that is,

$$\mu(dy, dz) = \lambda\mathrm{Leb}(dy)Q(y, dz).$$

The Poisson random measure we desire is $N([0,t]) := M([0,t] \times \{1\})$. We are assured that N is a Poisson random measure since M is. Let Λ denote the mean of N. Then

$$\begin{aligned}\Lambda[0,t] &= \mathbb{E}\, N([0,t]) = \mathbb{E}\, M([0,t] \times \{1\}) = \mathbb{E}\, M 1_{[0,t]\times\{1\}} \\ &= \int_{\mathbb{R}_+ \times \{0,1\}} \mu(dy, dz) 1_{[0,t]\times\{1\}} \circ (y, z) = \lambda \int_0^t dy\, \frac{\lambda(y)}{\lambda} = \int_0^t dy\, \lambda(y),\end{aligned}$$

which implies $\Lambda[0,t] = c(t) = \nu[0,t]$.

B.3 The stochastic process of a single-server queue

Now that we know how to construct a Poisson random measure with mean λLeb we construct the stochastic process for $Q = \{Q_t\}_{t\in\mathbb{R}_+}$ for the number of agents in an $M/M/1$ queue at time t. We assume the arrival rate is λ and the departure rate is μ. Let $\{X_n\}_{n\in\mathbb{N}}$ form the Poisson random measure N with mean measure λLeb, that is, N has the form given by (18). Then N can be thought of as the arrival process for the $M/M/1$ queue. We let $T_n = X_{n+1} - X_n$ denote the time between the n-th customer and the $(n+1)$-st customer (the inter-arrival time).

For the queueing process, we need to set the waiting time and departure time for n-th arrival. Let $\{S_n\}_{n\in\mathbb{N}}$ be an independency of exponentially distributed random variables with scale parameter μ. The random variable S_n will be the amount of service needed for the n-th arrival. The waiting times will be $\{W_n\}$ and are defined as follows: set $W_0 = 0$ and take

$$W_n = [W_{n-1} + S_{n-1} - T_{n-1}]^+.$$

This is Lindley's recurrence relation introduced in []. Set $D_0 = 0$ and let

$$D_n := [D_{n-1} - X_n]^+ + X_n + S_n, \tag{24}$$

where $[\cdot]^+ = \max\{\cdot, 0\}$. We can think of D_n as the departure time of the n-th arrival under a first-in-first-out (FIFO) discipline. With this we define $Q = \{Q_t\}$ as the process

$$Q_t := \sum_{n=1}^{\infty} 1_{[0,t]\times(t,\infty)} \circ (X_n, D_n) = \sum_{n=1}^{\infty} 1_{[0,t]\times(t,\infty)} \circ (X_n, X_n + W_n + S_n), \tag{25}$$

Under this setup, one can still prove some of the usual useful theorems about queues. Some proofs are much easier. For example, we can easily prove Burke's Theorem in this setup. We state it here in it's usual form.

Theorem B.3 (Burke's Theorem). *Consider an $M/M/1$ system with arrival rate λ. Suppose the system starts in a steady state. Then the following are true:*

1. *The departure process is Poisson with rate λ.*
2. *At each time t, the number of jobs in the system at time t is independent of the sequence of departure times prior to time t.*

Theorem B.4 (Burke's Theorem). *Let $\{S_n\}_{n\in\mathbb{N}}$ form a Poisson random measure N with mean measure λLeb, let $\{Y_n\}_{n\in\mathbb{N}}$ be an independency of exponentially distributed random variables with scale parameter μ, and let $\{Q_t\}$ be the $M/M/1$ queueing process given by (25).*

B.4 Useful Theorems for Poisson random measures

The proofs for these theorems can be found in [2, pg. 264].

Theorem B.5. *Let ν be a measure on $(E, \mathcal{E})$, and Q a transition probability kernel from $(E, \mathcal{E})$ into $(F, \mathcal{F})$. Assume that (i) the collection $X = \{X_n\}$ forms a Poisson random measure with mean ν, and (ii) the variables Y_i are conditionally independent given X and have their respective distributions $Q(X_i, \cdot)$.*

1. *Y forms a Poisson random measure on $(F, \mathcal{F})$ with mean νQ, and*
2. *(X, Y) forms a Poisson random measure on $(E \times F, \mathcal{E} \otimes \mathcal{F})$ with mean $\nu \times Q$.*

Corollary B.6. *Suppose that X forms a Poisson random measure on $(E, \mathcal{E})$ with mean ν, and that Y is independent of X and is an independency of variables with distribution π on $(F, \mathcal{F})$. Then (X, Y) forms a Poisson random measure on $(E \times F, \mathcal{E} \otimes \mathcal{F})$ with mean $\nu \times \pi$.*

References

[1] N. Cetin, A. Burri, and K. Nagel. "Parallel Queue Model Approach to Traffic Microsimulations". In: *In Proceedings of Swiss Transportation Research Conference*. 2002.

[2] E. Çınlar. *Probability and Stochastics*. Graduate texts in mathematics. Springer, 2011.

[3] N. Geroliminis and A. Skabardonis. "Identification and Analysis of Queue Spillovers in City Street Networks". In: *Intelligent Transportation Systems, IEEE Transactions on* 12.4 (2011), pp. 1107–1115. DOI: 10.1109/TITS.2011.2141991.

[4] F. P. Kelly. "Networks of Queues". In: *Advances in Applied Probability* 8.2 (1976), pp. 416–432.

[5] F. P. Kelly. "Networks of Queues with Customers of Different Types". In: *Journal of Applied Probability* 12.3 (1975), pp. 542–554.

[6] W. A. Massey. "Open Networks of Queues: Their Algebraic Structure and Estimating Their Transient Behavior". In: *Advances in Applied Probability* 16.1 (1984), pp. 176–201.

[7] C. Osorio and M. Bierlaire. "An analytic finite capacity queueing network model capturing the propagation of congestion and blocking". In: *European Journal of Operational Research* 196.3 (2009), pp. 996–1007. DOI: http://dx.doi.org/10.1016/j.ejor.2008.04.035.