Estimating Changes in Parking Capacity and Urban Form From Vehicle Automation

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Estimating Changes in Parking Capacity and Urban Form From Vehicle Automation

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Project Description

We developed models that estimate the costs and benefits of locating electric vehicle charging infrastructure in specific locations depending on specific levels of vehicle automation. For many municipalities across the nation, a challenge has been to identify and secure the financial resources necessary for enabling capital equipment to reduce environmental emissions and energy costs. Electric vehicles provide the potential for lower operating costs per mile but have generally have higher capital costs at present. In addition, electric vehicles for municipal use need charging stations to ensure vehicle capabilities during business hours. The City of Pittsburgh has signaled a desire to convert a significant portion of their non-emergency vehicle fleet to electric vehicles, and needs to make decisions on where to charge and house a potential fleet of vehicles. The decision of where to locate the charging infrastructure affects costs, availability and resiliency during an outage. The arrival of partially autonomous technology such as parking valet and other features enables another set of capabilities that municipalities should consider when planning new infrastructure for both public and private electric vehicles. These include flexible parking infrastructure and automated wireless charging.

Public charging stations are expensive, and generally have low charging utilization rates when cars remain in the spaces long after charging is complete. Analyses on optimizing alternative fuel and electric vehicle infrastructure are common for many different sets of criteria. A research gap remains on assessing how higher levels of vehicle automation can change these results. Automation enables a potential increase in charger utilization and reduction in the spatial limitations of where vehicles charge. Additionally, it may give more control over timing and location of charging demand than traditionally-driven vehicles would allow. This research investigates these potential effects by analyzing the following research question: What are potential electric vehicle charging infrastructure siting efficiencies and associated energy and environmental impacts from level 4 and level 5 automation?

Primary Results

This project developed a method to characterize the impact of privately-owned autonomous electric vehicles on electric vehicle charger placement, distribution, utilization, and power demand. Using Seattle, WA as a case study, a least total cost optimization for charging station owner and driver costs is conducted for vehicle automation levels 0-3, 4, and 5. Moving from levels 0-3 to level 4 and level 5 automation reduces the peak electrical load for EV charging by approximately 31% and 68%, respectively. Moving from levels 0-3 to level 4 automation decreased the optimal number of chargers by 65%, lowered total cost by 46%. Moving from levels 0-3 automation to level 5 automation decreased the optimal number of chargers by 84% and total costs by 69%. Additional vehicle miles traveled and operating costs incurred by drivers for drop off and pick up were estimated with level 5 automation. The results suggest that highly automated vehicle technology used in privately-owned electric vehicles could reduce the cost of deployment for recharging infrastructure and reduce peak electrical demand associated with recharging. The results were published as a Technical Report (Mersky and Samaras, 2020, following this summary), and are under review at an academic journal. Several government, professional, and academic presentations were also completed, as listed below.

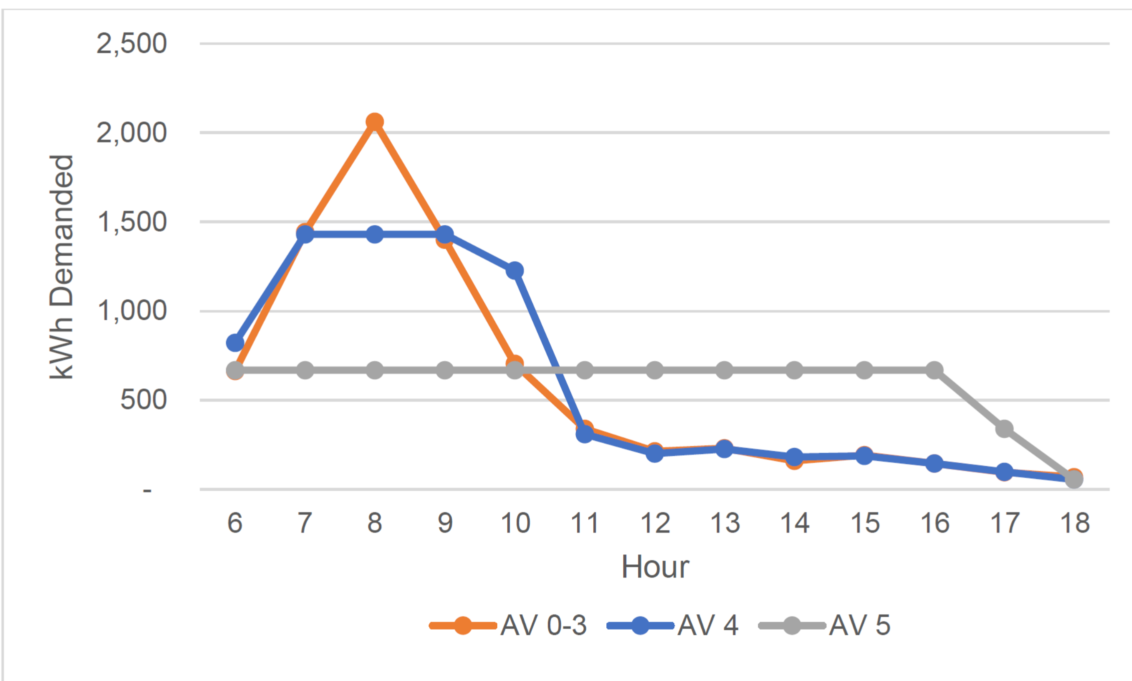

Figure 1: Charging Profiles Under Automation Levels in Seattle, WA. Under levels 0-3 automation, demand peaks with the arrival times, between 7 a.m. and 9 a.m., with demand at just over 2,000 kWh between 8 and 9 a.m. After this point electric demand rapidly decreases until 11 a.m., after which it continues to slowly decrease. The pattern under level 4 automation is similar, except that the 7 a.m. to 9 a.m. peak is level at just under 1,500 kWh, reducing about fourth of the peak demand. Under level 5 automation, electric demand stays steady at just

under 700 kWh until 4 p.m., when it starts decreasing as people leave their workplaces. This is a 31% decrease of the peak electrical demand under level 4 automation and a decrease of 68% under level 5 automation, when compared to no automation. This shows that simply taking advantage of the automated queueing allowed by automation can significantly smooth the demand peaks without specific consideration to grid management.

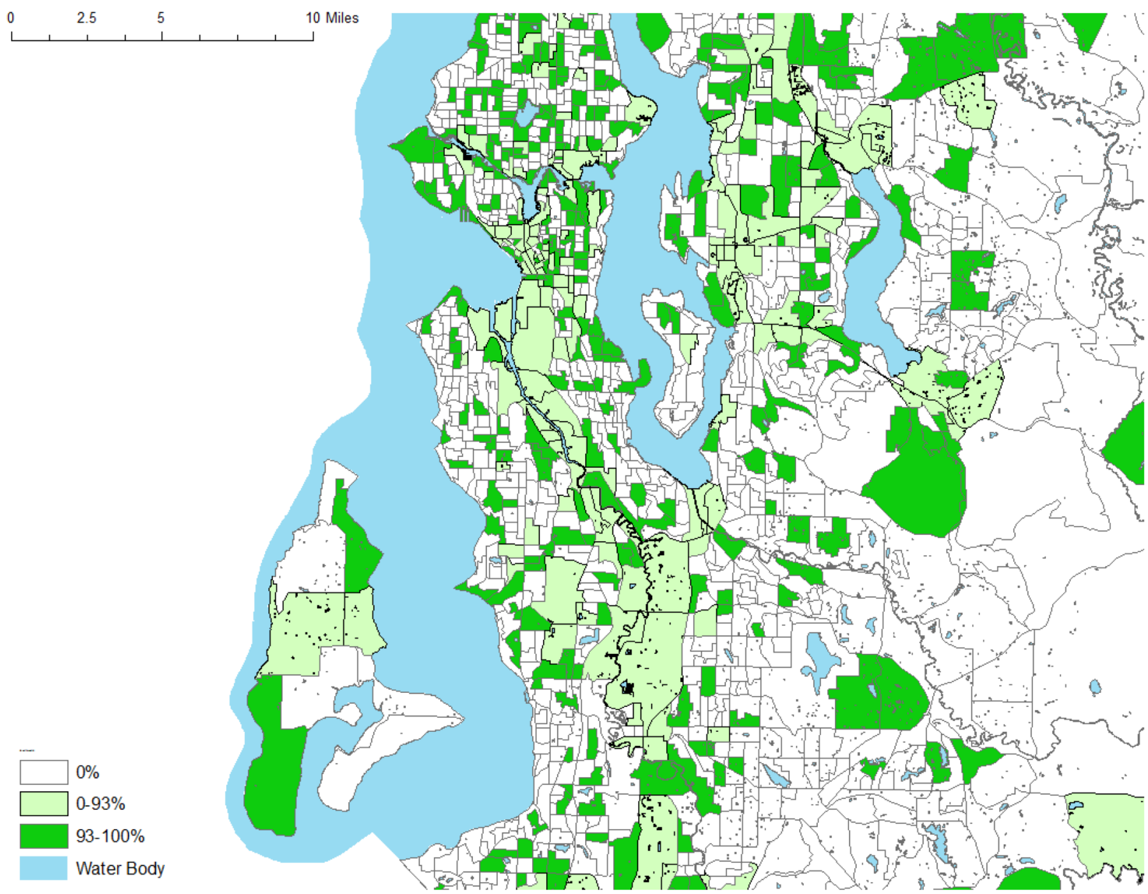

Figure 2: Percent Decrease in Electric Vehicle Chargers from Level 0 to Level 5 Automation in Seattle, WA.

Presentations and Publications

1. Mersky, A.C., Samaras, C. (2020): Impact of Vehicle Automation on Electric Vehicle Charging Infrastructure Siting and Energy Demand. Carnegie Mellon University. Technical Report. https://doi.org/10.1184/R1/13408730.v1
2. Samaras, C. (2020). The Transition to Electrified Transportation, Civil and Environmental Engineering, Bucknell University, April 2, 2020.
3. Samaras, C. (2020). Will Electric and Driverless Cars Decarbonize Transportation? University of Texas - Austin, March 11, 2020.

4. Mersky, A.C., Samaras, C. (2019). Impact of Vehicle Automation on Electric Vehicle Charging Infrastructure Siting and Energy Demand. NBER Workshop on Economics of Electric and Autonomous Vehicles. June 7, 2019, Palo Alto, CA.
5. Samaras, C. (2020). Energy and Emissions Impacts of Automated Vehicles Under Uncertainty, SAE Government and Industry Forum, Washington, D.C., January 21, 2020.
6. Samaras, C. (2019). Opportunities and Challenges During the Transition to Automated Vehicles. Traveler's Institute Symposium, Keynote Speaker. November 21, 2019, Pittsburgh, PA.
7. Samaras, C. (2019). The Impact of Automated Vehicles on Cities. National Renewable Energy Laboratory, Washington, D.C., (Governmental Briefing), May 23, 2019.
8. Mersky, A.C., Samaras C. (2018). Impact of Autonomous Vehicles on Electric Vehicle Charging Infrastructure. ASCE International Conference on Transportation and Development, Pittsburgh, PA. July 15-18, 2018.

