Smart Charging Management for Shared Autonomous Electric Vehicle Fleet: A Puget Sound Case Study

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Abstract

Increasing, experts are forecasting the future of transportation to be shared, autonomous and electric. As shared autonomous electric vehicle (SAEV) fleets roll out to the market, the electricity consumed by the fleet will have significant impact on energy demand and will drive variation in energy cost and reliability, especially if the charging is unmanaged. Meanwhile, SAEVs are considered important assets for the grid because their charging behavior can be controlled dynamically, unlike privately-owned electric vehicles (EVs). The addition of Renewable Energy Sources (RES) further complicates the matter. Grid infrastructure, which was designed to carry relatively consistent levels of generation, struggles to cope with the spatial and temporal volatility of RES generation. Existing literature has already explored how EV smart charging (SC) can improve energy system efficiency. These studies focus on privately-owned EVs and individual driver behavior (trip pattern, access to charging infrastructure, charging choice, etc.), but fleet managed SAEVs (that are continually in-service) cannot utilize the same SC strategies prescribed to privately-owned EVs (utilized for only 5% of the day, on average [53]). With the rapid development of autonomous vehicle technologies and shared mobility services, more research is needed to understand the energy implications of fleet SC behaviors and the impact of SC on mobility service quality.

This research proposes a SC framework to identify potential benefits of active SAEV charging management that strategically shifts SAEV electricity demand away from high-priced peak use hours (price-based SC) or towards hours with high renewable generation (generation-based SC). Different SC scenarios are tested using an agent-based SAEV simulation model to 1) study the impact of battery capacity and charging infrastructure type on the SAEV fleet performance and operational costs with SC; 2) study the cost reduction potential of SC considering energy price fluctuation, uncertainty, and seasonal variation; and 3) quantify the opportunity for EV-RES coupling with SAEV SC.

A case study from the Puget Sound region demonstrates the proposed SC algorithm using trip patterns from the regional travel demand model, energy prices, and renewable generation data. Preliminary results show that SC can be beneficial to both SAEV fleet operator (by reducing energy costs) and grid operator (by valley filling). In the first part, we examine the SAEV fleet performance with SC under Time-of-Use (TOU) electricity pricing to adhere to current expectations of peak/off-peak electricity usage times. Case study results indicates energy cost savings up to 34%, compared to unmanaged charging. In the second part, we explore a dynamic SC strategy where real-time energy prices are considered (in anticipation of a future in which a smart grid determines dynamic energy prices) and predict energy cost savings up to 43% compared to unmanaged charging. Lastly, we explore the potential for more sustainable sources of energy to power these fleets and find that SAEV-solar direct coupling can achieve a self-consumption rate ranging from 81% to 99%.

Keywords: shared mobility, autonomous vehicle, electric vehicle, smart grid, smart charging, agent-based modeling, demand side management, vehicle grid interaction, time-of-use pricing, real-time pricing, renewable energy sources

Table 1: List of Acronyms

SAEV	Shared Autonomous Electric Vehicle
TOU	Time-of-Use
RTP	Real-time Pricing
SC	Smart Charging
LMP	Locational Marginal Price
SOC	State of Charge
RES	Renewable Energy Sources
LR	Long Range EV (200+ mile)
SR	Short Range EV (100+ mile)
FC	DC Fast Charging
LV2	Level 2 Charging
PV	Photovoltaic
UMG	Unmanaged Charging
DIS	Distributed Charging

1 Introduction

In the 21th Century, innovations are revolutionizing the transportation sector and the electricity sector. In the transportation sector, three technological trends are vehicle automation, vehicle electrification, and shared mobility. Autonomous vehicle, also known as driverless car or self-driving car, is a vehicle that uses a variety of technologies to sense its environment and navigating without human input. As of April 2018, 52 manufacturers obtained autonomous vehicle testing permits in California [48]. Electric vehicle (EV), also known as battery electric vehicle or plug-in electric vehicle, is a vehicle that is propelled by electric motors that convert the energy stored in the battery. While the first passenger EVs were developed in the early 20th Century, it ceased to exist due to the undeveloped battery technology. Modern EVs (e.g. Nissan Leaf and Tesla Model S) hit the market in the early 21th Century and are growing rapidly. The number of registered battery EV increased from less than 1 thousand to 466 thousand globally between 2006 and 2016 [2]. Shared mobility, on the other hand, is a general concept that is made accessible by modern mobile communication technologies. For example, car-sharing (sequential sharing such as Zipcar and UberX) and ride-sharing (concurrent sharing such as UberPool and Lyftline) are both considered shared mobility services that are increasing popular in recent years. In a survey of more than 4,500 mobility consumers, 17% of the respondents report frequent use (once or more per week) of ride-sourcing services [12]. Therefore, many researchers in the transportation community are forecasting the future of transportation to be shared, autonomous and electric and referring to such technological advancement in urban mobility as the "three revolutions" [55]. When these new mobility technologies become widely available, they will have significant impact on urban transportation, energy use and land use. Fulton et al. [25] suggest that such combination would cut transportation energy use by 70%, cut CO2 emission by 80%, cut the cost of transportation by 40%, and achieve savings approaching $5 trillion per year globally in 2050, compared to the current private-vehicle ownership dominant transportation system. Therefore, we can envision a future where Shared Autonomous Electric Vehicles (SAEVs) provide urban mobility services.

In the electricity sector, improvement are being made to the existing infrastructure so that it is capable of delivering reliable, affordable and clean energy, while managing the increasing complexity and needs of electricity in the 21st Century. Smart Grid is a technology that allows for two-way communication between the energy supply and demand, and the sensing along the transmission lines so that responsive adjustments can be made to improve grid performance. Utilizing smart grid technologies, the energy system can be more efficient in transmission, faster to recover after power disturbances, more cost-effective in operations and system management, and more flexible to accommodate large-scale renewable energy integration [45]. Pratt et al. [49] quantify the benefit of the smart grid via 9 mechanisms and estimate these mechanisms can directly reduce energy use and emissions for the U.S. electricity sector by 12%, with the potential for an additional 6% reduction indirectly. Within these 9 mechanisms, energy use conservation, building energy system diagnostics, integration of EVs, and integration of renewable generation are the most influential mechanisms and account for 14% out of 18% of the total energy reduction potential.

The growth of EV connects the transportation sector and the electricity sector in a significant way. SAEVs may trigger large scale deployment of market EVs that expedite the adoption of smart grid (to regulate EV charging). Smart grids may, in turn, affect the adoption of EVs and EV charging behavior. As the two major engineering systems merge, more research is needed in order to prepare for the system complexity and the opportunities and challenges that may come along. In this thesis, we take a first exploration at the pairing of SAEVs with charging management and investigate its potential impacts on urban mobility and energy systems.

2 Literature review

In anticipation of the adoption of SAEVs, many transportation researchers are actively studying how SAEVs can improve the urban transportation system and affect travel behavior. Meanwhile, energy researchers are discovering solutions for large scale EV deployment and their impact on the energy infrastructure and grid operation. This section summarizes previous research relevant to this work: Shared Autonomous Mobility and EV-Grid interaction. The former body of research primarily focuses on the transportation implications of shared autonomous vehicles and does not consider the EV-Grid interaction and active charging management, while the latter body of research generally examines EV-Grid interaction and energy system optimization with simplistic transportation assumptions under private EV ownership or small scale commercial EV fleets.

2.1 Shared Autonomous Mobility

In recent years, issues surrounding car-sharing, mobility on demand services, and autonomous vehicles have become emerging topics in transportation research. Shared Autonomous Mobility has significant implications for transportation energy consumption. First, shared autonomous vehicles (SAVs) may increase vehicle miles traveled (VMT) due to unoccupied vehicle travel and improved vehicle accessibility for travelers who do not currently possess driving privileges (people who cannot afford vehicle ownership or who are impaired for driving activities). Many researchers have found that SAVs/SAEVs can be effective at replacing privately-owned vehicles. Fagnant et al. [20] [19] presented an agent-based model for SAVs which simulated environmental benefits of such a fleet as compared to conventional vehicle ownership and use in a dense urban core area. Simulation results indicated that each SAV can replace 11 conventional privately-owned vehicles, but generates up to 10% more travel distances due to unoccupied VMT, without ridesharing. When the simulation was extended to a case study of low market penetration (1.3% of trips) in Austin, Texas, each SAV was found to be able to replace 9 conventional vehicles and on average generated 8% more VMT due to unoccupied travel. Brownell and Kornhauser [14] evaluated the necessary autonomous vehicle fleet size for personal rapid transit and smart paratransit. The model predicts a fleet size of 1.6 to 2.8 million six-passenger vehicles to serve state-wide demand in New Jersey. Martinez et al. [42] presented a study to evaluate the impacts of automated shared taxis with ride-sharing in Lisbon, Portugal. The authors developed an agent-based simulation model to simulate 1.2 million trips and scenarios reflecting a situation where private car, taxi and bus trips are replaced by automated taxis. The study indicates a decrease in cost by 55%, highly increased transportation accessibility in the city, and carbon emission reductions of almost 40%.

Secondly, vehicle automation and communication may reduce energy consumption by allowing eco-driving and reducing congestion, but increase energy consumption to power the automation hardware (sensors and processors). Gawron et al. [26] suggest that the vehicle automation hardware could increase vehicle energy use by 3 to 20% due to increases in power consumption, weight, drag, and data transmission. However, when potential operational effects of vehicle automation are included (e.g., eco-driving, platooning, and intersection connectivity), the net result is up to a 9% reduction in energy consumption. Since autonomous vehicles are still at the testing phase, its impacts on transportation energy consumption remain highly uncertain and require further research.

Thirdly, SAVs may allow efficient ride-sharing (ride-splitting, dynamic carpooling or concurrent car-sharing) and increase average vehicle occupancy or compliment mass transit systems, thus reducing the total VMT and reduce total energy consumption from the transportation system. In fact, transportation network companies (TNCs) already offer such products to allow customers to be paired in real-time with others traveling along a similar route. Many researchers have attempted to model SAV operation to serve origin-destination trips with dynamic ride-sharing. Fagnant et al. [21] expand the existing agent- and network-based SAV simulations [20] [19] by enabling dynamic ride-sharing and found that ride-sharing is critical to avoiding new congestion problems and reducing SAV energy consumption. Krishna et al. [28] use cell phone data to model travel activities and found that nearly 60% of all single-person trips occurring each weekday in Orlando appear matchable to other trips taking place with less than 5 minutes of added total travel time, suggesting substantial opportunities for VMT reduction and shared-fleet activities with SAV operation. Farhan et al. [22] use an agent-based model to quantify the impact of dynamic ride-matching on the operational efficiency of a fleet SAEVs and found that the fleet can provide comparable service to travelers with cost savings and overall reduced VMT, compared to ride-hailing service. Levin et al. [38] implement a SAV simulation framework using a cell transmission model simulator on a city network and found that a fleet of SAVs with dynamic ride-sharing is highly effective at reducing congestion by combining traveler trips to increase vehicle occupancy. Zhang et al. [58] also simulated SAVs with dynamic ride-sharing, within a limited 10 mile by 10 mile grid based city at a one minute time step interval. The study assumes a 50% willingness to share rides, and found that only 6.7% of vehicle-trips were shared. However, despite the low sharing rates, dynamic ride-sharing shortens the average delay per trip up to 37% during peak hours, providing faster and more reliable rides than a fleet without ride-sharing. By comparing these studies, we found that the performance of dynamic ride-sharing is highly dependent on matching algorithm, simulation assumptions (such as constraint on passenger wait time, additional travel time, and willingness to share), and study area. More research is needed to understand the differences between ride-sharing and ride-hailing and the market respective market penetrations, so we choose not model dynamic ride-sharing in our study.