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Impact of Vehicle Automation on Electric Vehicle Charging Infrastructure Siting and Energy Demand

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Abstract
This paper presents a method to characterize the impact of privately-owned autonomous electric vehicles on electric vehicle charger placement, distribution, utilization, and power demand. Using Seattle, WA as a case study, a least total cost optimization for charging station owner and driver costs is conducted for vehicle automation levels 0-3, 4, and 5. Moving from levels 0-3 to level 4 and level 5 automation reduces the peak electrical load for EV charging by approximately 31% and 68%, respectively. Moving from levels 0-3 to level 4 automation decreased the optimal number of chargers by 65%, lowered total cost by 46%. Moving from levels 0-3 automation to level 5 automation decreased the optimal number of chargers by 84% and total costs by 69%. Additional vehicle miles traveled and operating costs incurred by drivers for drop off and pick up were estimated with level 5 automation. The results suggest that highly automated vehicle technology used in privately-owned electric vehicles could reduce the cost of deployment for recharging infrastructure and reduce peak electrical demand associated with recharging.

1: Introduction
A major cost associated with widespread deployment of electric vehicles (EVs) is the necessary public recharging infrastructure. Public charging stations are expensive and can have low charging utilization rates when cars remain in the spaces long after charging is complete. Analyses on optimizing alternative fuel and electric vehicle infrastructure are common for many different sets of criteria. A gap in the literature remains on how higher levels of vehicle automation can affect electric vehicle recharging infrastructure needs. Automation enables a potential increase in charger utilization and reduces the spatial limitations of where vehicles charge. Additionally, it may give more control over timing and location of charging demand than traditional vehicles allow. This paper investigates these potential effects by analyzing the following research question: What are the potential electric vehicle charging infrastructure efficiencies and associated energy and environmental impacts from level 4 and level 5 automation?

Both level 4 automation, where a vehicle can direct itself absent human oversight within a controlled operational design domain, and level 5 automation, where vehicles can control themselves absent human oversight in all conceivable normal operation circumstances (SAE International 2014), have the potential to increase EV charger utilization and change the optimal distribution of charging stations. Under level 4 automation, a parking facility could be designed to allow for complete autonomous control within the facility, allowing for autonomous electric vehicles to navigate themselves once in the facility. Currently, electric vehicles charging unattended occupy a charger for the entire time that the vehicle is parked, regardless of whether electricity is being delivered. Level 4 automation may allow for facilities to be designed where vehicles navigate themselves to an open charger with wireless or automated connections and then, when completely charged, leave the charging space and go to a conventional parking spot. This would enable another vehicle to use the charger, and higher charger utilization would allow for fewer individual charging stations to be needed, which and result would decrease total charging infrastructure costs. Similar benefits could also be gained from changes to charging infrastructure itself to allow charging units to be connected to multiple vehicles and charge them in a sequence, known as smart charging solutions. Such solutions, however, are still limited by the need to be located within comfortable walking distances to vehicle trip origins and destinations.

A larger and more comprehensive charging infrastructure network is necessary to extend the range of vehicles that are charged solely at home, as well as enable charging for people without access to charging infrastructure where they live. Level 5 automation, where vehicles could drop off and pick up passengers and travel in driverless mode to charging facilities, could relax or remove this restriction. Doing so would allow for chargers to be concentrated at fewer locations, reducing supporting infrastructure costs, as well as located away from areas with high real estate prices. Chargers can also only be installed in integer units giving any specific facility's charging capacity a stepwise function. The ability to move vehicles greater distances can improve upon the gains from level 4 automation by ensuring that vehicles whose demand would require an additional charger can be pooled together, even if their destinations are distant from each other. This would reduce the total number of chargers needed.

Vehicle automation and autonomous refueling infrastructure can also be used to help smooth electric demand patterns. Many drivers tend to travel in similar patterns, and uncontrolled electric vehicle charging can add to current electricity grid demand. If these vehicles all recharge at similar times due to similar travel schedules, the power grid peak demand periods could be exacerbated. Demand smoothing could occur with vehicles not being charged when first plugged in, but instead having the vehicle managing smart charging with consideration to the price and demand signals of the power grid. Using smart charging or pricing systems on infrastructure is one way to potentially address this challenge (See Table 1 below). However, without automation, existing chargers would require the controls and capabilities to optimize charging times, and vehicles may occupy a charger longer than necessary. Automation coupled with smart charging may enable even greater power demand smoothing opportunities with lower total infrastructure costs. A vehicle charging and queuing system may allow for demand to be moved to off-peak times, as well as move to other locations if there are local grid infrastructure constraints. The values used in this paper evaluate automation, but the methods could be adapted to scenarios where existing chargers with additional control infrastructure could allow multiple vehicles to connect to one charger and demand optimized across these vehicles.

This paper contributes to the literature by developing an optimization to understand how driver EV charger placement, utilization, and costs are affected by different levels of automation. This paper uses Seattle, WA as a case study, and uses the Puget Sound 2014 Household Travel Survey (Kilgren 2015) unweighted trips and assumes 100% EV adoption for those trips in the dataset, which enable a simulation with existing driver parking demand and distanced traveled in the survey sample. The model minimizes charging station owner as well as driver costs. Charging station owner costs are defined as real estate costs for a parking space, charging equipment capital cost, and charging equipment maintenance costs. Driver costs are defined as either the costs of walking when using Levels 0-4 automated vehicles; or the costs of additional vehicle operation when using fully autonomous Level 5 vehicles, including energy and depreciation. The paper is organized as follows: Section 1 continues with a literature review and then lists the data sources used. Section 2 details the methods used to process the data into usable input for the optimization models and then defines the optimization models. Section 3 presents and discusses the results obtained from the optimization models. Section 4 summarizes the results. Section 5 ends the paper by listing the primary limitations of the results and models presented in this paper and how future work can build and improve on the contributions made by this paper.

1.1: Literature Review

Table 1 summarizes several studies on the optimization or grid effects of electric vehicle charging. It notes: the region of study, whether the authors modeled electric vehicle adoption separate from vehicle ownership/travel, the source of travel data, the methodology of optimization or electric demand modeling, whether the vehicle was assumed to charge along their route or while parked, whether the paper was focused on stations, vehicles, or the grid, and whether the study considered time of demand separate from the total. Among all the papers reviewed, none investigated the effects that higher levels of automation will have on EV charger optimization.

Most of the reviewed papers focused on the charging infrastructure owner costs, with only a minority investigating electric grid owner or vehicle driver costs. Driver costs were only directly investigated by (Chen et al. 2013), (Nie and Ghamami 2013) and (Ghamami et al. 2016), the latter two times in combination with the charging infrastructure owner costs. Some reviewed papers, such as (Frade et al. 2011), which investigated owner costs, indirectly captured driver costs by limiting them. These papers are focused on optimizing infrastructure for parked vehicles and do not consider the possibility of automation, driver costs, therefore, are solely the value lost by distance parked from preferred destination, and inherently limited by the maximum distance they are willing to walk. Other papers, such as (Chen et al. 2013), indirectly capture owner costs by setting a budget that must be met while minimizing driver costs.

The most common data sources were the Census (Frade et al. 2011; Sathaye and Kelley 2013) and household travel surveys, either national (Hilshey et al. 2013) or local (Chen et al. 2013), or foreign equivalents (Frade et al. 2011; Mehta et al. 2017). The most common solution methods were various forms of optimization, with the most common subgrouping being linear or mixed integer optimization (Chen et al. 2013; Frade et al. 2011; Worley et al. 2012; Xi et al. 2013).

This paper expands on previous work using local household travel survey data and mixed linear optimization, such as (Chen et al. 2013). This paper contributes to the literature by jointly minimizing driver and charging equipment owner costs and also by creating a method to evaluate the effects of different levels of vehicle automation on the optimal solution. This paper further contributes by expanding the scope of infrastructure owner costs to include real estate opportunity costs, rather than just construction and maintenance costs.

Table 1. Summary of Assorted Studies Investigating the Optimization or Grid Effects of Electric Vehicle Charging

Study	**Region**	**Electric Vehicle Adoption Variable**	**Travel Data Source**	**Method**	**While Parked or Along Route**	**Owner, Driver or Grid Focused**	**Time Dependent**
(Sweda and Klabjan 2011)	Chicagoland (Chicago)	No	US Census	Agent Based	Both	Operator	No
(Worley et al. 2012)	Chicagoland (Chicago)	No	None	Mixed Integer Optimization	Both	Operator	No
(Bae and Kwasinski 2012)	None	No	None	Fluid Dynamic Traffic Model & M/M/s Queueing	Along Route	Grid	Yes
(Knapen et al. 2012)	Flanders, Belgium	No	Multiple	Activity Based Model	Along Route	Grid	Yes
(Chen et al. 2013)	Puget Sound (Seattle)	No	Regional Household Travel Survey	Mixed Integer Optimization	While Parked	Driver	No
(Hilshey et al. 2013)	New England	No	National Household Travel Survey	Monte Carlo	While Parked	Grid	Yes
(Nie and Ghamami 2013)	Chicago, IL to Madison, WI	No	None	Karush–Kuhn–Tucker Approach (KKT)	Along Route	Operator and Driver	No
(He et al. 2013)	None	No	None	Active-Set Algorithm & KKT	While Parked	Operator and Grid	No
(Sathaye and Kelley 2013)	Texas Triangle	Yes	US Census, TEXDot	Root Finding Method	Along Route	Operator	No
(Xi et al. 2013)	Central-Ohio	Yes	Mid-Ohio Regional Planning Commission	Linear Integer Programming	While Parked	Operator	No
(Frade et al. 2011)	Lisbon, Portugal	Yes	Multiple	Mixed-Integer Optimization	While Parked	Operator and Grid	Yes
(Huang et al. 2015)	Sioux Falls (South Dakota)	No	None	Multipath Refueling	Along Route	Operator	No

Study	Region	Electric Vehicle Adoption Variable	Travel Data Source	Method	While Parked or Along Route	Owner, Driver or Grid Focused	Time Dependent
				Location Model (Fuel Capturing Location Model)			
(Ghamami et al. 2016)	Chicago–Madison–Minneapolis Corridor	Yes	Hybridcars.com	Mixed-Integer Non-Linear, Simulated Annealing	Along Route	Driver and Operator	No
(Zhu et al. 2016)	Beijing	No	None	Genetic Algorithm-Based Method	While Parked	Operator	No
(Mehta et al. 2017)	Singapore	Yes	Land Transport Authority Singapore	Genetic Algorithm	While Parked	Grid	Yes
This Paper	Puget Sound (Seattle)	No	Regional Household Travel Survey	Mixed Integer Optimization	While Parked	All	No

1.2: Data Sources

The primary data source used is the Puget Sound 2014 Regional Travel Survey (Kilgren 2015). This survey includes a list of respondent trips with origin and parking location by Travel Analysis Zone (TAZ), census tracts, census block, and parking location name. The locations of census tracts and TAZs were obtained from the Puget Sound Regional Council GIS database (Norton n.d.). Travel zones, census blocks, and census tracts include water bodies in files to show shores and islands. For locational purposes, all water area was removed from zonal, tract, and block shapefiles. Real estate assessment data was taken from 2006 King County GIS data ("KCGIS Data Download" 2014). According to Zillow, King County real estate prices recovered from the recession and reached 2007 levels between 2015 and 2016 (Zillow Inc 2017); therefore, these data were used as given. EV fuel economy was estimated using a range of EPA fuel economy ratings (EPA n.d. X) and taken as 35 kWh per 100 miles. King County per capita income of $42,000 in 2015 is from the Census Bureau and is not statically different than the area's median worker's income (U.S. Census Bureau 2017). Electric prices were taken from a Bureau of Labor Statistics report on the metropolitan area and used 2015 retail prices of about $0.10 per kWh (US DOL 2017). All monetary values are in 2015$.

2: Methods

2.1: Data Sorting and Calculations

Trips were aggregated from the trip data set of the Puget Sound 2014 Regional Travel (Kilgren 2015). This data set included about 48,000 trips total. Trips were included for our model if:

- The trip's purpose was travel to the person's workplace
- They were by a car or carpool
- The person recording the trip was the driver
- The vehicle was parked in either a parking lot or on the street near the destination, not in a Park N Go lot, for intermodality
- The trip started between 6 a.m. and 6 p.m.

Various additional filters were used to remove error values or incomplete responses that affected the data of interest. After filtering the data approximately 3,500 trips were used for our model.

From each trip, the following information was extracted:

- Destination census block group
- Trip distance
- Hour of arrival, rounded down
- Hour of exit, defined as the sum of the duration of time spent at destination and the hour of arrival, rounded down
- The respondent unique ID associated with the trip

The maximum potential utilization rate of all autonomous enabled charging was estimated using a 10,000 iteration Monte Carlo simulation. In these scenarios it is assumed that a single parking space per charger will charge the vehicles and that the level 4 or 5 autonomous vehicles will drive themselves into and out of the charging and normal parking spaces. For each iteration a random trip was sampled from the pool of all non-zero distance trips in the travel survey. This trip's distance was used, along with a 20 miles of electric range per hour charge rate for a Level 2 EV charger (6.6 kW) (Smith and Castellano 2015), to determine the time required for a full charge for each vehicle. After a full charge was achieved, 1 additional minute was assumed to elapse during switching to the next vehicle. This continued until at least 8 hours had passed, when the vehicle left the charger. This was applied for all autonomous charging scenarios. The utilization rate was the time that a vehicle was charging divided by the total time elapsed. Maximum utilization was found to have a mean of 31% and a standard deviation of 6.8%. The histogram of the maximum utilization iterations is shown in Fig. 1. For the level 0-3 automation scenario it is asusmed that each vehicle will use a charging space for the whole time that parking is needed.

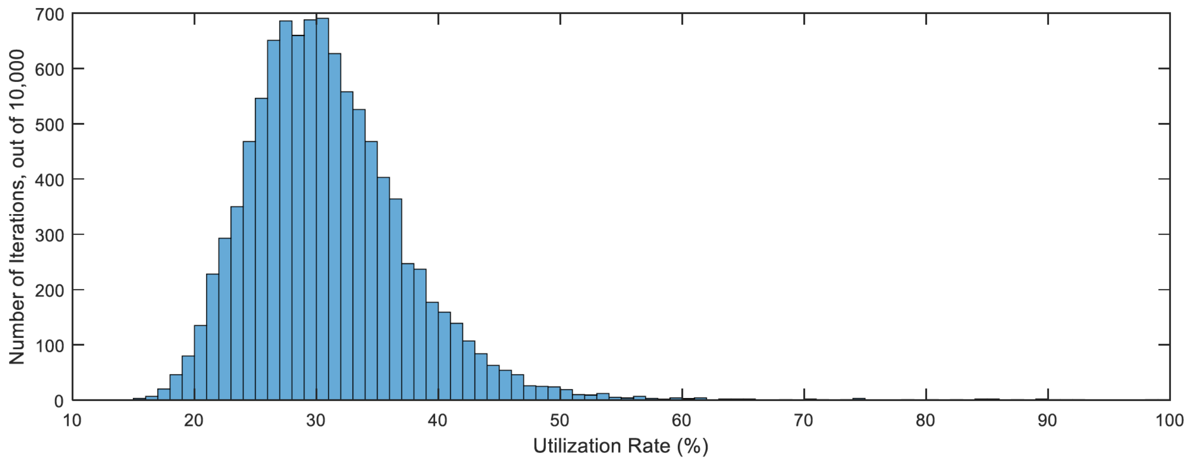

Fig. 1. Maximum Utilization Rate Histogram

Parking demand was aggregated based on destination census block. For each block, we calculated the peak number of spots demanded, the total number of trips ending in the block, the total number of miles traveled to the block, the average number of miles per trip for the zone, and the average number of trips demanded per peak spot demanded. The number of spots demanded in each hour is calculated in Equation 1. These were calculated from the Puget Sound 2014 Regional Travel Survey (Kilgren 2015), starting at values of 0 at 6 a.m. and ending at 6 p.m.

For each hour and zone jointly, the parking spot demand was calculated as shown in Equation 1, starting at 6 a.m., with demand and departures of 5 a.m. defined as 0. Peak parking demand for a zone was defined as the maximum demand of all hours between 6 a.m. and 7 p.m. This calculates the maximum number of spots of parking in any zone that would be demanded for one specific hour, as cars both leave and arrive throughout the day.

Equation 1: Hourly Parking Spot Demand

$$Demand_t = Demand_{t-1} + Arrivials_t - Depatures_{t-1}$$

The arrival rate, shown in Fig. 2, is highest in the early morning, peaking at 8 a.m. It then drops rapidly. Departures, shown in Fig. 3, are more evenly distributed and more concentrated in the early afternoon, peaking at 5 p.m. When taken together, these result in a peak driver parking demand occurring at 9 a.m. Commute distances in Seattle, shown in Fig. 4, are highly concentrated around short distances. The peak is up to 2 miles and generally follows a normal distribution. Fig. 5 shows the histogram of the parking duration for the trips. Parking duration appears to follow a bimodal distribution with a small peak at 4 hours and a steep peak at 9 hours long.