Lastly, when the SAVs are electric, both travel and charging activities need to be considered in the fleet operation. Chen et al. [15] proposed an agent-based model that simulates a fleet of Shared Autonomous Electric Vehicles (SAEVs), considering electric vehicle and charging infrastructure decisions. They found that each SAEV can replace 3.7 to 6.8 privately owned vehicles, due to the additional charging and range constraints. In this study, SAEV charging is governed by the remaining range and trip rejection. Bauer et al. [6] developed an agent-based model to predict the battery range and charging infrastructure requirements of a fleet of SAEVs operating on Manhattan Island using taxi-trip data. They found that such operation will reduce Green House Gas emissions by 73% and energy consumption by 58% compared to an automated gasoline vehicles. Loeb et al. [40] proposed a model simulating performance characteristics of SAEV fleets that focuses on charging station and charging time requirements, using realistic vehicle speeds, allowing flexible charging strategies, and requiring all demand for trips under 47 miles to be met. The study concluded that reducing charge times lowers fleet response times, however fleet size increase offers significant improvement in response times in Austin, Texas. Both Bauer and Loeb assumed continuous charging when the SAEV is idling to ensure the fleet always has adequate range remaining, the difference being that Loeb adds a 30 minutes time delay before idling vehicles are assigned to charging. While these studies have explicitly modeled SAEV operations and charging activities, they failed to identify the potential challenges in the EV-grid interaction process, let alone the potential for fleet charging management when the smart grid and dynamic energy pricing for active demand management are promising.

2.2 EV Grid Interaction

In a survey developed by National Renewable Energy Laboratory and Lawrence Berkeley National Laboratory [33], industry respondents were asked to prioritize various topics related to EV-grid interaction. Topics with the highest priority include long term EV effects on distribution grids; business models for EV charging infrastructure; demand side management in smart grids; grid storage and load-shifting; effects of time-of-use rate on charging costs; and interactions between renewable energy generation and EV charging activities. As the EV market grows, many studies have attempted to adopt EV for grid services, including ancillary services, RES generation storage, and energy supply via vehicle-to-grid technology, assuming EV owners have monetary incentives to use their EV for ancillary services. Shaukat et al. [52] reviewed key enabling technology for transportation electrification within a smart grid system, and its impact on economy, reliability and eco-friendly systems. However, such opportunities exist largely because privately-owned EVs are only utilized for only 5% of the day for transportation, on average [53], and have relatively low energy demand. With the growth of shared mobility, the average vehicle utilization and need for electricity will increase significantly. Due to the high utilization of an average SAEV and the lack of data related to how a large EV fleet with high utilization can be used for grid service, in this study, we do not consider the SAEV fleet to act as storage batteries for the grid nor participate in the frequency regulation market. In the following sections, we review past literatures relevant to our study: EV smart charging (SC) and EV-RES coupling.

2.2.1 EV Smart Charging

In the electricity market, the cost of supplying electricity (wholesale) varies throughout the day. In contrast, the prices paid by consumers in the retail market have traditionally been static (constant rate or time-of-use rate). However, future smart grids are expected to incorporate dynamic pricing for effective Demand Side Management, thus improving market efficiency [35]. Under this scenario, EVs are incentivized to adopt SC behaviors, which is a charging strategy that shifts EV charging demand based on EV state-of-charge (SOC), grid loads, and energy price. The goal of SC is to benefit both the EV owner/fleet operator and the system operator by reducing energy costs, increasing renewable generation, and improving grid reliability.

Many previous studies examine EV SC from the energy system operator's perspective. Jian et al. [31] proposed an efficient centralized valley-filling (charging when the system load is relatively low) charging strategy for EVs using capacity margin index and charging priority index, and found that it can alleviate the negative impacts arising from the EV charging loads on power grids. Wu et al. [59] proposed algorithms for the scheduling and dispatch of aggregators of EV fleets, and participate in the day-ahead market based on the forecast electricity price and EV power demands to regulate off-peak charging behavior. Zhang et al. [60] proposed a decentralized valley-filling charging strategy using day-ahead pricing scheme, and achieved a 28% reduction in generation costs. Zhang et al. [61] proposed a decentralized valley-filling strategy and tested the strategy using existing EV characteristics, national household travel survey, California Independent System Operator (CAISO) demand, and estimates for future renewable generation in California in a charging operation simulation. They found good performance for overnight net load valley filling if the costs to be minimized are proportional to the net load.

In another body of research, many researchers have studied the effectiveness of EV SC from the both EV owner's perspective and grid operator's perspective. Schneider et al. [50] model different charging scenarios, including unmanaged scenario, central network operator scenario, and Time-of-Use (TOU) scenario. The study showed that controlled charging can reduce load impact costs (the true costs of unit energy generation) by 45%. Kara et al. [32] investigate the benefits of SC to different stakeholders, and found a 24.8% energy cost reduction for EV owner while decrease the contribution to the system peak load by 37%, using TOU pricing. Moon et al. [43] proposed an EV charging strategy that determines the balanced state where system loads and costs are considered simultaneously, thus allowing the discordance between electricity prices and system load fluctuations to be managed. When the charging is guided by the TOU price signal, it yields an energy saving of 44.1% for EV owners from the uncontrolled scenario, but the system costs are not minimized since the TOU signal cannot reflect the system load state accurately. As a result, the shifted demand reaches another peak load around 24:00 and increases system generation costs. In Canada, Behboodi et al. [7] proposed a charging strategy that enables electric vehicle owners to participate in real-time pricing (RTP) electricity markets to reduce their charging costs. They found that the strategy can benefit both consumers and utilities; consumers can take advantage of inexpensive renewable resources, and utilities can avoid overloading the distribution system. These works inspired us to consider both TOU pricing and RTP schemes in our study. In summary, EV SC with either centralized or decentralized coordination can benefit both EV owner or Grid operator only if the current electricity market mechanism is modified to incentivize SC, especially at high EV penetration.

2.2.2 EV-RES Coupling

Another aspect of SC initiative is to increase grid capacity for distributed energy generation such as Photovoltaic (PV) and Wind. Due to the scale and complexity of the distribution grid, many researchers choose a Microgrid context to study the EV-grid interaction. Kavousi-Fard et al. [34] investigate the viability of the reconfigurable microgrids in facilitating the integration of EVs and RES (PV and wind). They found improvement in the microgrid's viability from both operation costs and reliability perspectives. With Vehicle-to-Grid technology that allows two-way energy transfer, EVs can serve as moving storage units and thus reduce the microgrid operation cost and increase the microgrid capability in supporting the renewable generation. Bhatti et al. [8] presents a real-time energy management scheme for EV charging using PV and energy storage, connected to the microgrid. They found a 58% decrease in charging costs and the scheme does not require energy from conventional generators. Anastasiadis et al. [4] [5] investigates the economic benefits from the coordinated control of distributed energy resources and EVs in a smart microgrid operation; and using EVs for peak shaving purposes with the presence of wind generator. The results show that EVs are capable of absorbing 50% to 60% of the unused wind generation. Mortaz et al. [44] proposed an optimization model for the microgrid energy management considering the energy and storage provided by EVs and energy generated from RES (Wind and PV), and found reductions in total operation costs of the microgrid. Aluisio et al. [3] developed a non-linear optimization procedure and demonstrated its ability to minimize the microgrid operation daily costs with the presence of EVs and both wind and PV generation. Van der Kam et al. [56] proposed a simulation of microgrid operations including solar panels, EVs, and load demand to study different EV charging control algorithms and the impact of SC and V2G on PV self-consumption and peak reduction. The PV self-consumption with SC controls exceed 75%, representing a significant improvement compared to no SC control. Ghofrani et al. [27] proposes a collaborative strategy between the PV participants and EV owners to reduce the generation forecast uncertainties, and found the total PV power utilization increases from 72% to 97%. In a microgrid context, EV-RES coupling can reduce the system operational costs, energy costs, and potentially enhancing microgrid reliability. Furthermore, these small scale studies provide a reference to model and solve large-scale EV and RES implementation problem.

Furthermore, some researchers already considered the long term scenarios of EV-grid interaction, assuming high EV penetration and high RES generation that is not confined in a microgrid. Fattori et al. [23] study the combination of PV energy and EVs under uncontrolled charging regime and under the application of SC and vehicle-to-grid strategies, with a maximum of 50% EV market penetration. They found that intelligent control of EV charging could better accommodate the PV energy generation. Forrest et al. [24] developed a simulation framework to study the potential impact of EV charging, considering high renewable penetration (PV and wind) and high EV penetration (28.88% to 80%). They found that EV SC can effectively reduce the system storage capacity and the required non-renewable energy capacity. Wang et al. [57] develops a novel agent-based coordinated dispatch strategy for EVs and distributed renewable generators (wind), taking into account both grid's and EV users' concerns and priorities. The results show such combination provides support for the grid, reduces the reliance on traditional fossil-fuel generators and benefits EV users. In summary, many existing literatures have examined SC to allow privately-owned EV to harness renewable energy generation and increase grid capacity for RES. Vehicle-to-Grid is often adopted because the assumed transportation demand per EV is relatively low, therefore the EV energy storage serves both the transportation demand and the general electricity demand.

2.3 Contribution

The gap between transportation research on SAEV mobility and energy research on EV-grid interaction is obvious. The majority of existing SAEV research assume a constant energy rate (except Bauer et al. [6] who investigate TOU scenario), and ignore the opportunity for active charging management. On the other hand, existing literatures related to EV-grid interaction focused on privately-owned EVs and individual driver behavior (trip pattern, access to charging infrastructure, charging choice, price sensitivity etc.) and ignore the promising future with shared mobility. Furthermore, few studies have examined a set of energy scenarios, thus fail to consider the impacts of price fluctuation over a long period of time. In summary, there is no study that considers the interaction between SAEVs and the distribution grid and investigate how active charging management (within the context of shared mobility and smart grid) can impact both the mobility fleet operator and utility provider. With the rapid development of autonomous vehicle technologies and shared mobility services, more research is needed to understand the fleet charging behavior for both fleet operators and utility providers.

Our aim is to model EV SC behavior from the fleet operator's perspective. Existing research already point out that a shared vehicle can effectively replace multiple privately-owned vehicles. As the vehicle utilization increases, the SAEV energy intensity will increase and flexibility for charging management will decrease. Even though the fundamental concept of SC, or load scheduling, is the same regardless of context, the implementation of SC strategy and the performance will differ between SAEVs and privately owned EVs. On top of that, the fleet operator needs to consider vehicle and infrastructure investment concurrently with charging strategy in their strategy to minimize operational costs. Considering the difference in travel and charging pattern between a privately-owned EV and a fleet EV providing mobility on demand services, the SC implications will be drastically different. Therefore, we developed an agent-based simulation model to investigate the usefulness of SC strategies that considers both SAEV travel demand and charging demand. Different SC scenarios are tested to 1) study the impact of battery capacity and charging infrastructure type on the SAEV fleet performance and operation costs when the cost of electricity vary by TOU; 2) study the cost reduction potential of SC considering the real-time energy price fluctuation, uncertainty, and seasonal variation; and 3) quantify the unique opportunity for EV-RES coupling with SAEV SC.

3 Methodology

3.1 SAEV Framework Overview

Chen et al. [15] proposed an agent-based model to simulate SAEV operation, which include charging station generation (phase 1), vehicle generation (phase 2), and vehicle operation. However, the charging assumption

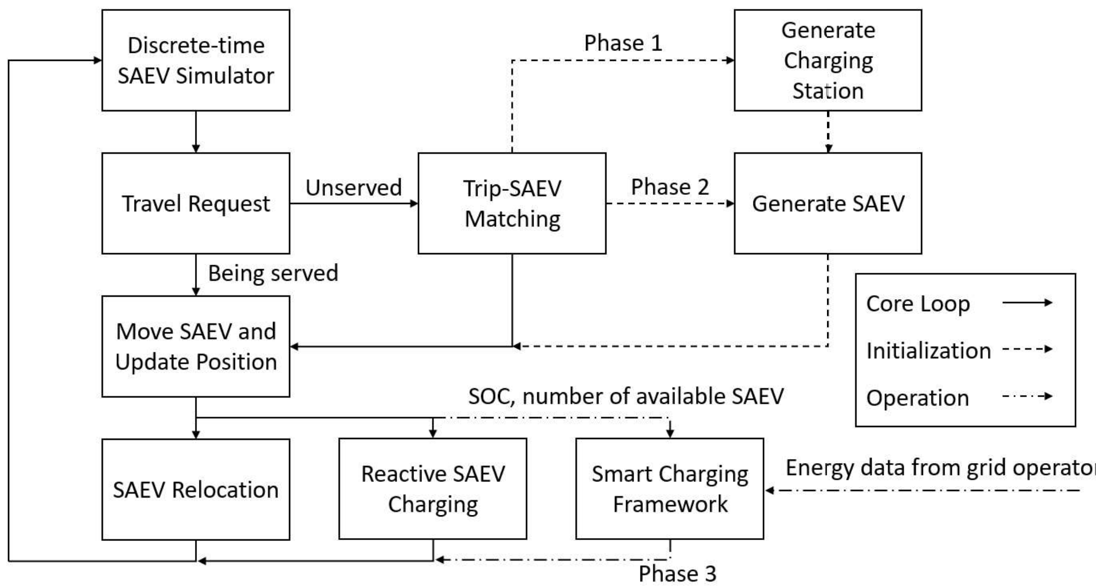


Figure 1: SAEV Simulation Model

in this model is rather simplistic and does not consider the vehicle-grid interaction. We adopted this agent-based model to study the effectiveness of SC strategies for a SAEV fleet by adding phase 3 that allows active charging management and charging behavior optimization (Fig. 1). Three energy schemes are developed: TOU Static Pricing Scheme (with respect to current retail energy market structure), RTP dynamic Scheme (with respect to the future smart grid), and Renewable Energy Scheme (with respect to high renewable energy penetration). The TOU Pricing scenario focuses on overall system performance and the impacts of EV battery and charging infrastructure type. RTP scenario examines the usefulness of a dynamic SC algorithm under fluctuation of energy prices due to seasonal variations of energy supply and demand, load uncertainties, and extreme events in a smart grid system. And finally, RE scenario focuses on the direct coupling of EV and RES and the unique renewable generation temporal pattern.

3.2 Transportation Model

Based on the model structure of Chen et al. [15], the discrete-time agent based model that we adopted to simulate SAEV operation has three phases. In phase 1, the number of charging stations needed for full service of the SAEV fleet is determined. When a SAEV requires recharge but no station is available within the remaining range of this vehicle, a new charging station will be generated at the vehicle's current location. This warm-up phase is repeated until the entire simulated region has charging station coverage. In phase 2, the number of vehicles needed for full service is determined. This is achieved by keeping a list of waiting trips, and if the trip is not matched with a vehicle in 30 minutes, a new vehicle is generated at the trip origin. In phase 3, the fleet operation is modeled with the charging station layout and fleet size from phase 1 and 2. When a trip request appears, the simulator will search for available vehicles within a five-minute travel time radius. The nearest vehicle with sufficient remaining range will be matched with the trip and travel to pick up the passenger. Once the trip is complete and the traveler is dropped off at the destination cell, the vehicle changes from in use to available status. If a SAEV is available and idling at the end of each time step, it will be assigned relocating status in attempt to achieve a spatially balanced vehicle distribution. The model updates at every five-minutes interval and the process repeats for 288 time intervals per day.

3.3 Energy Model

We chose an aggregator-based approach in the SAEV simulator to manage SAEV charging. Such approach assumes that centralized charging coordination can be achieved by the fleet operator. In other words, the fleet operator can dispatch any SAEV to charge as long as the vehicle is available. A charging management module that provides SC decisions to the fleet operator is added in phase 3. Because the SAEV simulator updates at every five-minute interval, the charging decision is updated accordingly (every five minutes) to reflect the ideal number of charging vehicles for the time step. Then, the fleet operator sorts all available vehicles by their individual battery SOC, and assign the SAEVs with the lowest SOCs to charging stations. However, if the number of vehicles that have less than 10 mile range left or reject two consecutive trips exceeds the number of charging vehicles recommended by the SC algorithm, reactive charging will be triggered to allow these vehicles to recharge. Such implementation is intended to prioritize transportation service over charging management because energy costs only contribute about 10% to the overall SAEV operation costs. In the following subsections, two base charging scenarios and three parallel energy scenarios are introduced.

3.3.1 Base Charging Scenarios

Traditionally, retail energy price is constant (flat rate). In this case, the SAEV fleet operator may choose to reduce the operational costs by minimizing SAEV charging frequency and/or the charging infrastructure needed to support the SAEV fleet. Therefore, we dedicate two base cases to reflect these scenarios and later use these scenarios as benchmarks to quantify the benefit of SC for a SAEV fleet. We define the first base scenario as the recharge-when-needed (unmanaged charging) scenario, which is the original charging logic behind the SAEV simulation [15] without active charging management in phase 3. In this case, EV will only recharge if the battery level is below a certain threshold or the EV rejects two consecutive passenger trips, which is similar to the refuel logic with conventional gasoline vehicles. Such charging strategy would minimize the charging frequency and the unoccupied VMT for charging. Then, we define the second base scenario as the minimum charging infrastructure scenario. In this case, the EV charging is managed (in phase 3) so that the number of chargers needed to support the SAEV fleet is minimized. To achieve this, EV charging demand is evenly distributed through out the day to maximize charger utilization. Due to the maximum utilization of charging infrastructure, the cost of charging infrastructure provision is minimized.

3.3.2 Time-of-Use Scenario

In the U.S., most utility companies use Static Pricing to charge customers for their electricity consumption. These static retail rates are fixed for months or years at a time to reflect average embedded supply costs. When the retail electricity rate is constant, implementing charging management cannot cut the fleet operator's utility bill. In the absence of price signals, we find that SAEV charging activities tend to concentrate during early evening hours when the PM travel peak occurs (unmanaged charging). Under such conditions, the utility providers are responsible for adjusting energy supply to level the energy market imbalance and match the additional energy demand from EVs. Ultimately, this will increase grid operation costs and threaten grid reliability.

In many states (including California and Washington), TOU pricing is being offered to incentivize off-peak energy use. The use of TOU rates is an approach to achieve some demand side management and to reduce peak energy usage. Providing attractive electricity rates based on TOU can influence EV charging behavior, especially for a price-sensitive commercial fleet operator. Because the rates and corresponding hours are predetermined, the SAEV fleet can use this rate information as a guideline to optimize its charging strategies aiming to reduce its energy costs. While the pricing itself is suboptimal, implementing SC using predetermined pricing brings us insights about fleet performance under different scenarios and the potential for fleet energy savings. Therefore, we investigate how TOU rates can affect fleet charging behavior and the the overall cost of mobility service in Chapter 5.

3.3.3 Real-time Pricing Scenario

While TOU rates can alleviate peak load in the grid, they are less desirable from a system standpoint since the price is not directly linked with system load and does not reflect the real-time energy costs. As a result, there is a substantial difference in efficiency between even the best TOU design and RTP for the utility provider [29]. Future smart grids are expected to incorporate dynamic pricing as one of the strategies for cost-effectively meeting utility load obligations. In 2007, Illinois was first in the nation to launch statewide voluntary residential hourly pricing programs: Ameren Power Smart Pricing [10] and ComEd Hourly Pricing Program [11]. Under the RTP assumption, SAEV SC can be designed to improve system efficiency by considering both real-time energy price and transportation demand. Under this scheme, the system energy costs can be minimized and can be further translated into both environmental and infrastructure savings in energy generation. Furthermore, RTP adds a new dimension of charging infrastructure sizing to the SC research problem as larger recharging capacity (more chargers) allow for more flexible fleet charging management. Therefore, we investigate the operational implications for the fleet operator under the assumption of RTP in Chapter 6.

3.3.4 Renewable Energy Scenario

Unlike TOU rates and RTP, which reflect energy supply and demand via prices, the renewable energy scheme is designed solely to focus on the unique generation pattern from renewable energy sources (RES) and to determine whether SAEV-RES coupling can be successful. Given the high level of uncertainty in production costs, government incentives for renewable generation, (smart) grid improvement and energy storage costs in the future, predicted energy prices with a high level of renewable penetration is difficult to obtain. Therefore, this portion of the thesis solely focuses on the unique temporal generation patterns of RES and does not consider the actual cost of energy. This is still important because the current energy system struggles with the generation pattern of RES. Curtailment of RES, particularly wind and solar energy, is becoming more widespread as RES penetrations increase [9]. Existing literature already support EVs to harness renewable energy generation and increase grid capacity for RES. In Chapter 7, we study the SC for RES directly and focus on the fleet charging behavior, the impact on mobility, and the usefulness of absorbing RES generation under the context of SAEV operation.

3.4 Simulation Setup

To complete a full simulation with both transportation model and energy model, the simulator will sequentially execute phase 1, phase 2, and phase 3. In this section, the goal and termination criteria will be described. After simulation inputs are specified (case study area, data sources, vehicle range, charging scenario, energy scenario, etc.), phase 1 begins and establishes charging station locations. It continues to run until the number of new stations is less than 1% of the total number of stations in the previous day. At the beginning of phase 2, all SAEVs generated in phase 1 are reset to zero and new SAEVs are generated. Phase 2 will run for a total of 20 days, with the fleet being reset at the end of each simulation day. The average number of SAEVs in the 20-day period is used as the final fleet size for phase 3. At the beginning of phase 3 (day 1), the fleet generally has a positive net flow of electricity (fleet SOC at the end of the day is higher than the SOC at the beginning). However, SOC reaches equilibrium after approximately 3 days. Therefore, the simulation will run continuously for 5 days and the results from the last day will be reported.

Figure 2: Case Study Area

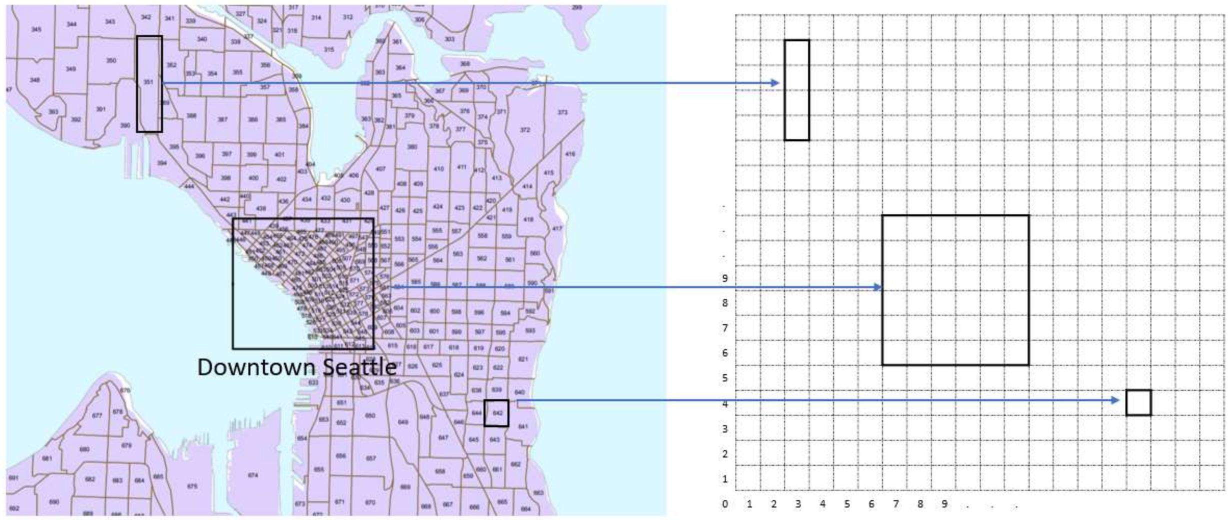
4 Case Study

In order to systematically examine the charging management strategies under three energy schemes, we select the Seattle metropolitan region (King County, Kitsap County, Pierce County, and Snohomish County) as the case study area (Fig. 2). Regional transportation demand and electricity price datasets used in the simulation model are described in this section.

4.1 Travel Demand Data

In the model proposed by Chen et al. [15] simulating SAEV travel in Austin, Texas, trips are created using a Poisson process and are based on population density and the National Household Travel Survey [15]. In order to better reflect local travel demand in the case study area, we update the trip generation module and use the Puget Sound Regional Council (PSRC) Regional Travel Demand Model [17] to generate travel demand. We use a projection method to convert trip locations from a zonal system (Traffic Analysis Zones) to a 2-d Cartesian coordinate grid system (cell identified by [X,Y] integer coordinates, each cell representing a 0.25 mile by 0.25 mile area) so that it is compatible with the SAEV simulator that operates in Manhattan distance (Fig. 3). Trip generation rates are obtained by aggregating trips between each cell pair by departure time at every hour. If the traffic analysis zone is represented by multiple cells, the trip generation rate is prorated accordingly; or if multiple traffic analysis zones fall into one cell, the trip generation rate is the summation from all traffic analysis zones. For example, if cell A, B, and C are the only cells within the boundary of zone #1, the trip generation rates at cell A, B and C are equal to 1/3 of the trip generation rate at zone #1.