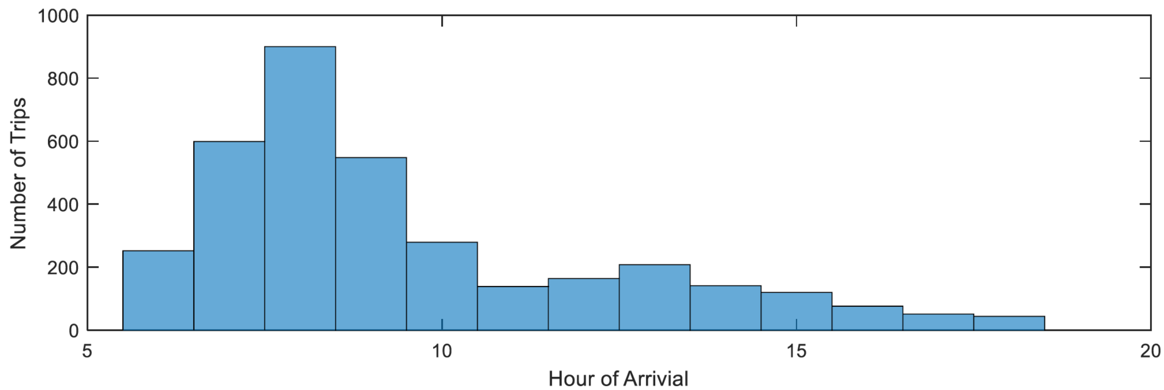

Fig. 2. Histogram of Driver Arrival Times

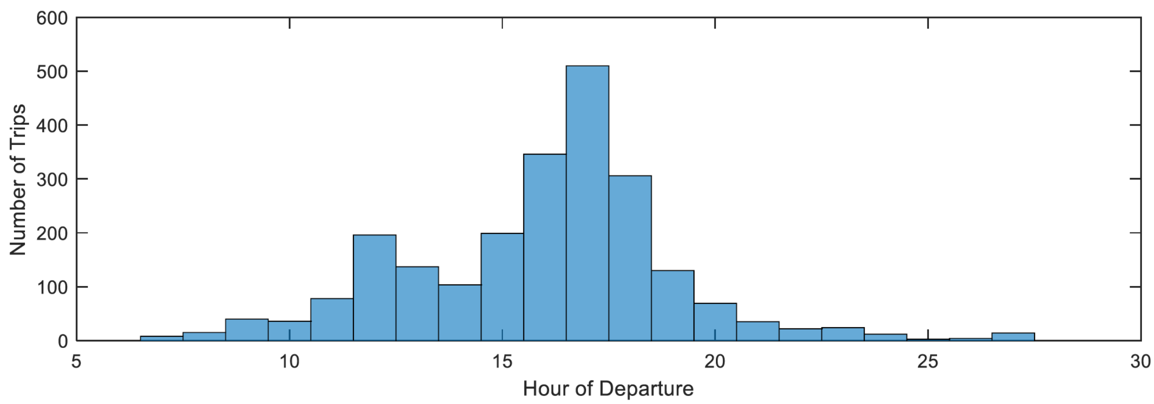

Fig. 3. Histogram of Driver Departure Times

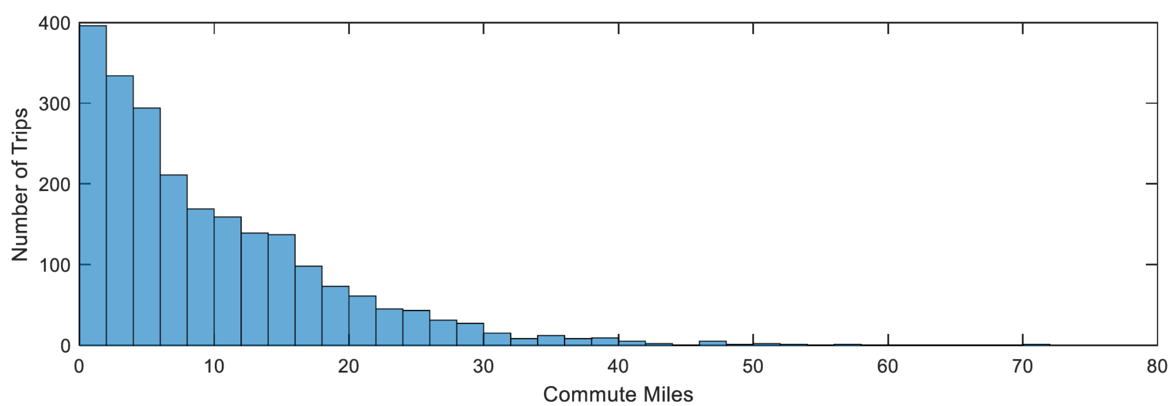

Fig. 4. Histogram of Commute Distances

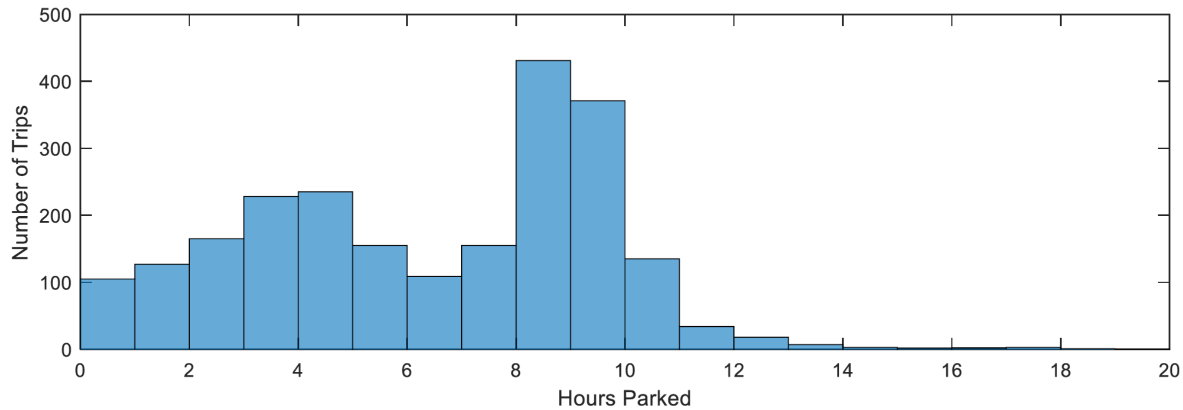

Fig. 5. Histogram of Parking Durations

King County, Washington has approximately 1,500 census block groups and commuting parking demand was found for about 900 of these. Distances between the census blocks were calculated from the Puget Sound Regional Councils GIS database (Norton n.d.). Manhattan distance was used — that is, the sum of the absolute value of the differences between the x and y centroids. This was used to derive the cost of walking and cost of driving. In both cases, two trips were expected every day of a 260-day work year. The cost of walking from a parking space to a destination was based upon King County's $41,700 per capita income, 2015$ (U.S. Census Bureau 2017), a 52-week year, a 40-hour work week, a 3-mph average walking speed (National Academies of Sciences, Engineering, and Medicine 2013), and a 50% assumed value of time discount for personal vehicle traveled, factored by a 220% increase for time value of walking when compared to personal vehicle travel (National Academies of Sciences, Engineering, and Medicine 2013). This leads to a yearly cost of ~ $5,400 a year per mile-spot, when diverting parking from desired zones, as shown in Equation 2.

Equation 2: Cost of Walking

$$7.35\frac{\$}{mi} \approx 41{,}700\frac{\$}{\mathrm{yr}} * \frac{1}{52}\frac{yr}{week} * \frac{1}{40}\frac{wk}{hr} * \frac{1}{3}\frac{hr}{mi} * 0.5 * 2.2$$

The costs of additional vehicle travel for a Level 5 EV to travel to another parking area was estimated using a $0.10 per kWh electricity cost (US DOL 2017), a 35 kWh per 100 mi fuel economy (EPA n.d. X), $0.005 / mi maintenance cost (Alexander and Davis 2013), and a $0.246 / mi depreciation cost (AAA 2015), the last cost not being specific to electric vehicles. All costs are in 2015$. This leads to about a $0.33 per mile cost a when diverting parking from desired zones, as shown in Equation 3. This is much less than the costs of walking. In a drop-off and pick-up scenario with vehicle automation, chargers can be expected to be further from demand where parking would be less expensive. This enables significant infrastructure cost savings by traveling further than the maximum allowable walking distance. We note that the costs of automation equipment have not been included in this estimate, which represents an optimistic assumption.

Equation 3: Cost of Driving

$$0.33\frac{\$}{mi} \approx \left(0.35\frac{kWh}{mi} * 0.1\frac{\$}{kWh} + \ 0.05\ \frac{\$maint.}{mi} + \ 0.246\ \frac{\$depr.}{mi}\right)$$

Real estate costs for parking spaces were estimated using data from King County GIS ("KCGIS Data Download" 2014). Parcel data points were spatially joined and aggregated into each census block. The specific data point used was the average assessed unimproved land value per square foot of all parcels in a block. The average was taken only from parcels that had positive real estate values. Unimproved values were used in the absence of gross-square-foot values for a parcel, which would allow the value of built structure space to be used, as opposed to the value of a parking lot. Some blocks had no parcels with positive assessed real estate values. Of these, only one was a full block. The others were pieces of census blocks, cut by the borders of the county and with small dimensions for distance calculations. The full block and two of the cut-off blocks also had travel demand. For the full census block, ID 530330211004, the average cost of the seven surrounding zones, 18.8 \$/sq-ft, was used. For block 530610507005, the average of the full two zones below it, 19.5 \$/sq-ft, was used. For block 530610509003, the average of the full two zones below it, 22.1 \$/sq-ft, was used. The few remaining blocks with no real estate and demand data were removed from consideration for charger placement. The size of a parking space was taken as $15m^2$, as defined by the Seattle city code for a standard space for "large vehicle" (City of Seattle 2017). This ignores the additional space required for navigation, which would change based upon scale and parking lot design. In addition, since Level 4 or Level 5 vehicles that parked themselves autonomously would not require space for doors to open, spaces could be narrower than traditional spots.

2.3: Charger Selection and Infrastructure Costs

Based on the costs of electric vehicle infrastructure equipment (Smith and Castellano 2015), we estimated the installed capital costs of Level 2 charging equipment to be \$10,000 per charger. This is based on \$4,000-6,000 single-port level 2 charger and \$600-\$13,000 (mean \$3,000), for installation (Smith and Castellano 2015). A conservative combined estimate of \$10,000 was used to account for the high variability in costs and the likelihood that retrofits would be needed for facilities without adequate electrical wiring capacity. Level 2 chargers can charge at a rate of 6.6 kW, providing a typical vehicle about 20 miles of range per hour of charging (Smith and Castellano 2015). Given the trip distance distribution seen in Fig. 4, this will fully recharge more than 95% of all trips considered in under 2 hours. DC charging would not make economic sense, given combined equipment and installation costs of \$40,000-\$90,000 (Smith and Castellano 2015). For levels 4 and 5 automation, where one charger can fulfill multiple vehicles, DC charging would cost more per mile per hour than level 2 charging (Smith and Castellano 2015), a gap that increases as one accounts for the time to switch out vehicles. This \$10,000 capital cost for a Level 2 charger was annualized over 15 years, using the City of Seattle's current 4.122% 30-year bond rate (City of Seattle n.d.) to about \$900 per year. Maintenance is likely to be insignificant except in cases of vandalism or a failure not covered by warranty (Smith and Castellano 2015). Wireless communication is likely to be necessary to allow for autonomous parking, and the U.S. Department of Energy lists current wireless infrastructure for charging costs as between \$100-\$900 a year (Smith and Castellano 2015). We assumed this was unnecessary in non-autonomous scenarios, but a necessary additional cost in autonomous scenarios with a cost of $500 per year per charger.

2.4: Optimization

2.4.1: Optimization Model Overview

This paper builds off of prior mixed linear optimization work in the literature and expands upon those models to capture join driver-owners cost minimization and to capture the possible effects of vehicle automation on owner and driver costs. This paper is focused on building a modular optimization model and uses the unweighted data as a direct input rather than building a model for travel demand. This model further expands on prior work by calculating charging station owner cost in terms of a real estate component, based on assessed unimproved real estate values and the average cost to install one charging station. In this paper's model, each charging space has a limited capacity and multiple spaces can be placed in each location. This paper uses the owner cost as a component of the objective function to find the socially optimum amount and distribution of spending. Charging station owner cost could also be used as a constraint, either in addition to or instead of in the objective function, to find the optimum way of allocating a given owner cost, which may be possibly less than the socially optimum one. This paper also uses trip distance, time, and assigned parking data to calculate the temporal changes in electricity demand caused by vehicle charging.

In addition to a base case model, showing optimization for no automation (levels 0-3), there are also individual models for level 4 and level 5 automation. For level 4 and level 5 automation, demand is served in terms of miles, rather than trips, to account for the ability of vehicles to queue themselves for charging without human intervention. The level 4 automation scenario could also be adapted to cover smart charging infrastructure scenarios. This would require adjusting infrastructure costs to account for the different technology and potentially limiting the number of vehicles that could be served by a single charger. For level 5 automation, the maximum access cost constraint is removed and costs (c) is redefined as a function relating distance from parking to destination to the costs of energy consumption and vehicle deterioration needed to travel that distance. As with Chen et al., this paper simplifies the solution by ignoring the increase in charging demand, but not cost, from changes in trip distance caused by parking diversions.

Table 2 summarizes all variables and constants used in the optimization models, as well as the constants' sources. Variable definitions given here are general, e.g. demand, and may have slightly different definitions or be calculated differently in the various scenarios, i.e. demand in number of stations (integer) or miles. The following sections detail how each variable is used and calculated in each scenario.

Table 2: Variable and Constant Definitions and Sources

Variable/Constant	Definition	Source
i, j	Travel Analysis Zone ID	N/A
c_{ij}	Driver cost of parking in zone i when traveling to zone j, $	N/A
$y_{\{mi\}ij}$	Demand for parking in zone i served in zone j, either number of stations or miles {mi} of charging needed	N/A
K_i	average number of trips per peak trip in zone i, can be fractional, count	Household Travel Survey(Kilgren 2015)
L	Charging infrastructure owner costs, $	(Smith and Castellano 2015) (City of Seattle n.d.) (Zillow Inc 2017)
x_j	# of chargers in j, integer	N/A
D_i	Demand for parking in zone i, either number of vehicles or miles	N/A
d_{ij}	walking distance between zone i and location j, miles	(Norton n.d.)
w_{ij}	Binary variable, true if any demand in zone i served in zone j	N/A
W	maximum walking distance, miles	(Chen et al. 2013)
A_j	real estate cost per parking space and charger at location j, $	("KCGIS Data Download" 2014)
B	costs per charging station, equipment and installation, $	(Smith and Castellano 2015)
E	cost of walking, $ / mile	(U.S. Census Bureau 2017)
U	maximum charger utilization rate, %	N/S
q	charger capacity, miles per shift	(Smith and Castellano 2015)
Q_j	zone charge capacity, miles	N/A
C_w	cost of wireless AV communication equipment maintenance, $ / year	(Smith and Castellano 2015)
F_e	fuel economy, kWh / mi	(EPA n.d. X)
P_{elc}	price of electricity, $ / kWh	(US DOL 2017)
$(A\|P, i)$	annuity value of current lump sum, $	(City of Seattle n.d.)

2.4.2: Levels 0-3 Automation Model

In Levels 0-3 automation, all chargers must be occupied by the same vehicle for the full time that a vehicle is present. Demand is taken as the peak amount of parking demanded in any census block. This model minimizes the sum of the charging station owner cost for building the infrastructure and the cost of drivers walking between their parking spaces and workplaces, as shown in Equation 4. The latter is limited by a maximum 0.25-mile walking distance, shown in Equation 10. For the cost of distance, each peak trip is multiplied by the total number of trips per peak trip for each zone, K_{ij}. This model is defined in Equation 4 through Equation 13.