The case study area contains 3700 Traffic Analysis Zones. After the coordinate transformation, they are represented by 193,600 cells in a 110 mile by 110 mile area. Approximately 1.2 million passenger trips are modeled on a typical weekday within the study area, representing 10% of the passenger trip demand in the region. These trips are randomly selected from the travel demand data, and reflect what Shaheen et al. [51] estimates as market potential for carsharing in the U.S. Average hourly link travel time by time-of-day from the travel demand model is used to model SAEV moving speed and represents the typical hourly road



a). TAZ in the study area b). TAZ projection into X-Y coordinates

Figure 3: Coordinates projection demonstration

network and congestion conditions. Since the additional travel demand from SAEV operation (empty VMT) is not reflected in the regional travel demand model, we assume the additional vehicle travel demand (less than 1% compared to total system traffic) is negligible in terms of general impact on congestion.

4.2 Regional Energy Profile

U.S. Energy Information administration provides data regarding the electricity generation by energy sources and this data is used as a reference to understand the existing regional energy profile in the study area[1]. The broader energy context is important for understanding the energy assumptions and interpreting the significance of the findings. According to EIA, Washington state has a very clean energy profile. In 2017, hydroelectric generation comprised 72.7% of total electricity generation, followed by natural gas (7.9%), nuclear (7.1%), wind (6.6%) and coal (4.8%). As a result of this energy profile, Washington is able to offer low retail energy prices compared to other states. The state is also able to maintain a low price volatility in the wholesale market because the percentage of volatile generation is low, approximately 14% compared to the national average of 40% (Fig. 4). Volatile generation include natural gas (production cost volatility), solar, and wind (energy output volatility). Due to high latitude and weather patterns, solar generation is not popular in the state of Washington and because of this, utility-scale PV data cannot be found. In Chapter 5, 6 and 7, three energy scenarios are presented using energy data from the Seattle metropolitan region. Detail description of each energy dataset can be found under each corresponding Chapter.

4.3 EV Technology Assumptions

In this study, two types of EVs are modeled and two types of charging infrastructure are modeled. The short range (SR) EV has a battery capacity of 40 kWh (similar to 2017 Nissan Leaf), while the long range (LR) EV has a battery capacity of 90 kWh (similar to 2017 Tesla Model 3). The charging rates vary by

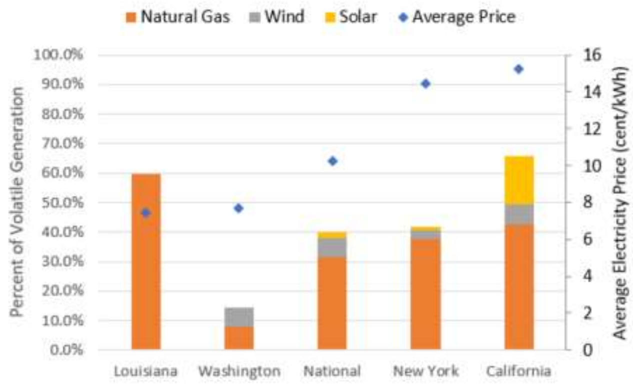


Figure 4: Energy Profile and Price by State [1]

battery size and charger type. For SR EVs, level 2 (LV2) EV chargers can charge the battery at a power of 7 kW, while DC fast charger (FC) can charge the battery at a power of 70 kW. For LR EVs, we assume the LV2 chargers can charge at a power of 20 kW, while FC can charge the battery at a power of 120 kW [54]. Due to the nonlinearity of the charging rate, we assume a 20% range reduction when FC is used, similar to Chen et al. [15] and Loeb et al. [40]. EPA [47] estimates the current average EV efficiency is 126 MPGe (27 kWh/100 mi). To prepare for the additional energy consumption from vehicle automation hardware and software, we increase the total estimated energy consumption by 20%, assuming Medium Connected and Automated Vehicle subsystem power of 240W estimated by Gawron et al. [26]. As a result, the final energy efficiency assumption is 0.33 kWh/mi for both LR and SR EVs. Combining the battery capacity and the energy efficiency assumptions, the final SAEV range at full charge are the followings: 107 mi. (SR-FC); 133 mi. (SR-LV2); 218 mi. (LR-FC); and 273 mi. (LR-LV2).

5 Base Charging Scenarios

Earlier in section 3.3.1, we introduced two base charging scenarios in SAEV operation. In this Chapter, we will present the simulation results based on these scenarios. As a result of the unmanaged charging strategy, the SOC is heterogeneous throughout the day, and the average SOC is bounded between 50%-60%. Charging activities are directly influenced by transportation demand. As the PM peak transportation demand is highest among the day, the SAEV charging activities peaks between (6 pm and 12 am) (Fig. 5). The charging behavior also reflects the difference between two types of chargers. DC fast chargers can charge EVs at a higher rate, thus the short duration of the charging event lead to the the mini spikes in the fleet charging profile while capping the amount of concurrently charging SAEVs under 8%. Meanwhile, LV2 chargers require up to 45% of the SAEV fleet to be charging at the same time. The slow charging rate also lead to longer charging duration and a smoother charging profile curve. Furthermore, we found that having either extended range (LR) or fast charger (FC) can guarantee a 27.3% reduction in SAEV fleet size compared to the SR-LV2 combination, but having both LR and FC at the same time would not result in additional reduction. In this study, this will be referred to as the unmanaged scenario. The significance of this scenario is that the unoccupied VMT to charge is minimized. The simulation results suggest that the average VMT for charging is between 1.7% and 2.1% for SR EVs; and between 0.9% and 1.1% for LR EVs.

Contrary to the the charging behavior in the unmanaged charging scenario, SAEV charging behavior is dictated by the amount of available chargers at any given time step in the distributed charging scenario. Therefore, the real-time transportation demand has little influence over SAEV charging behavior. As a result, the battery SOC fluctuates (because transportation demand vary by time of day) but the percent of charging EV is fairly consistent (Fig. 6). Due to the maximum utilization of charging infrastructure, the cost of charging infrastructure is minimized. The SAEV simulation shows that the distributed charging scenario reduces the amount of chargers by 40% to 60% compared to unmanaged charging. However, even though the SAEV charging is managed, it is not a SC strategy since neither energy price nor energy generation is considered in the charging management process. Without factoring in the energy system dynamics and electricity pricing structure, it is still suboptimal to the utility operators. In this paper, this scenario will be referred to as the distributed charging scenario.

In summary, these two base scenarios represent two different SAEV operational objectives: the former is a strategy to minimize VMT for charging, assuming the limited amount of spatially-discrete charging stations; and the latter is minimize the amount of charging infrastructure for SAEV fleet and demand charge (a type of electricity pricing based on the peak electricity usage during a billing period) from utility bill if such charge is applicable.

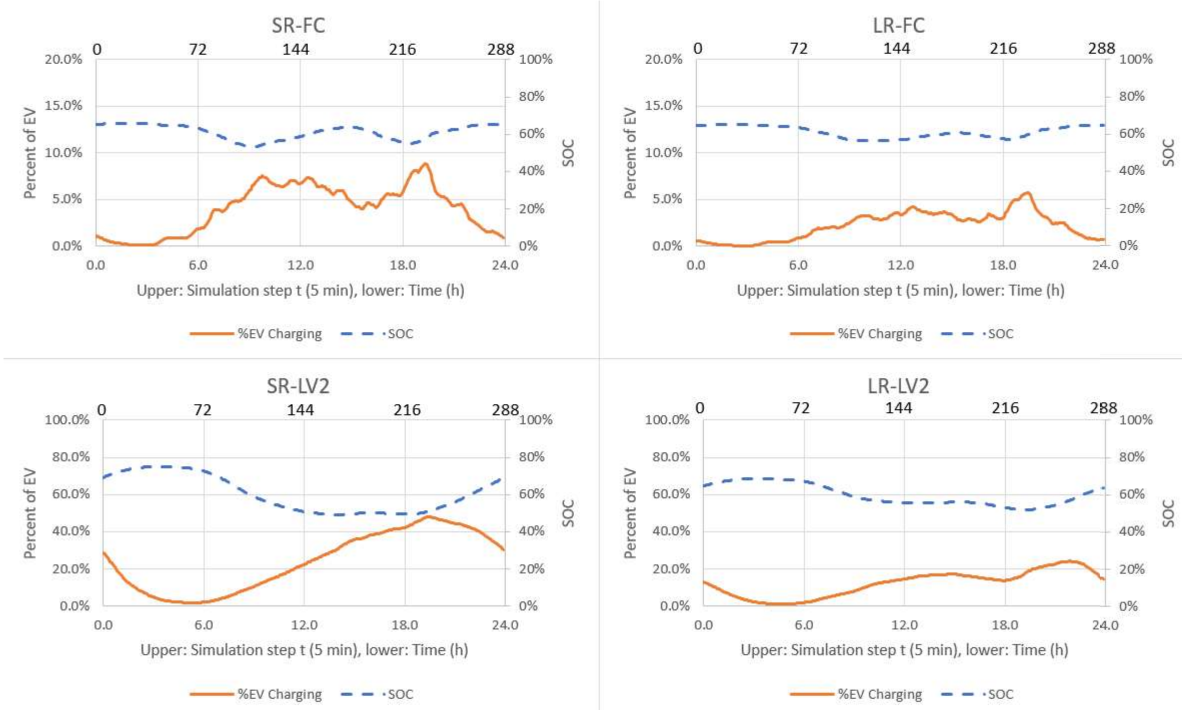


Figure 5: Fleet Charging Behavior and SOC Pattern (Unmanaged)

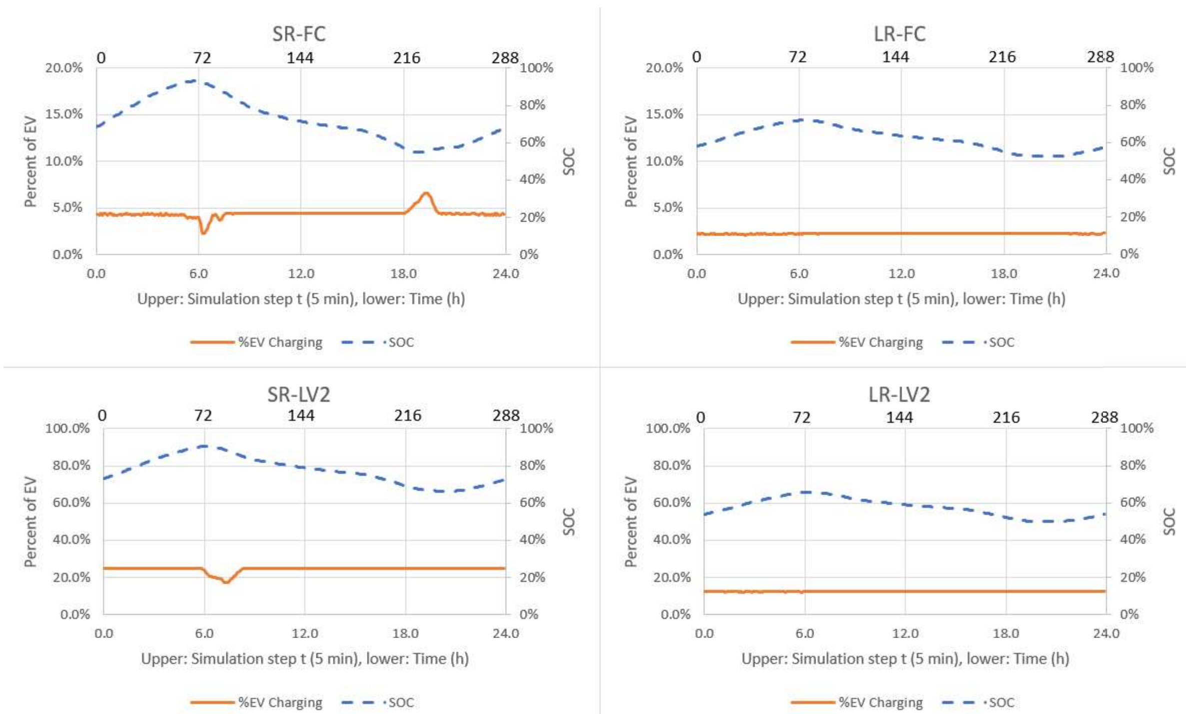


Figure 6: Fleet Charging Behavior and SOC Pattern (Distributed)

6 Time-of-Use Pricing Scheme

With smart meters, utilities are able to introduce new types of pricing programs that better reflect the temporal fluctuations in the cost of electricity production and distribution. Among the many approaches for designing a time-varying energy cost structure, time-of-use (TOU) rate is most commonly used [46]. With the introduction of smart pricing, the SAEV operator will need to consider its charging strategy as the SAEV charging behavior affects the operational costs. In this Chapter, we will present a SC scheme designed for TOU rates and the SAEV simulation results with such charging strategy. For the case study, we use TOU pricing from Seattle City Light, the utility provider in the downtown area, because it serves roughly 40% of the Traffic Analysis Zones in the study area. The 2017 general service TOU rates include two tiers: off-peak (0.0497 $/kWh, from 10 pm to 6 am) and on-peak (0.0746 $/kWh, from 6 am to 10 pm). In addition to the energy charge, a demand charge (a charge based on peak demand usage within a given month) is applied at a rate of $0.27 per kW per month off-peak and $3.05 per kW per month on peak [39].