Objective:

Equation 4

$$\min\left[\sum_{i}^{I}\left(\sum_{j}^{J}\{c_{ij} * y_{ij} * K_i\}\right) + L\right]$$

Decisions:

- y_{ij} = peak parking demand of zone i served in location j, (stations to build in j), integer

What we Want:

Equation 5

$$x_j = \text{\# of chargers in j} = \sum_{i}^{I} y_{ij}$$

Constraints:

Equation 6

$$\sum_{j}^{J}(y_{ij}) = D_i, \forall \text{ i, (all parking demand served)}$$

Equation 7

$$\sum_{i}^{I}(y_{ij}) \leq x_j, \forall \text{ j, } \quad \text{(charging supply constraint)}$$

Equation 8

$$y_{ij} \geq 0 \ \forall \text{ i } \forall \text{ j } \ \text{(non-negativity constraint on parking demand)}$$

Equation 9

$$x_j \geq 0 \ \forall \text{ j (non negative station assignment)}$$

Equation 10

$$d_{ij} * w_{ij} <= W \ \forall \ i \ \forall \ j \text{ (maximum walking distance)}$$

Given:

Equation 11

$$L = \sum_{j}^{J} \left(x_j * (A_j + B) * (A|P,i) \right), \text{(owner cost)}$$

Equation 12

$$c_{ij} = d_{ij} * E * 2 * 260, \text{(walking costs)}$$

Equation 13

$$w_{ij} = \begin{Bmatrix} 1, & if\ y_{ij} > 0 \\ 0, & else \end{Bmatrix}, \text{(binary check if anyone walked between i and j)}$$

$$solved\ as\ \{w_{ij} * 900{,}000 \geq y_{ij}\}$$

Input Parameters:

- $D_i =$ parking demand at zone i, peak vehicles, count
- $A_j =$ real estate cost per parking space and charger at location j, $
- $B =$ costs per charging station, equipment and installation, $
- $d_{ij} =$ walking distance between zone i and location j, miles
- $E =$ cost of walking, $ / mile
- $W =$ maximum walking distance, miles
- $K_i =$ average number of trips per peak trip in zone i, can be fractional, count
- $(A|P,i) =$ annuity value of current lump sum, $

2.4.3: Level 4 Automation Model

With level 4 automation, several vehicles can queue to use to a single charger, allowing the charger to serve more than one vehicle per day. To account for this, demand is redefined as the aggregate miles that drivers must drive to reach their destination in each zone. Each charger can then charge up to its 20 miles of EV range per hour capacity times the expected utilization rate of 31%, based upon the county's trip-length distribution. Each trip between blocks is assumed to have the average number of miles of the trips from the origin block, $D_{Avg\text{-}i}$. The model for level 4 automation is described in Equation 14 through Equation 25. Equation 25 is a simplification, used to convert between aggregate miles, $Y_{mi\text{-}ij}$, and individual trips, Y_{ij}, in order to calculate driver costs. This scenario could also be adapted for smart charging scenarios. The values for the cost of electric vehicle chargers and maintained would need to be adjusted for the new technologies. Additionally, a constraint may need to be added to cover a potential limit

on the number of vehicles a single charger could serve, as a physical hook-up would be needed for each individually parked vehicle.
Objective:

Equation 14

$$\min\left[\sum\nolimits_{i}^{I}\left(\sum\nolimits_{j}^{J}\{c_{ij} * y_{ij}\}\right) + L\right]$$

Decisions:

- y_{ij} = total trips ending in zone i served in location j, count

What we Want:

Equation 15

$$x_j = \text{\# of chargers in j} = \frac{\left(\sum_i^I y_{ij}\right)}{U * q}\text{, integer}$$

Constraints:

Equation 16

$$\sum_{j}^{J}\left(y_{mi_{ij}}\right) \geq D_i, \forall \text{ I, (all parking demand served)}$$

Equation 17

$$\sum_{i}^{I}\left(y_{mi_{ij}}\right) \leq Q_j, \forall \text{ j, (charging supply constraint)}$$

Equation 18

$$y_{ij} \geq 0 \;\forall \text{ i } \forall \text{ j (non-negativity constraint on parking demand)}$$

Equation 19

$$x_j \geq 0 \;\forall \text{ j (non-negative station assignment)}, integer$$

Equation 20

$$d_{ij} * w_{ij} <= W \;\forall\, i\; \forall\, j \text{ (maximum walking distance)}$$

Given:

Equation 21

$$L = \sum_{j}^{J}\left(x_j * \left(\left(A_j + B\right) * (A|P, i) + C_w\right)\right)\text{, (owner cost)}$$

Equation 22

$$c_{ij} = d_{ij} * E * 2 * 260\text{, (walking costs)}$$

Equation 23

$$w_{ij} = \begin{Bmatrix} 1, & if\ y_{ij} > 0 \\ 0, & else \end{Bmatrix}\text{, (binary check if anyone walked between i and j)}$$

$$solved\ as\ \{w_{ij} * 900{,}000 \geq y_{ij}\}$$

Equation 24

$$Q_j = x_j * U * q\text{, zone charge capacity, miles}$$

Equation 25

$$y_{mi_{ij}} = y_{ij} * D_{avg_i}$$

Input Parameters:

- $D_i =$ parking demand at zone i, peak driver miles
- $D_{avg_i} =$ mean trip distance for trips ending in zone i, miles
- $A_j =$ real estate cost per parking space and charger at location j, $
- $B =$ costs per charging station, equipment and installation, $
- $d_{ij} =$ walking distance between zone i and location j, miles
- $E =$ cost of walking, $ / mile
- $W =$ maximum walking distance, miles
- $U =$ maximum charger utilization rate, %
- $q =$ charger capacity, miles per shift
- $(A|P, i) =$ annuity value of current lump sum, $
- $C_w =$ cost of wireless AV communication equipment maintenance, $ / year

2.4.4: Level 5 Automation Model

For level 5 automation, the maximum walking distance is removed to account for the ability of vehicles to drop off and pick up their passengers. The cost of walking is therefore replaced with energy and vehicle depreciation costs for this extra distance of vehicle travel, as calculated in Equation 33. Otherwise, the model is identical to that of level 4 automation and is defined in Equation 26 through Equation 36.

Objective:

Equation 26

$$\min\left[\sum_i^I \left(\sum_j^J \{c_{ij} * y_{ij}\}\right) + L\right]$$

Decisions:

- $y_{ij} =$ total trips ending in zone i served in location j, count

What we Want:

Equation 27

$$x_j = \text{\# of chargers in j} = \frac{\left(\sum_i^I y_{ij}\right)}{U * q}$$

Constraints:

Equation 28

$$\sum_j^J \left(y_{mi_{ij}}\right) \geq D_i, \forall \text{ I, (all parking demand served)}$$

Equation 29

$$\sum_i^I \left(y_{mi_{ij}}\right) \leq Q_j, \forall \text{ j, (charging supply constraint)}$$

Equation 30

$$y_{ij} \geq 0 \ \forall \text{ i } \forall \text{ j (non-negativity constraint on parking demand)}$$

Equation 31

$$x_j \geq 0 \ \forall \text{ j (non-negative station assignment)}$$

Given:

Equation 32

$$L = \sum_j^J \left(x_j * \left(\left(A_j + B\right) * (A|P, i) + C_w\right)\right), \text{(owner cost)}$$

Equation 33

$$c_{ij} = d_{ij} * F_e * P_{elc} * 2 * 260, \text{(drop-off/pick-up energy cost, \$)}$$

Equation 34

$$w_{ij} = \begin{Bmatrix} 1, & if\ y_{ij} > 0 \\ 0, & else \end{Bmatrix}, \text{(binary check if anyone walked between i and j)}$$

$$solved\ as\ \{w_{ij} * 900{,}000 \geq y_{ij}\}$$

Equation 35

$$Q_j = x_j * U * q, \text{ zone charge capacity, miles}$$

Equation 36

$$y_{mi_{ij}} = y_{ij} * D_{avg_i}$$

Input Parameters:

- D_i = parking demand at zone i, peak driver miles
- D_{avg_i} = mean trip distance for trips ending in zone i, mile
- A_j = real estate cost per parking space and charger at location j, \$
- B = costs per charging station, equipment and installation, \$

- $d_{ij} =$ walking distance between zone i and location j, miles
- $U =$ maximum charger utilization rate, %
- $q =$ charger capacity, miles per shift
- $F_e =$ fuel economy, kWh / mi
- $P_{elc} =$ price of electricity, $ / kWh
- $(A|P, i) =$ annuity value of current lump sum, $
- $C_w =$ cost of wireless AV communication equipment maintenance, $ / year

3: Results and Discussion

The optimal number of chargers, given by our models, for levels 0-3, level 4, and level 5 automation are of 1,900, 680, and 331 chargers, respectively. These cover a total of 2,300 trips and 1,900 peak trips. This leads to each charger covering an average of 1.2, 3.5, and 7.4 trips, with 4.4%, 13%, and 27% of the 13 hours through 6 a.m. and 6 p.m. spent charging vehicles. The maximum utilization rate that the model would assign is the 31% expected utilization rate calculated in Section 3.1. The annualized equipment and parking costs, to build upon these scenarios, for levels 0-3, level 4, and level 5 automation are $1.75 million, $932,000, and $436,000, respectively, while the total driver and owner costs, are $1.75 million, $937,000, and $540,000, respectively.

The difference between these two sets of values show the potential transfer of cost payment from charger/parking facility owners to drivers, assuming driver parking fees are constant. Without any automation the ability to move to cheaper areas is limited by walking distances, hence effectively all the extra costs to handle EVs is covered paid by the charger owner. Under limited automation or smart charging scenarios the ability to increase utilization of chargers encourages charger owners to move some chargers to cheaper, but more distant, locations. This however is still bounded by walking limitations and drivers incur only 0.5% of net social costs. It is only when automation decouples parking locations from the need to walk to final destinations under level 5 when significant costs can be transferred to drivers, in the form of increased energy consumption and wear in tear, totaling 19% of net social parking costs. In all automation scenarios, however, net social savings dwarf the potential increase in driver costs. Moving from no automation or smart charging to level 4 automation or smart charging entails transferring just 0.6% of net social savings to drivers, while moving to full automation, from no automation, transfers 13% of net social savings from charger owners to drivers. These transfers could be removed or lessoned by changes in parking fees, without changing the socially optimal charger placement.

The histograms of the distribution of chargers for levels 0-3, level 4, and level 5 automation are shown in Fig. 6 through Fig. 8. These histograms don't include the zones with zero chargers and truncate the largest groupings. Fig. 9 through Fig. 11 show the percentage decrease in number of charging stations, by census block, when increasing the level of automation. The legend groups these by equal percentile size groups. When moving from no automation to level 4 automation, roughly a quarter of the blocks keep the same number of, or no, chargers, another quarter decrease the number of chargers by as much as a third, another quarter decrease by up to two-thirds, and the final quarter decrease by up to 100%. When moving from no automation to level 4 automation, one-third of the blocks register no change, one-third decrease by up to one-half, and the remaining third decrease by up to 100%. When moving between level 4 and level 5 automation, one-third of the blocks register no change in chargers, one-third decrease by up to 93%, and the remaining third decrease by up to 100%.