6.1 Charging vehicle assignment function

To minimize electricity consumption costs under the TOU pricing, charging during on peak hours should be avoided. Additionally, to minimize charging infrastructure provision costs, charging activity should be evenly spread through off-peak hours. The best scenario possible is that all SAEV charging activities are shifted to off-peak hours. Under this logic, the first step is to determine the ideal number of charging vehicles per each time step of the off-peak (Equation 6.1) Secondly, the number of additional SAEVs that should be sent to charge is determined, considering the number of SAEVs already in charging status (Equation 6.2). The total amount of concurrently charging SAEVs is constrained by the charging infrastructure constraint to regulate charging intensity, which is defined as the maximum amount of concurrently charging SAEVs (Equation 6.3). Finally, the fleet operator assigns a set of individual SAEVs that are low in battery to charging stations (Equation 6.4). In Equation 6.4, the set of available SAEVs are sorted by their SOC and the SOC of the $N_n th$ vehicle becomes the recharge threshold (if N_n is greater than the total number of available vehicles then all the available vehicles will be sent to charge). Additionally, a minimum charging constraint of 80% SOC is imposed to avoid consecutive charging activities in a short period of time.

At any simulation time step t:

$$N_t = S_t \times X_{inf} \tag{1}$$

$$N_n = N_t - N_e \tag{2}$$

With the charging infrastructure constraint determined by:

$$X_{inf} = C \times \frac{D_d}{n_c \times r_{op} \times R_{charging}} \tag{3}$$

For all available SAEVs, the vehicles that satisfy the following conditions will be sent to charge:

$$SOC_{ev} \leq SOC_{N_n}, \ s.t. \ SOC_{ev} < 80\% \tag{4}$$

where :

X_{Inf} is the charging infrastructure constraint (maximum number of concurrent charging vehicles);

C is a constant to ensure correct unit conversion;
t is the simulation time step that represents 5 minutes in real time, $t \in [0, 288)$;
D_d is the total daily SAEV fleet energy demand in kWh;
n_c is the total number of simulation time steps per day, for the case study $n_c = 288$;
r_{op} is the proportion of time steps that falls into energy off-peak, for the case study $r_{op} = 33\%$;
$R_{charging}$ is the SAEV recharge rate (mile/time step/veh), refer to SAEV recharge rates in section 4.3;
N_t is the ideal number of charging vehicles at time step t;
S_t is a step signal (0/1) to indicate whether t is within energy off-peak period;
N_n is the number of new SAEVs sent to charge at time step t;
N_e is the number of currently charging SAEVs at time step t;
SOC_{ev} represents the battery level in percentage of each individual SAEV;
SOC_{N_n} represents the charging threshold (the SOC of the N_nth available SAEV sorted in ascending order).

6.2 Fleet Charging Behavior

At each simulation time step t, N_n is suggested to the SAEV fleet operator. With intelligent charging recommendations, the fleet operator can strategically control the number of charging vehicles. Therefore, the SC algorithm subsequently influences the fleet average state-of-charge (SOC) over time. Fig. 7 shows the fleet charging behavior under TOU price SC scheme for four different range and charging infrastructure combinations. SR EVs reach full charge (above 90% SOC) in all scenarios before 3 am and are unable to further take advantage of the off-peak electricity rate. When the transportation demand increases in peak AM travel hours, SR EVs exhaust energy (under 50% SOC) shortly thereafter and requires intermediate battery recharge at midday. This shows us that the SR EVs do not have the battery capacity to avoid charging on peak under a typical two-tire TOU price scheme, especially when the EV utilization is not uniformly distributed (some vehicles incur more daily vehicle miles traveled than others). As a result, SR EVs exhibit a suboptimal charging behavior under TOU electricity pricing. LR EVs, however, show the ability to adopt a more desirable charging behavior that complies with the off-peak charging schedule. By taking a closer look at the charging activities, we found that in the LR-FC scenario, charging activities resume around 6 pm, suggesting that some EVs (about 3%) are running out of battery and need to recharge on-peak; while in the LR-LV2 scenario, on peak charging activities are negligible. When we compare these results with the charging behavior in the unmanaged scenario (section 3.3.1, Fig. 5), we found that SC management can shift 77% (LR-FC) and 92% (LR-LV2) of on-peak charging demand to off-peak periods predefined by the utility provider. Assuming the same off-peak duration of eight hours, the estimated battery capacity requirement is 290 miles to completely avoid on-peak charging activities.

By comparing the different type of chargers (LV2 and FC), we found that LV2 chargers require the fleet operator to charge up to 78% of all SAEVs in a single time step, compared to the maximum of 13% for DC FC. These results suggest that FC allows better charger sharing among the SAEVs and requires fewer chargers to be installed; while LV2 chargers require 6 times more chargers to be installed to support the SAEV fleet. For the SR-LV2 combination, more than 40% of the SAEVs are charging when the transportation demand is still high during the PM peak. This offer some explanation on why the SR-LV2 combination requires a fleet size that is 40% larger compared to other combinations (Table 2).

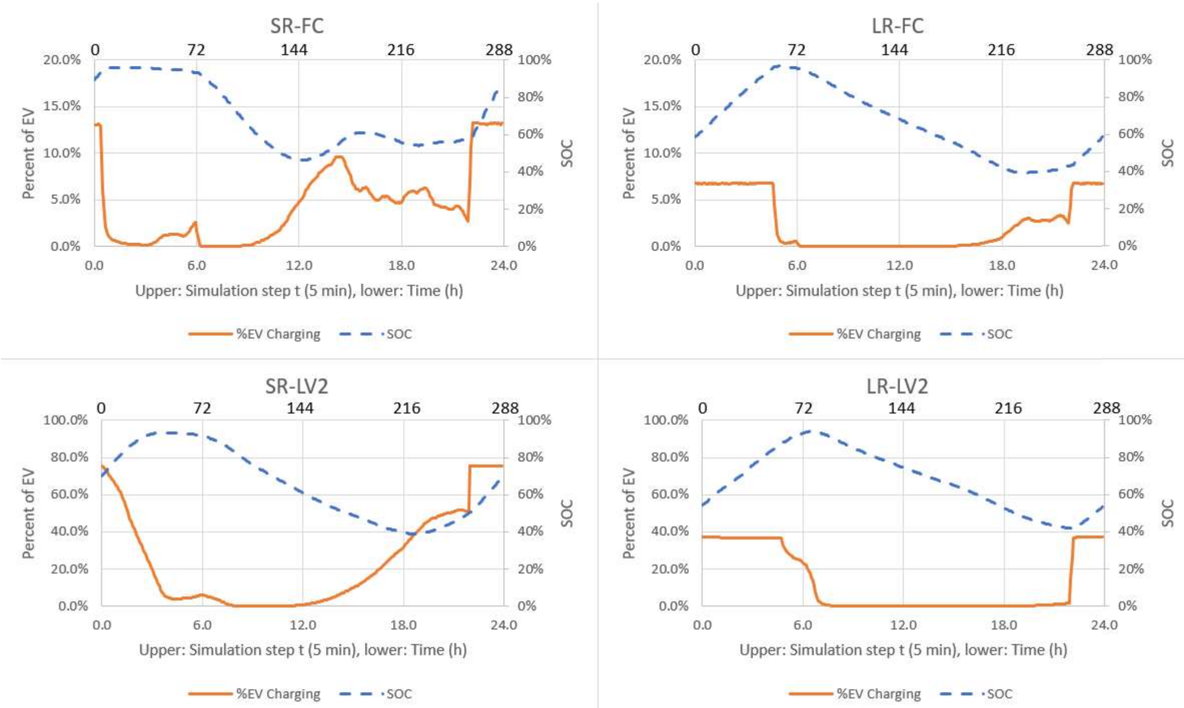


Figure 7: Fleet Charging Behavior and SOC Pattern (TOU)

6.3 SAEV Simulation Results

In terms of serving trips, the DC fast charger with SC slightly increases passenger wait time, while the LV2 charger with charging management can reduce passenger wait time by up to 21.7%, compared to unmanaged charging. These results suggest that SC can shift charging demand and can allow more SAEVs to stay in service during hours with high transportation demand. Another benefit of SC is achieving electricity cost reductions ranging from 10% to 34.2%. Within the four vehicle range-charging infrastructure combinations, SR EVs can only achieve a maximum 11.5% reduction in average electricity cost by charging management, which reflects their inflexibility in charging schedule (mandatory on-peak charging is unavoidable). By contrast, LR EVs can achieve a minimum 34.2% reduction in average electricity cost by charging management. With the exception of SR-LV2, all other managed charging scenarios are able to reduce the number of unserved trips compared to unmanaged charging (Table 2).

The negative effects from active charging management include additional unoccupied vehicle miles traveled to charge, due to the increased number of charging events. As a result, the percentage of unoccupied miles increases compared to the unmanaged scenario (Table 2). One limitation of our study is that we cannot quantify the negative impacts from the additional miles traveled such as causing roadway congestion and battery degradation. On average, the average unoccupied vehicle miles traveled to charge increases from 1.4% to 1.9%.

Table 2: Simulation Results and Cost Breakdown, TOU

	SR-FC umg	SR-FC dis	SR-FC offpeak	LR-FC umg	LR-FC dis	LR-FC offpeak	SR-LV2 umg	SR-LV2 dis	SR-LV2 offpeak	LR-LV2 umg	LR-LV2 dis	LR-LV2 offpeak
Total trips	1288099											
% unserved trips	0.01%											
Fleet size	50,295	50,295	50,295	49,644	49,644	49,644	69,217	69,217	69,217	49,639	49,639	49,639
Number of chargers	4,446	2,224	6,677	2,852	1,134	3,402	33,211	19,891	56,587	11,980	6,141	18,574
Daily VMT per veh (mi.)	168.5	171.9	171.3	167.8	168.2	170.2	121.3	123.8	122.2	168.3	168.4	169.9
Avg % unoccupied VMT	9.8%	11.1%	11.0%	8.7%	8.9%	9.9%	9.1%	10.1%	9.6%	9.3%	9.1%	9.7%
Avg % VMT for charging	2.1%	3.0%	2.6%	1.1%	1.2%	1.4%	1.7%	3.3%	2.1%	0.9%	0.9%	1.4%
Average wait time (min)	2.05	2.12	2.20	1.87	1.88	2.00	1.88	1.55	1.56	2.33	2.24	1.93
Per-veh-mile electricity cost, $	0.029	0.025	0.026	0.029	0.024	0.019	0.027	0.024	0.023	0.027	0.024	0.018
Per Mile Costs based on Average Cost Assumption ($)												
Vehicle	0.130	0.130	0.130	0.195	0.195	0.195	0.130	0.130	0.130	0.195	0.195	0.195
Autonomous system	0.033	0.032	0.032	0.033	0.033	0.032	0.045	0.044	0.045	0.033	0.033	0.032
Maintenance	0.024	0.024	0.024	0.024	0.024	0.024	0.034	0.033	0.034	0.024	0.024	0.024
Charger	0.002	0.001	0.004	0.002	0.001	0.002	0.003	0.002	0.005	0.001	0.001	0.002
Total per-veh-mile cost	0.223	0.214	0.220	0.288	0.279	0.273	0.243	0.235	0.240	0.284	0.278	0.272
Total per-occupied-mile cost	0.247	0.241	0.247	0.315	0.306	0.303	0.267	0.263	0.266	0.313	0.306	0.301
Per Mile Costs based on Low Cost Assumption ($)												
Vehicle	0.108	0.108	0.108	0.130	0.130	0.130	0.108	0.108	0.108	0.130	0.130	0.130
Autonomous system	0.016	0.016	0.016	0.016	0.016	0.016	0.023	0.022	0.022	0.016	0.016	0.016
Maintenance	0.013	0.013	0.013	0.013	0.013	0.013	0.018	0.018	0.018	0.013	0.013	0.013
Charger	0.001	0.001	0.002	0.001	0.000	0.001	0.001	0.001	0.002	0.000	0.000	0.001
Total per-veh-mile cost	0.172	0.165	0.169	0.194	0.186	0.180	0.180	0.175	0.177	0.190	0.185	0.178
Total per-occupied-mile cost	0.191	0.185	0.190	0.213	0.204	0.200	0.198	0.196	0.195	0.210	0.204	0.197
Per Mile Costs based on High Cost Assumption ($)												
Vehicle	0.130	0.130	0.130	0.195	0.195	0.195	0.130	0.130	0.130	0.195	0.195	0.195
Autonomous system	0.081	0.080	0.080	0.082	0.081	0.080	0.113	0.110	0.112	0.081	0.081	0.081
Maintenance	0.049	0.048	0.048	0.049	0.049	0.048	0.068	0.066	0.067	0.049	0.049	0.048
Charger	0.004	0.002	0.005	0.002	0.001	0.003	0.005	0.003	0.008	0.002	0.001	0.003
Total per-veh-mile cost	0.297	0.287	0.293	0.362	0.352	0.346	0.346	0.334	0.344	0.358	0.352	0.346
Total per-occupied-mile cost	0.329	0.322	0.329	0.397	0.387	0.384	0.381	0.375	0.380	0.394	0.387	0.383

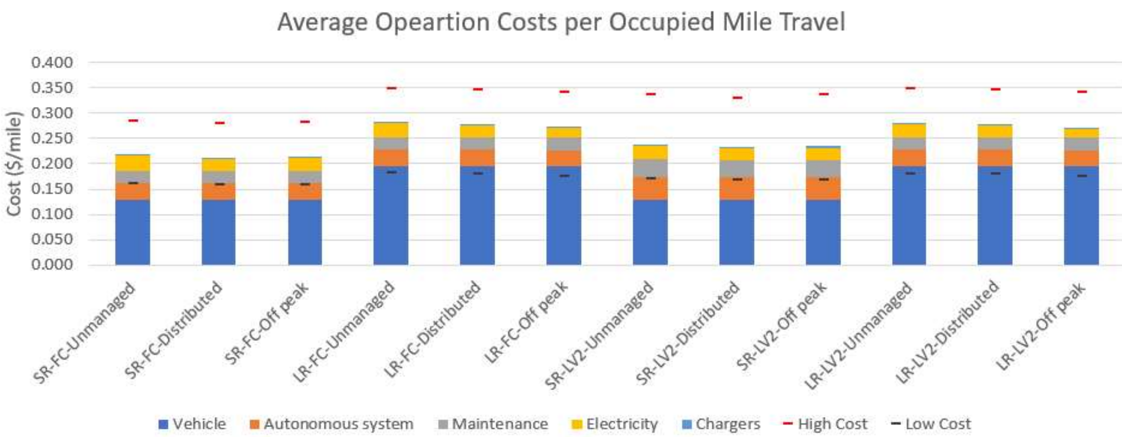


Figure 8: Per mile SAEV operation cost breakdown assuming TOU rates

6.4 Economic Analysis

Simulation results offer some insight into how charging management with combinations of battery capacity and charging infrastructure impact fleet operations and energy costs, but a complete financial analysis is necessary to truly grasp the trade-off between fleet choice/charger choice and total operational costs.

Table 3 summarizes capital and recurring costs associated with SAEV operation in three scenarios: high-, medium-, and low-cost. In recent years, the costs of EV, battery, and chargers has decreased as the volume of EVs manufactured increased exponentially. Furthermore, experts expect the battery costs to further decrease. Therefore we base the medium- and high-cost scenarios for EVs based on the current market values; and the low-cost based on predicted battery cost drop to 100 $/kWh [30]. Smith and Castellano [54] summarize the costs of EV supply equipment in the U.S. We developed the high-, medium- and low-cost scenarios based on the highest-, average-, and lowest-cost of EV charger in non-residential settings.

However, the cost of vehicle automation is still highly uncertain at Level 5 (fully autonomous). As a result, vehicle maintenance costs (insurance, inspection, repair etc) are also uncertain for a SAEV fleet. We reviewed various documents and information from the autonomous vehicle manufacturers to come up with the estimated cost of on board autonomous system and the annual maintenance costs for a SAEV. Finally, we assume energy prices will remain comparable to the current rates when SAEVs enter the market, in this case with Seattle City Light TOU rates.

In the SC with TOU pricing scheme, we found that vehicle-related costs (vehicle, battery, autonomous system, maintenance) is still the primary cost component (87% to 93%) compared to the energy-related costs (7% to 13%). Therefore it is unlikely that SC will directly influence SAEV operator on vehicle choice (LR EV vs SR EV) (Fig. 8). However, in the operation context, within each vehicle/charger combination, the unmanaged charging scenario (Fig. 5) yield a higher costs per occupied mile traveled compared to distributed charging (Fig. 6) or SC (Fig. 7).

Table 3: Vehicle & charger cost assumptions

Item	High	Medium	Low	Note
Short Range EV	30000	30000	25000	$/vehicle, similar to Nissan Leaf
Long Range EV	45000	45000	30000	$/vehicle, similar to Tesla M3
Autonomous System	25000	10000	5000	$/vehicle, sensors and controller
Level 2 Charger	5000	3000	1000	$/charger, non-residential [54]
DC Fast Charger	25000	16750	8500	$/charger, non-residential [54]
Vehicle Maintenance	3000	1500	800	$/vehicle/year, include registration, inspection etc.

For scenarios featuring SR EVs, distributed charging yields a lower per occupied VMT cost compared to unmanaged charging and off-peak SC; for LR EVs, off-peak SC outperforms two baseline scenarios. As expected, the LR EVs favors SC because their battery capacity is large enough which allows them to charge primarily during off-peak and take advantage of the low energy price. With LR EVs, off-peak SC can reduce the average per-occupied-mile operational costs by up to 3.1% (high-cost), 3.9% (medium-cost), and 6.2% (low-cost), compared to unmanaged charging. Meanwhile, SR EVs cannot avoid on-peak charging due to limited battery capacity. In which case, the charging infrastructure cannot be fully utilized during the off-peak pricing period and the cost of additional chargers made SC strategy suboptimal compared to distributed charging. With SR EVs, distributed charging can reduce the average per-occupied-mile operational costs by up to 2.2%, (high-cost), 2.5% (medium-cost), and 2.9% (low-cost), compared to unmanaged charging. Model results also imply that FC outperforms its counterpart LV2 chargers. Even though FC are more expensive to purchase and install, it allows faster turnaround between charging EVs, which allowed the overall fleet to be more efficient and cost-effective per mile.

Overall, SR-FC combination with distributed charging strategy is able to offer the lowest operating cost ($0.241/occupied mile) compared to other scenarios, assuming medium-cost. The high cost and low cost assumptions yield $0.322/occupied mile and $0.185/occupied mile, respectively. However, the cost difference between the four combinations are almost unnoticeable in the low cost scenario, which representing the future where the cost of battery at 100 $/kWh. The cost estimates presented only reflect operator-side costs, and do not account for changes in user costs (e.g. reduced passenger wait time and unserved trips) (Table 2).

6.5 Summary

Under the TOU pricing structure, SC strategies have demonstrated the ability to reduce energy costs for the SAEV fleet operator while maintaining or improving the level of mobility service, despite the fact that the overall unoccupied mile travel to charge increases with the charging management. These miles occur mostly during off-peak hours and have little to no impact on the fleet operation and performance. Due to the high utilization rate of an average SAEV, the charging schedule is less flexible than that of a private EV. Therefore, EV battery capacity is found essential in allowing flexible charging schedule in the SAEV SC implementation. For LR EVs, off-peak SC can provide energy cost savings to offset the additional costs of charging infrastructure. However, only LR-LV2 combination has shown the ability to be fully compliant with the off-peak charging schedule (when FC is used, the EV range is reduced by 20% to account for the charging nonlinearity). Meanwhile, SR EVs have shown little ability to store energy during off-peak, thus exhausting energy rapidly and requires frequent recharge on-peak. In which case, the additional chargers offer low return on investment and having additional costs will drive the overall energy-related costs for the fleet operation. Based on the projected EV costs and energy costs in the case study area, SR SAEVs have shown the ability to offer the same level of mobility service at a lower cost, even though SC is less effective. Therefore, we recommend distributed charging as the best charging strategy for SR EVs. SC strategies have consistently demonstrated the ability to reduce overall per-occupied mile costs and are recommended for long range SAEVs.

Financial analysis reveals the total per occupied mile cost difference between based scenario and SC are slim assuming TOU rates. There are two contributing factors. The first one being that the TOU rates are about one half of the national average energy price, thus energy savings cannot generate a significant impact on overall costs. The second reason is that the additional miles to charge raises the overall costs (especially for SR EVs). If the distance to charging infrastructure is taking into consideration in the SC optimization process (to prioritize vehicles that are closer to charging stations to reduce miles to charge), the unoccupied miles to charge may be reduced. This is a research gap to be filled in the future. In the SAEV simulation, we assume parking for idle vehicle is available at each simulation zone (0.25 mile by 0.25 mile cell). This assumption might not hold if parking policy is violated or if, for security reasons, the fleet operator prohibits overnight street parking. In either case, SAEV would likely be relocated to a parking hub where the charging infrastructure is located for an extended idling period. This will add unoccupied mile to park and increase the overall VMT. Since the unoccupied mile to charge overlaps with unoccupied mile to park, it will likely favor charging management in total per-occupied mile cost because the per occupied VMT cost in the unmanaged charging scenario will increase.