The hourly electric demand from the chargers is shown in

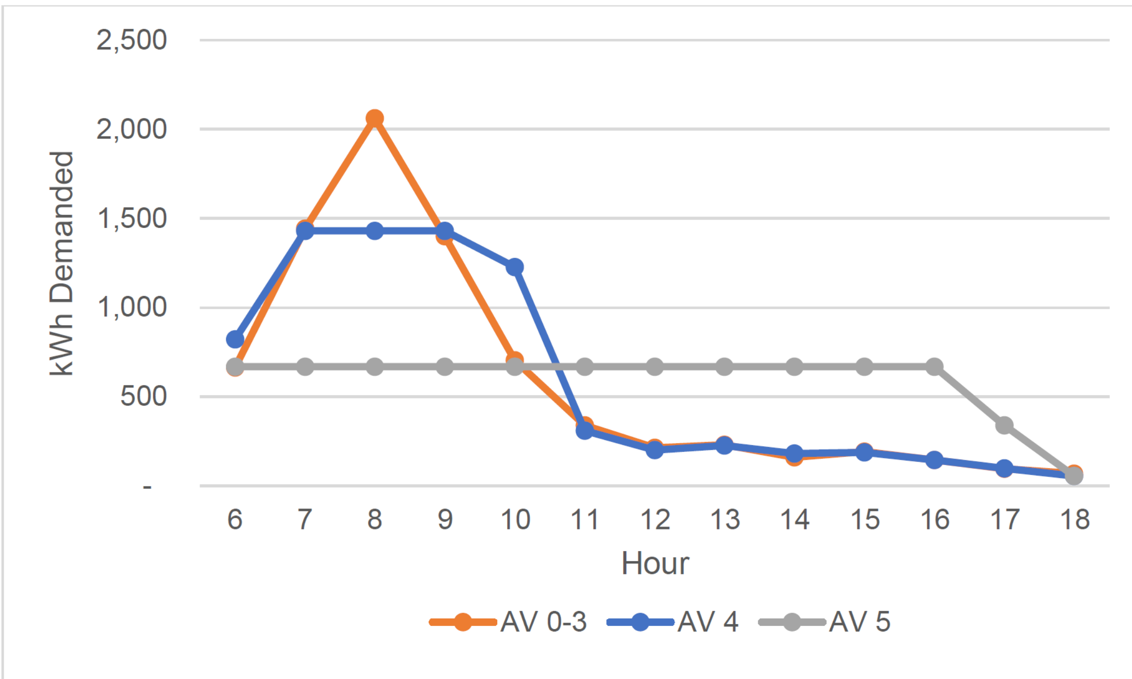

Fig. 12. Under levels 0-3 automation, demand peaks with the arrival times, between 7 a.m. and 9 a.m., with demand at just over 2,000 kWh between 8 and 9 a.m. After this point electric demand rapidly decreases until 11 a.m., after which it continues to slowly decrease. The pattern under level 4 automation is similar, except that the 7 a.m. to 9 a.m. peak is level at just under 1,500 kWh, reducing about fourth of the peak demand. Under level 5 automation, electric demand stays steady at just under 700 kWh until 4 p.m., when it starts decreasing as people leave their workplaces. This is a 31% decrease of the peak electrical demand under level 4 automation and a decrease of 68% under level 5 automation, when compared to no automation. This shows that simply taking advantage of the automated queueing allowed by automation can significantly smooth the demand peaks without specific consideration to grid management.

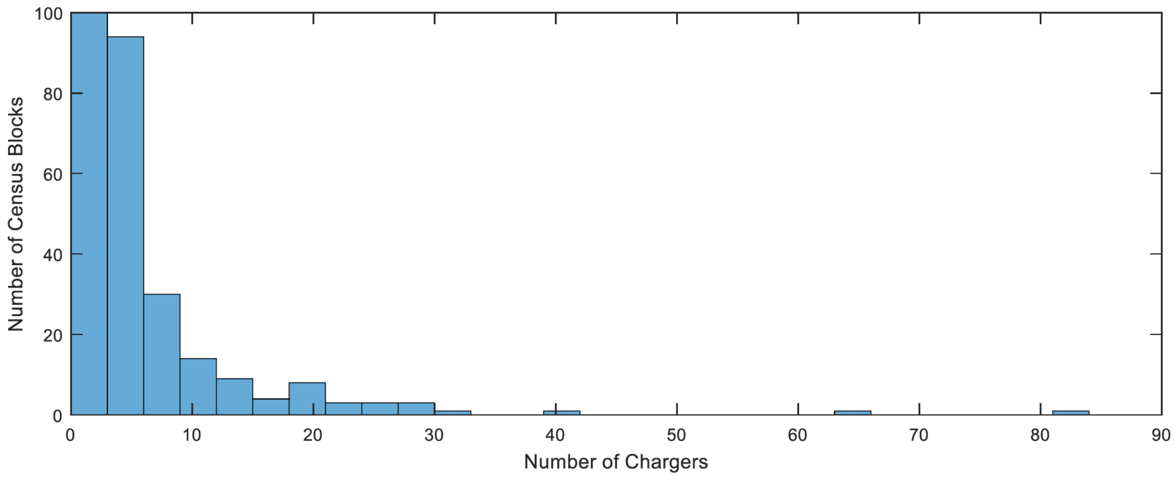

Fig. 6. Histogram of Charger Distribution for Levels 0-3 Automation, 995 Blocks with 0, 1,900 Total Chargers

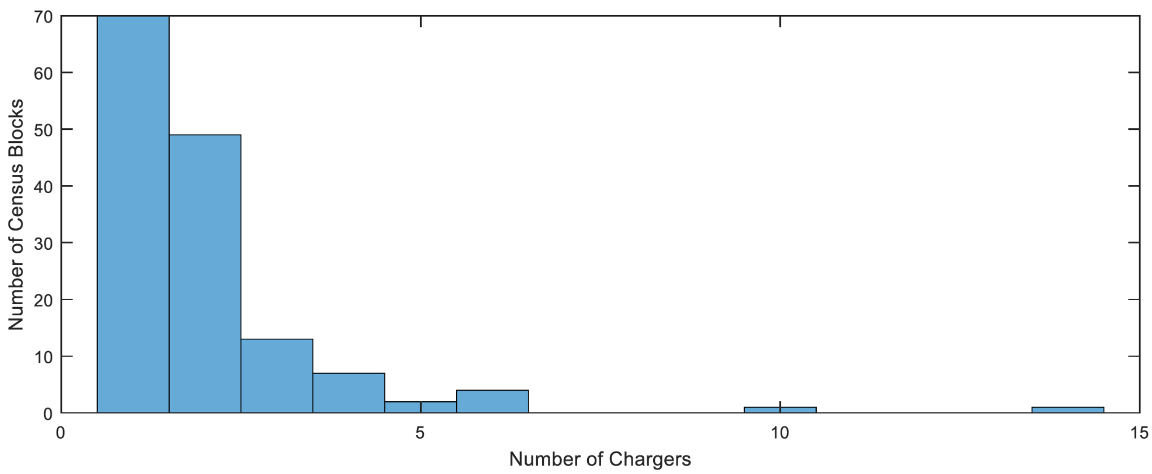

Fig. 7. Histogram of Charger Distribution for Level 4 Automation, 960 Blocks with 0, 680 Total Chargers

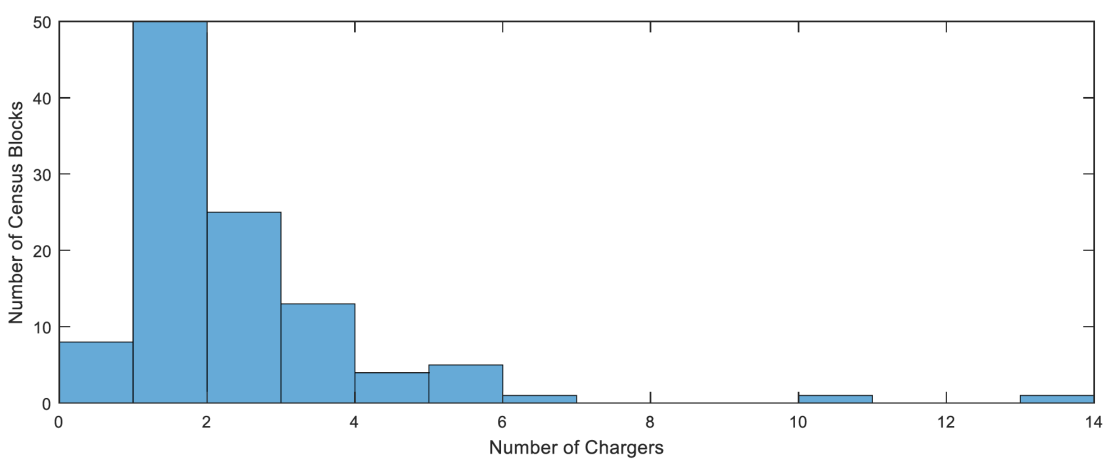

Fig. 8. Histogram of Charger Distribution for Level 5 Automation, 1,275 Blocks with 0, 331 Total Chargers

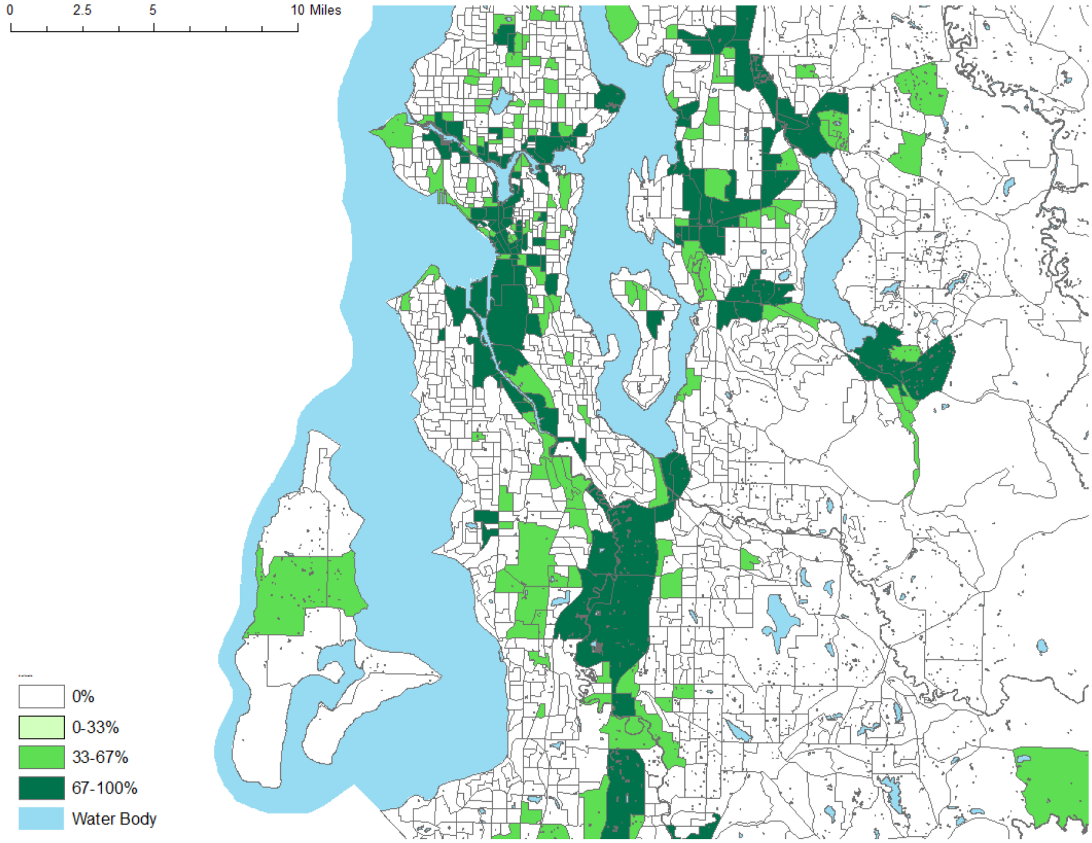

Fig. 9. Percent Decrease in Chargers from Level 0 to Level 4 Automation: Percentile Groups