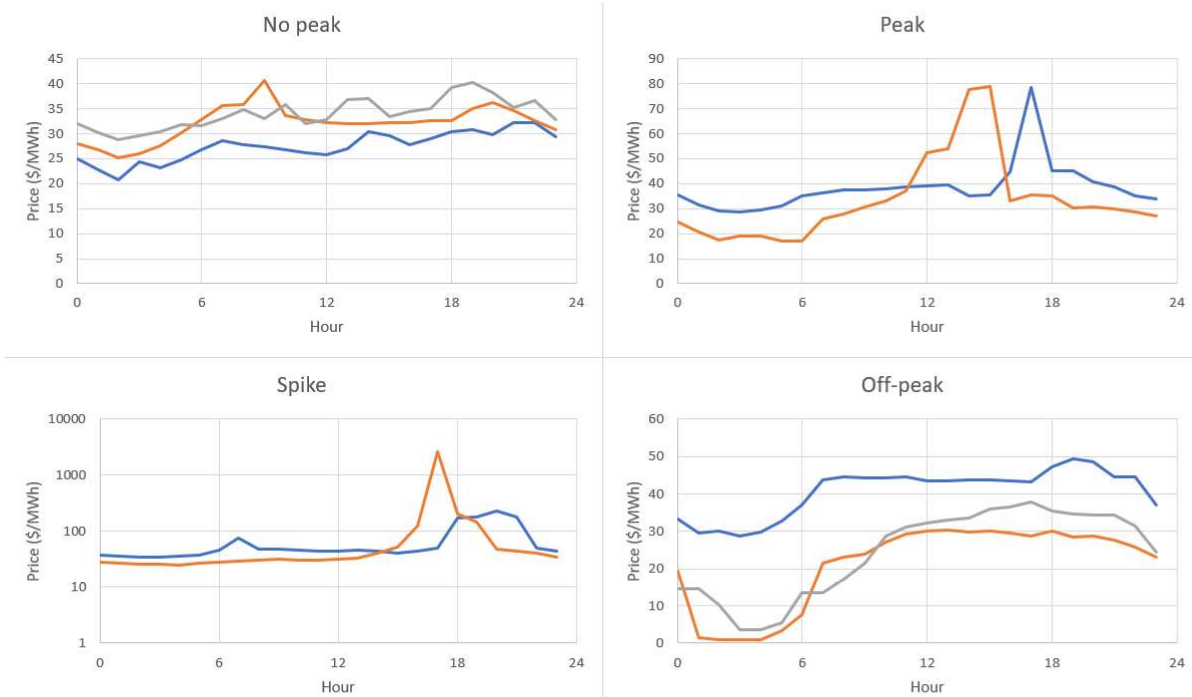


Figure 9: Four Categories of RTP

7 Real-time Pricing Scheme

Real Time Pricing (RTP) is a time-varying rate that generally apply to electricity usage on an hourly basis [46]. In this Chapter, we will present a SC framework assuming RTP environment for SAEV operation in a future smart grid, and demonstrate its effectiveness in reducing electricity cost for the fleet operator. Since RTP program is not currently offered in the case study area, we translate the regional Locational Marginal Price (LMP) into hourly energy price to model a RTP environment. In our case study, the LMP is published by ColumbiaGrid in the Planning and Expansion Functional Agreement [16] and it is updated hourly. Since it is unrealistic to model all possible price scenarios, we uniformly sampled 10 days of LMP data (the Wednesday of every fifth week) from 2017 and simulated SAEV operations based on the prices from these 10 days (Fig. 9). To account for sampling errors and to calibrate the SAEV simulation results, we sorted all LMP into 4 distinctive price categories: spike (daily maximum price exceeds 100 $/MWh, compared to an average price of 40 $/MWh); peak (the daily maximum price deviates more from the daily average compared to the daily minimum price); off-peak (the daily minimum deviates more from the daily average compared to the daily maximum price); and no peak (price variance less than 15 $(\$/MWh)^2$) and they account for 16%, 31%, 22%, and 31% of all price data, respectively. Finally, we compare the sampled LMP data against the categorized LMP dataset to determine the sampling error. Note that the absolute costs from the TOU Pricing Scheme and the RTP Scheme are not directly comparable because the TOU Price is a retail rate while the LMP is a wholesale rate.

7.1 Hour-ahead energy price prediction model

Previous researchers have demonstrated the possibility of EV charging scheduling optimization considering real-time grid loads. However, only Behboodi et al. [7] explored the opportunity for EV owners to participate in the real-time pricing electricity markets. In anticipation of real-time smart pricing in future smart grid systems, it is important to consider the underlying uncertainties with the real-time energy market. In order to reflect price uncertainty and price prediction error, we first create a price prediction model and use it to make energy price prediction whose outputs are used to make SC decisions.

In recent years, machine learning techniques have been adopted by the forecasting community for time series forecasting. Bontempi et al. [13] present a overview of machine learning techniques in time series forecasting and focus on the formalization of one-step forecasting, using local learning techniques, and the transition from one-step forecasting to multi-step forecasting. This paper provides valuable references on the problem formulation in the time series forecasting using supervised learning. In order to demonstrate the proposed dynamic SC algorithm with future price uncertainties, we first developed an Hour-Ahead price prediction model that mimics the models used by Regional Transmission Organizations (e.g. ISO New England [18]). The advantage of such an approach is that the machine learning model does not sensitive and proprietary (such as individual customer energy usage, status of power plant, etc.) but can still capture the overall energy price pattern. Our model is created using a boosted decision tree model that trains on one year of LMP data. Multi-step prediction is made up to 24 hours into the future through a recursive prediction process. A percentile ranking method is used to evaluate the attractiveness of a price point within a 24-hour period, based on both predicted value in the remainder of the 24 hours and actual value in the hours that have already occurred. The SAEV simulator uses the predicted price index and fleet status to make SC decisions. It is worth noting that some regional transmission organization publish predicted energy prices, which can be used in this framework to replace the decision tree-based prediction model.

7.2 Charging vehicle assignment function

In a RTP environment, the optimal charging strategy is to shift EV charging activities to hours where energy prices are low, subject to the amount of chargers available. However, unlike TOU pricing where the price and corresponding off-peak hours are predetermined by the grid operator, neither the fleet operator nor the grid operator can accurately predict the energy prices in the future. Therefore, it is impossible to optimize the charging strategy without perfect price information in daily operations. While the EV charging assignment function (binary step function) we introduced in the previous chapter is also applicable in the RTP scenario, we found that it is prone to prediction error. We modified the EV charging assignment function by using a Sigmoid function to replace the binary step function (section 6.2) and adding the fleet SOC as a decision variable in an attempt to reduce the impact from price prediction error. The output of the Sigmoid function is bounded between 0 and 1 (similar to the step function) while the function is differentiable and its derivative can be controlled by parameter adjustments. The results suggest that the sigmoid assignment function can further reduce the SAEV energy costs by up to 8%. Under this logic, the first step is to determine the ideal number of charging vehicles (Equation 7.5) Secondly, the amount of new vehicles that should be sent to charge is determined (Equation 7.6). The total amount of concurrently charging SAEVs in constrained by the charging infrastructure constraint to regulate charging intensity (Equation 7.7). Finally, the fleet operator assigns a set of individual EVs that are low in battery to charging stations (Equation 7.8). In Equation 7.8, the set of available SAEVs are sorted by their SOC and the SOC of the $N_n th$ vehicle becomes the recharge threshold (if N_n is greater than the total number of available vehicles then all the available vehicles will be sent to charge). Additionally, a minimum charging constraint of 80% SOC is imposed to avoid consecutive charging activities in a short period of time.

$$N_t = (1 - \frac{1}{1 + e^{c_1 \times Rank_t + c_2 \times SOC_{avg,t} + c_3 \times (x-2) + c_4}}) \times X_{Inf} \tag{5}$$

$$N_n = N_t - N_e \tag{6}$$

With the charging infrastructure constraint determined by:

$$X_{inf} = C \times \frac{x \times D_d}{n_c \times R_{charging}} \tag{7}$$

For all available SAEVs, the vehicles that satisfy the following conditions will be sent to charge:

$$SOC_{ev} \leq SOC_{N_n}, \ s.t. \ SOC_{ev} < 80\% \tag{8}$$

where:

X_{Inf} is the charging infrastructure constraint (maximum number of concurrent charging vehicles);
x is the charging multiplier relative to the minimum charger requirement (section 3.3.1); for the case study, $x \in [2, 5]$;
t is the simulation time step that represents 5 minutes in real time, $t \in [0, 288)$;
N_t is the ideal number of charging vehicle at time step t;
C is a constant to ensure correct unit conversion;
$Rank_t$ is the percentile rank of electricity price at time step t within a given day, $Rank_t \in [0, 1]$, where 0 represents the highest price and 1 represents the lowest price;
$SOC_{avg,t}$ is the average SOC across all SAEVs, $SOC_{avg,t} \in [0, 100\%]$;
c_1, c_2, c_3 and c_4 are parameters to adjust the sensitivity of the charging index with respect to $Rank_t$, $SOC_{avg,t}$, and X_{Inf}, for the case study, these parameters are set to 20, -2, -2, and -9 respectively based on empirical results;
D_d is the total daily SAEV fleet energy demand in kWh;
n_c is the total number of simulation time steps per day, for the case study $n_c = 288$;
$R_{charging}$ is the SAEV recharge rate (mile/time step/veh), recharge rates can be found in section 4.3;
N_n is the number of new SAEVs sent to charge at time step t;
N_e is the number of currently charging SAEVs at time step t;
SOC_{ev} represents the battery level in percentage of each individual SAEV;
SOC_{N_n} represents the charging threshold (the SOC of the N_nth available SAEV sorted in ascending order).

The portion inside the parentheses in (6) can also be referred to as the charging index function. Fig. 10 shows a example of the charging index as a two dimensional Sigmoid function of the price index (lateral axis) and the fleet battery SOC (longitudinal axis), and x=5.

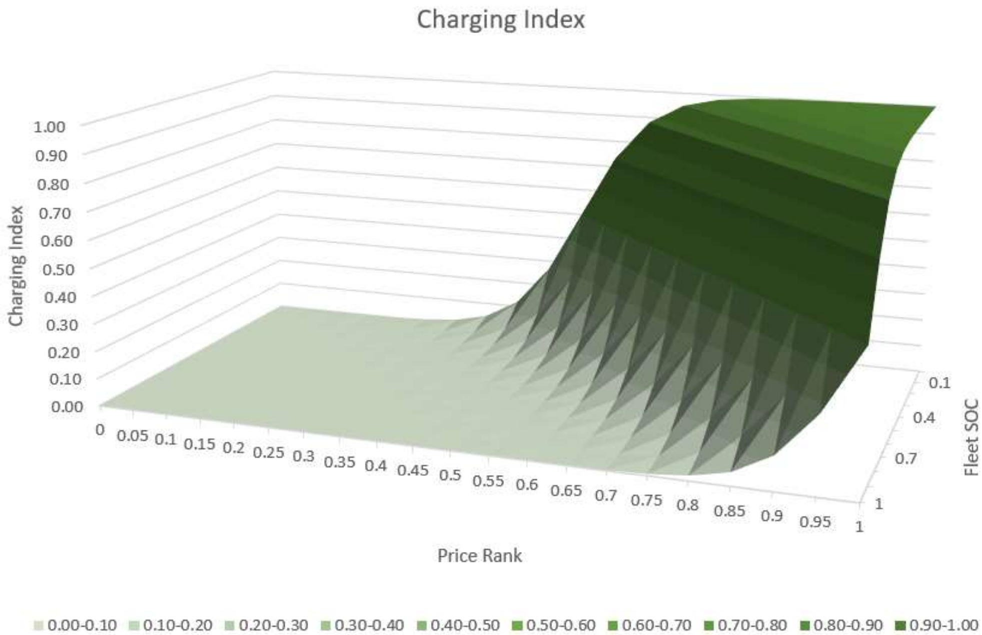


Figure 10: A visual demonstration of the charging index as a function of price and SOC

7.3 Fleet Charging Behavior

Based on the findings from the TOU scenario, we only examined RTP scenario with FC, because LV2 chargers are lacking the responsiveness (a full charge requires 4+ hours) for dynamic SC and are not cost effective. Fig. 11 shows two example of SAEV fleet charging behavior under different charger constraints, with a 24-hour RTP profile that is categorized as significant price peak. Due to the real-time energy prices fluctuations, it is difficult to generalize the SAEV charging behavior. Broadly speaking, SAEV battery capacity negatively correlates with on-peak charging intensity (amount of concurrently charging SAEVs) due to the discordance between low-cost charging opportunity (overnight) and peak transportation demand (business hours). When the optimal charging schedule is concentrated at night, the battery will need to store more energy to be able to serve travel demand. However, the results suggest that when the battery capacity is limited, the SAEV fleet struggles to store sufficient energy and is likely to resort to unmanaged charging behavior in order to maintain its ability to serve transportation demand. This eventually leads to involuntary on-peak charging to meet the transportation demand, despite the high electricity prices on-peak.