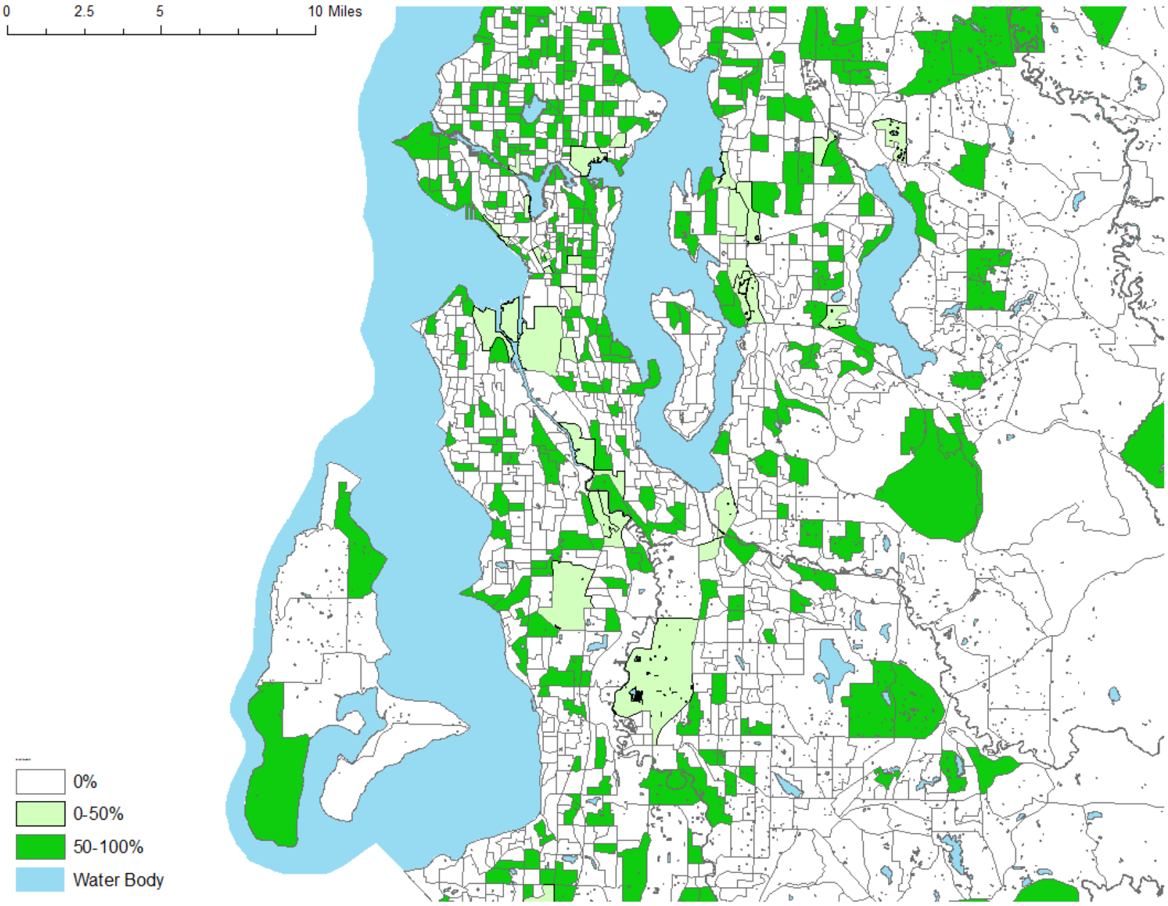

Figure 10: Percent Decrease in Chargers from Level 4 to Level 5 Automation: Percentile Groups

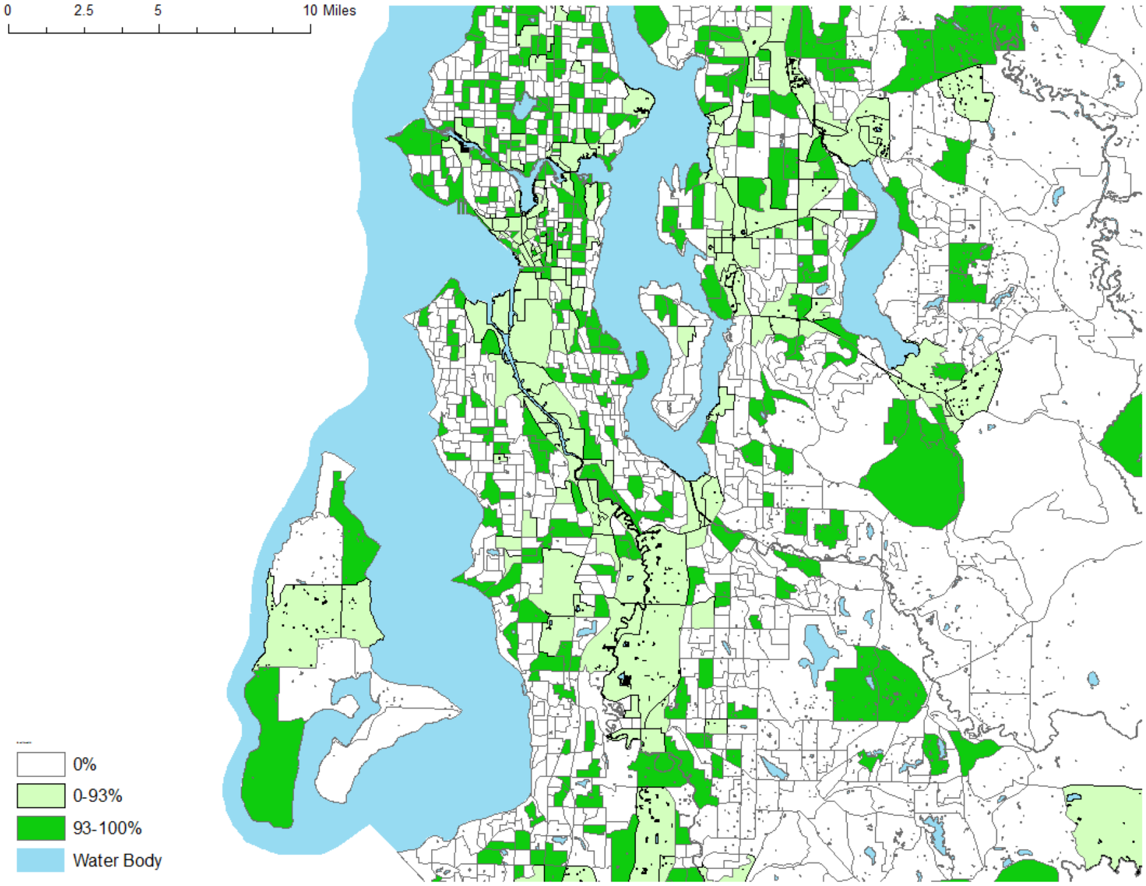

Fig. 11. Percent Decrease in Chargers from Level 0 to Level 5 Automation: Percentile Groups

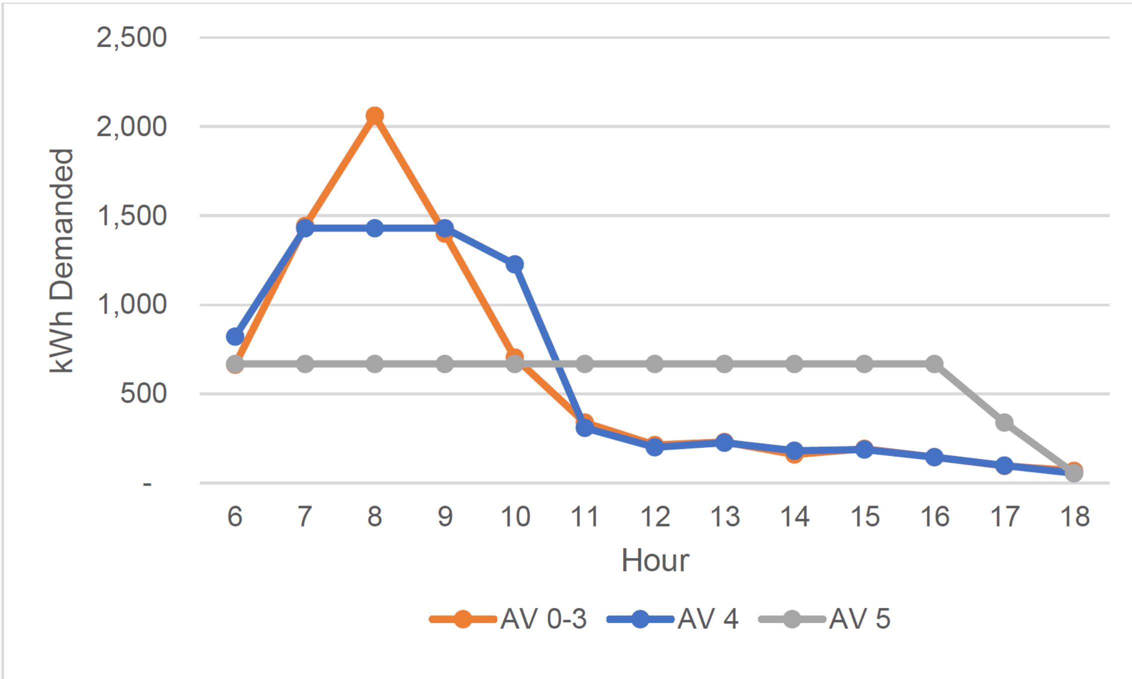

Fig. 12. Hourly Electric Demand Under Each Level of Automation

4: Conclusion

This paper presented a method to characterize the impact of privately-owned autonomous electric vehicles on electric vehicle charger placement, distribution, utilization, and power demand. EV charger placement was optimized based on minimizing charging station owner and driver costs. Without any automation, we assumed each vehicle would occupy a charger for the entire duration that it is parked, whether or not it was finished charging. For level 4 automation it was assumed that vehicles could vacate themselves from a charger when they are fully charged and allow another vehicle to charge, with a 1-minute time to switch vehicles. For no automation and level 4 automation, the driver costs were limited by a maximum 0.25-mile walking distance. For full, level 5 automation, driver cost was unbounded.

The electrical demand of the optimal solution for these scenarios was also estimated. Moving from levels 0-3 to level 4 and level 5 automation reduces the peak electrical load by 31% and 68%, respectively. This is from a peak load of about 2,000 kWh in the peak hour or 1 kWh per peak vehicle. If the number of peak EV trips were to be 1 per worker for the whole population, over 2 million in King county (U.S. Census Bureau 2017), then this peak would be over 1,000 MWh. Moving from no automation to level 4 automation lowered charging station owner costs by 47% and total costs, including both charging station owner and driver costs, by 46%. Moving from levels 0-3 automation to level 5 automation decreased charging station owner costs by 75% and total costs by 69%. Without any automation, the cost borne by drivers is insignificant as each vehicle can only serve one driver at a time and drivers' distances between their workplace and their parking spots are limited. This cost increases in significance in the level 4

automation scenario, where a driver walking distances are longer to share a charger with other drivers. The total cost borne by drivers, however, is only 0.5% of the total charging station owner cost. The cost borne by drivers is much more significant with level 5 automation, where a vehicle travels autonomously to much greater distances than are possible via walking with the equipment cost savings. Here the cost borne by drivers is 24% of the total equipment and real estate costs. Due to this, increasing the relative cost borne by drivers will only significantly change the level 5 automation scenario, by decreasing the movement of charging stations.
Electric vehicles are experiencing market growth and significance while automated technologies are being introduced to the market. This paper has shown that these two technologies have potential synergies and a novel method to take advantage of these synergies while optimizing electric vehicle infrastructure deployment. It has also shown that taking advantage of the potential synergies between these technologies would allow for significant decreases in support infrastructure cost. This would also allow for smoothing of the electric demand caused by electric vehicles.

5: Limitations and Future Work

The model was found to be computationally feasible for levels 0-3 and level 4 automation. A proven optimal solution to the level 5 automation scenario could not be found, due to computational limits. The solution reported is no more than 1.7% from the optimal solution. This reflects a possible gap of $9,000, which is under the assigned cost of a single charging station. Given more resources, the true optimal solution could likely be found, though the decrease in social cost would not be large enough to change the paper’s conclusions.
None of our scenarios directly accounted for the temporal aspect of parking demand in the optimization model itself. For no automation, the maximum hourly demand of each individual zone was used. This has the potential to overestimate the optimal number of stations, as neighboring zones may have different peak demand times. For the automated-vehicle scenarios, the total number of miles traveled was used. Many of these miles might be spaced close together and need to be charged in less than the full timeframe, a possibility suggested by the distribution of parking durations shown in Fig. 5. This leads to a potential underestimation of the optimal number of stations necessary to fulfill demand. Accounting for this temporal dimension would have greatly increased computational complexity. Given the limits reached when modeling level 5 automation, this complexity was beyond the resources available to the authors for this paper. Creating and running a time-sensitive set of models would provide more precise solutions.
This paper used the Puget Sound Household Travel Survey's (Kilgren 2015) trips as a direct and unweighted demand input. Using the data directly provides more concentration of travel demand than reality and using the data unweighted introduces likely bias; however, the main goal of this paper is to present the novel methodology for optimizing charging infrastructure for automation and testing the potential gains from this technology and joint approach. These potential gains come from the ability to queue vehicles for a charger and eliminate the maximum-walking-distance constraint. The first potential gain is affected by the trip-length distribution, which is strongly low weighted, even when accounting for data bias. The second potential gain is affected by the concentration of demand and by the distribution of real estate costs relative to demand. The concentration of demand is likely to be higher when directly

using the survey data. The results should, therefore, still be informative on this method's potential benefit. Without a demand model, areas of no visible demand are, in effect, removed from the model and see no chargers in any scenario, decreasing the ability to draw spatial distribution conclusions. Adding a demand distribution model would allow for specific spatial distribution conclusions to be drawn. Additionally, by using the data directly and in its entirety, for drivers, we ignore the question of who will adopt electric vehicles and which adopters will need workplace charging. Not everyone may purchase EVs and some who do will have sufficient range and charging at home.

The most specific spatial data provided by Puget Sound Household Travel Survey (Kilgren 2015) were census blocks. Distance was determined using the centroids of these zones. Travel within a zone was always considered free, while travel from the border of one zone to another was counted as being equivalent to between their centroids. This is a fundamental limitation of the data source. The increase of vehicle costs for level 4 and level 5 automation was not included in the model. The model only optimized for fleets that are fully level 0-3, level 4, or level 5 autonomous vehicles. Optimization models accounting for mixed fleets and/or deciding which level of automation is optimal given vehicle pricing would allow further insights. Distances for parking diversions were calculated as Manhattan distance. This is a potential underestimation, when accounting for the significant presence of bodies of water. Diversion costs also ignored increases in traffic congestion, which could be significant in the level 5 scenario.

The cost of a single parking space was taken as the space's individual physical footprint times the census block's average assessed unimproved real estate value. Parking spaces need navigational area as well, which changes as the number of spaces in a lot or garage increases. Market real estate value and usage is also affected by zoning and current built infrastructure, both of which this paper ignores. A more accurate real estate model accounting for the value of current parking infrastructure would allow for a more accurate balance of driver and owner costs. The cost of walking was based upon a constant, the median income. Car ownership and type of vehicle ownership is influenced by income. Therefore, using the median income may underestimate the true cost walking. Future studies could account for this.

This paper only considered private vehicles for driver usage. Possible car-sharing was not evaluated, nor did the model attempt to account for the possibility of only charging overnight at the commuters' homes. Future work could attempt to determine demand based upon home charging availability and the potential of car sharing. This would also add a cost to time to charge, beyond there being enough time to reach a full charge.

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References

AAA. (2015). “Annual Cost to Own and Operate a Vehicle Falls to $8,698, Finds AAA.” *AAA NewsRoom*, <http://newsroom.aaa.com/2015/04/annual-cost-operate-vehicle-falls-8698-finds-aaa-archive/> (Jun. 1, 2017).

Alexander, M., and Davis, M. (2013). *Total Cost of Ownership Model for Current Plug-in Electric Vehicles*. Electric Power Research Institute, Palo Alto.

Bae, S., and Kwasinski, A. (2012). “Spatial and Temporal Model of Electric Vehicle Charging Demand.” *IEEE Transactions on Smart Grid*, 3(1), 394–403.

Chen, T., Kockelman, K., and Khan, M. (2013). “Locating Electric Vehicle Charging Stations: Parking-Based Assignment Method for Seattle, Washington.” *Transportation Research Record: Journal of the Transportation Research Board*, 2385, 28–36.

City of Seattle. (2017). *Parking space standards. 23.54.030.*

City of Seattle. (n.d.). “Investor Relations.” *Seattle*, <https://www.seattle.gov/investor-relations> (May 22, 2017).

EPA. (n.d. X). “Compare Side-by-Side.” *Fuel Economy*, <http://www.fueleconomy.gov/feg/Find.do?action=sbs&id=35246&id=35765&id=35970&id=35277> (Aug. 24, 2015).

Frade, I., Ribeiro, A., Gonçalves, G., and Antunes, A. (2011). “Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal.” *Transportation Research Record: Journal of the Transportation Research Board*, 2252, 91–98.

Ghamami, M., Zockaie, A., and Nie, Y. (Marco). (2016). “A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel.” *Transportation Research Part C: Emerging Technologies*, 68, 389–402.

He, F., Wu, D., Yin, Y., and Guan, Y. (2013). “Optimal deployment of public charging stations for plug-in hybrid electric vehicles.” *Transportation Research Part B: Methodological*, 47, 87–101.

Hilshey, A. D., Hines, P. D. H., Rezaei, P., and Dowds, J. R. (2013). “Estimating the Impact of Electric Vehicle Smart Charging on Distribution Transformer Aging.” *IEEE Transactions on Smart Grid*, 4(2), 905–913.

Huang, Y., Li, S., and Qian, Z. S. (2015). “Optimal Deployment of Alternative Fueling Stations on Transportation Networks Considering Deviation Paths.” *Networks and Spatial Economics*, 15(1), 183–204.

“KCGIS Data Download.” (2014). *King County GIS Center*, <http://www5.kingcounty.gov/gisdataportal/> (Dec. 2, 2016).

Kilgren, N. (2015). “Spring 2014 Household Survey.” *Puget Sound Regional Council*, <https://www.psrc.org/travel-surveys-spring-2014-household-survey> (Dec. 8, 2016).

Knapen, L., Kochan, B., Bellemans, T., Janssens, D., and Wets, G. (2012). “Activity-Based Modeling to Predict Spatial and Temporal Power Demand of Electric Vehicles in Flanders, Belgium.” *Transportation Research Record: Journal of the Transportation Research Board*, 2287, 146–154.

Mehta, R., Srinivasan, D., Khambadkone, A. M., Yang, J., and Trivedi, A. (2017). “Smart Charging Strategies for Optimal Integration of Plug-in Electric Vehicles within Existing Distribution System Infrastructure.” *IEEE Transactions on Smart Grid*, PP(99), 1–1.

National Academies of Sciences, Engineering, and Medicine. (2013). *Transit Capacity and Quality of Service Manual*. The National Academies Press, Washington, DC.

Nie, Y. (Marco), and Ghamami, M. (2013). “A corridor-centric approach to planning electric vehicle charging infrastructure.” *Transportation Research Part B: Methodological*, 57, 172–190.

Norton, A. (n.d.). “GIS Shapefiles.” *Puget Sound Regional Council*, <http://www.psrc.org/data/gis/shapefiles> (Nov. 17, 2016).

SAE International. (2014). *Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems*. SAE International.

Sathaye, N., and Kelley, S. (2013). “An approach for the optimal planning of electric vehicle infrastructure for highway corridors.” *Transportation Research Part E: Logistics and Transportation Review*, 59, 15–33.

Smith, M., and Castellano, J. (2015). *Costs Associated With Non-Residential Electric Vehicle Supply Equipment*. U.S. Department of Energy.

Sweda, T., and Klabjan, D. (2011). “An agent-based decision support system for electric vehicle charging infrastructure deployment.” *2011 IEEE Vehicle Power and Propulsion Conference (VPPC)*, 1–5.

U.S. Census Bureau. (2017). “Data Profiles for King County, Washington.” *2011-2015 American Community Survey 5-Year Estimates*, <https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2015/> (May 18, 2017).

US DOL. (2017). “Average Energy Prices, Seattle-Tacoma-Bremerton – May 2017.” *Bureau of Labor Statistics*, <https://www.bls.gov/regions/west/news-release/averageenergyprices_seattle.htm> (Jun. 16, 2017).

Worley, O., Klabjan, D., and Sweda, T. M. (2012). “Simultaneous vehicle routing and charging station siting for commercial Electric Vehicles.” *Electric Vehicle Conference (IEVC), 2012 IEEE International*, 1–3.

Xi, X., Sioshansi, R., and Marano, V. (2013). “Simulation–optimization model for location of a public electric vehicle charging infrastructure.” *Transportation Research Part D: Transport and Environment*, 22, 60–69.

Zhu, Z.-H., Gao, Z.-Y., Zheng, J.-F., and Du, H.-M. (2016). “Charging station location problem of plug-in electric vehicles.” *Journal of Transport Geography*, 52, 11–22.

Zillow Inc. (2017). “King County WA Home Prices & Home Values.” *Zillow*, <https://www.zillow.com:443/king-county-wa/home-values/> (May 22, 2017).