7.4 SAEV Simulation Results

The SC strategy based on real-time pricing provides insight on the performance of SAEVs under various price categories. With LR-FC, if the price pattern is categorized as significant energy peak or significant energy off-peak, the energy cost reduces as the charger constraint is relaxed. However, if the grid experiences an energy spike, the benefit of SC is not proportional to the amount of chargers in the system. Such results are due to the different characteristics between valley-filling (concentrating charging overnight) and peak-shaving (avoiding energy price peaks or spikes). In order to achieve valley-filling, which is the general strategy of most EV SC implementation, the fleet-average SOC oscillate with maximum amplitude. The problem with

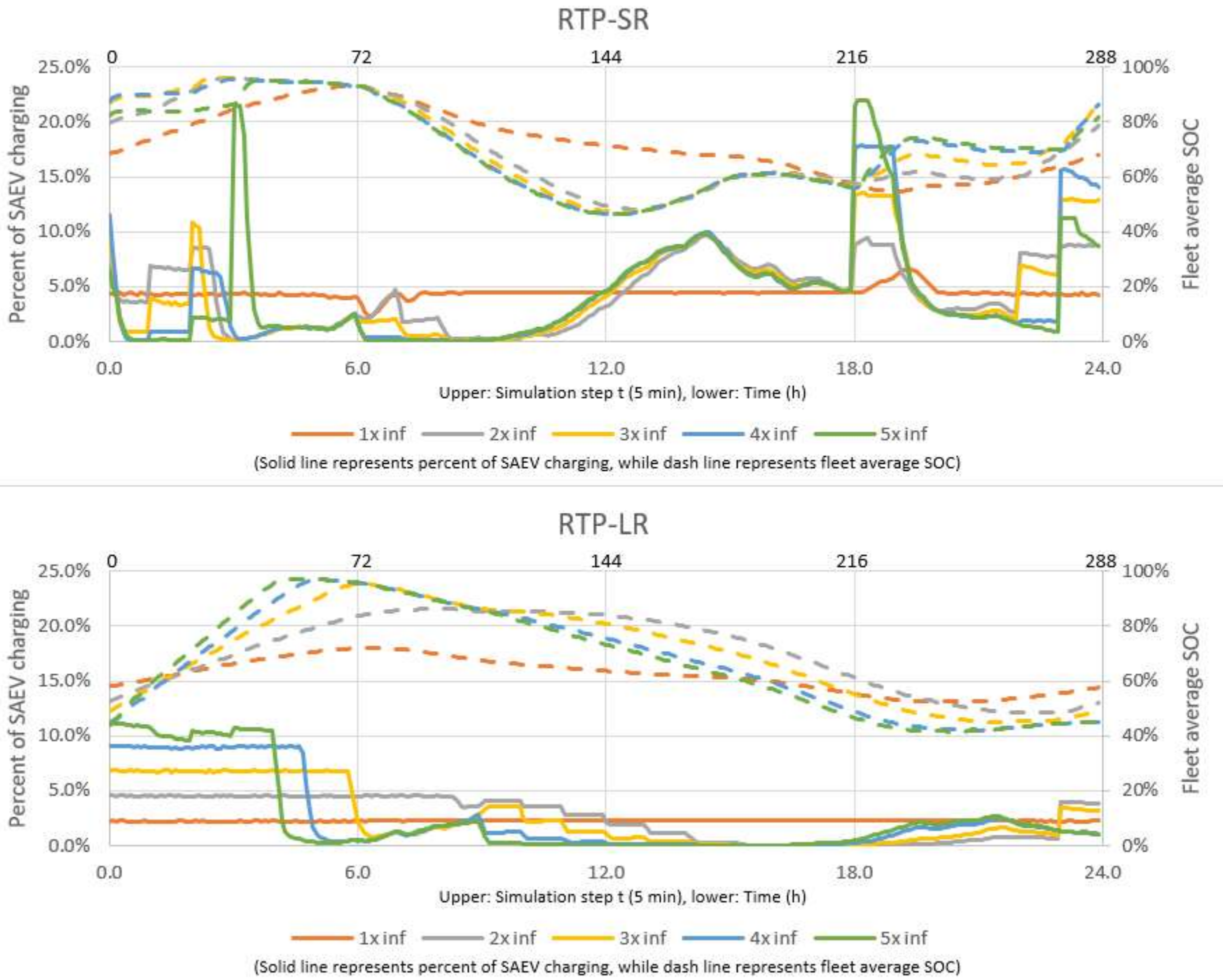


Figure 11: Fleet Charging Behavior and SOC Pattern (RTP)

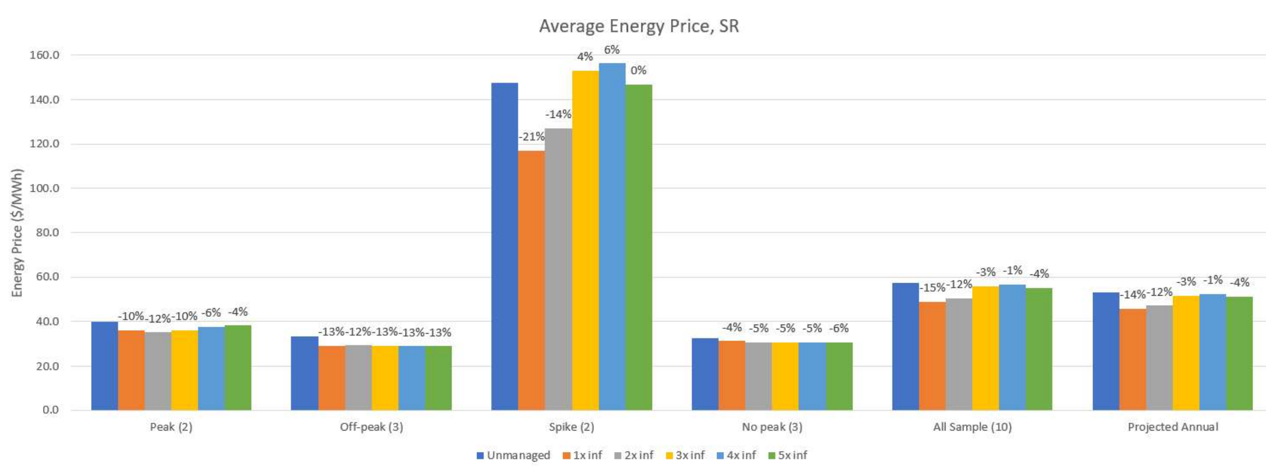


Figure 12: SAEV energy price assuming RTP, SR-FC

Table 4: Simulation Result, RTP

	SR					
	Unmanaged	1x inf	2x inf	3x inf	4x inf	5x inf
Total trips	1288099					
% unserved trips	0.01%					
Fleet size	50,295					
Number of chargers	4,446	2,224	4,448	6,672	8,896	11,120
Daily VMT per veh (mi.)	168.5	171.9	172.4	172.1	171.8	171.6
Average % unoccupied VMT	9.8%	11.1%	11.3%	11.2%	11.1%	11.0%
Average % VMT for charging	2.1%	3.0%	3.0%	3.0%	2.9%	2.7%
Average wait time (min)	2.05	2.12	2.18	2.17	2.17	2.18
Per-veh-mile electricity cost, $	0.018	0.015	0.016	0.017	0.017	0.017
Per-veh-mile chargers cost, $	0.002	0.001	0.002	0.004	0.005	0.006
	LR					
	Unmanaged	1x inf	2x inf	3x inf	4x inf	5x inf
Total trips	1288099					
% unserved trips	0.01%					
Fleet size	49,644					
Number of chargers	2,852	1,134	2,268	3,402	4,536	5,670
Daily VMT per veh (mi.)	167.8	168.2	169.8	170.6	170.5	170.3
Average % unoccupied VMT	8.7%	8.9%	9.5%	9.9%	9.9%	9.9%
Average % VMT for charging	1.1%	1.2%	1.5%	1.7%	1.6%	1.5%
Average wait time (min)	1.87	1.88	1.92	1.96	1.97	1.98
Per-veh-mile electricity cost, $	0.020	0.016	0.011	0.011	0.011	0.012
Per-veh-mile charger cost, $	0.002	0.001	0.001	0.002	0.002	0.003

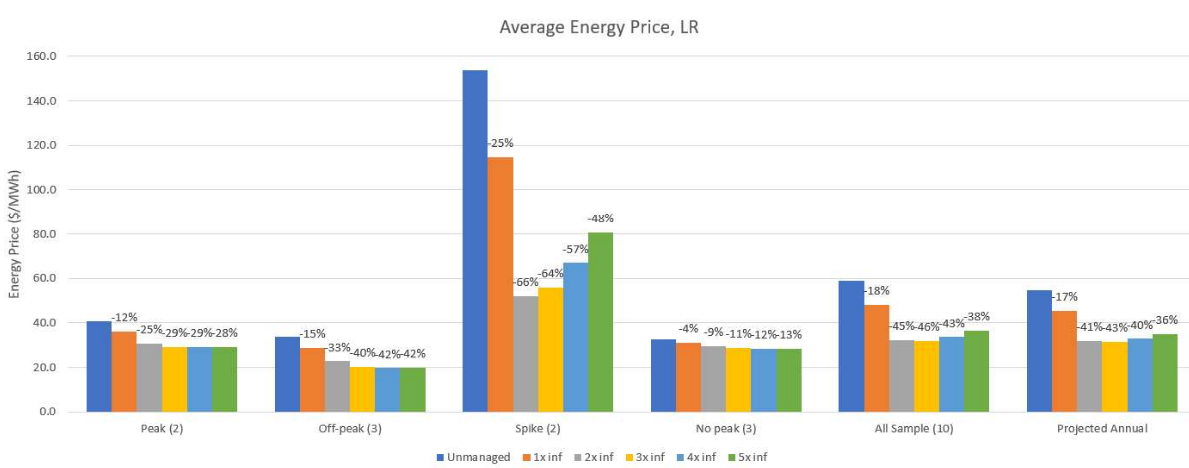


Figure 13: SAEV energy price assuming RTP, LR-FC

the valley-filling strategy is that the risk of involuntary charging on-peak increases if the battery capacity is limited and the vehicle usage rate is high. In the RTP scenario, the penalty of such activity is much higher than the potential rewards obtained from off-peak charging, since the peak electricity price can be higher than the average electricity price by one order of magnitude.

For days with small price variation, the SC yields at most 13% reduction on electricity costs, regardless of the charging infrastructure constraint. For LR-FC combination, the weighted average annual energy cost savings with dynamic SC ranges from 36% to 43% (Fig. 13). While the SC was able to significantly reduce the energy cost with LR EVs, it is not effective for SR EVs. None of the scenarios with SR EVs is able to reduce the energy costs beyond 15%. The weighted average annual energy savings with dynamic SC ranges from 1% to 12%, lower than the 14% reduction achieved by the distributed charging (Fig. 12). The negative effects from active charging management include additional unoccupied mile travel for charging (up to 42%) and slightly increased passenger wait time (up to 0.1 minute/trip), compared to unmanaged scenario. As a result, the average unoccupied miles traveled increases by up to 15% compared to the unmanaged scenario (Table 4).

7.5 Energy Cost Analysis

Because the RTP is not based on retail rates, an economic analysis is not appropriate. Instead, we present a cost analysis focusing on the cost of electricity and cost of charging infrastructure, the primary trade-off in the dynamic SC management, to understand how infrastructure decisions affect total energy-related costs (electricity + charger). In the LR EVs scenario, we found that the fleet is able to reduce its electricity costs significantly from SC. Among the LR EV scenarios examined, the total energy-related costs are minimized when the charger is constrained at 2x, at a 43.4% cost reduction compared to the unmanaged charging scenario, even though the per-mile electricity cost is not the lowest amongst all scenarios (Fig. 14). Dynamic SC is not effective for SR EVs, with the limited battery capacity being the primary bottleneck. As a result, adding more charging infrastructure only increase the overall energy-related expenses. The energy related costs are minimized if SAEV charging is distributed, and such strategy can reduce energy-related costs by 18.2% compared to the unmanaged scenario (Fig. 14) (Table. 4).

In theory, providing more charging infrastructure gives the fleet operator the opportunity to take advantage of the low electricity costs. However, we found that the energy-related costs increase as the number of chargers increases. While this might be counterintuitive, it suggests that the one of the essential requirement for successfully implementation of the SC strategy under RTP environment is the accurate prediction of ideal charging periods. As charging intensity (charging infrastructure constraint) increases, the challenge of accurate prediction also rises. Due to the discordance between charging opportunity (overnight) and transportation demand (business hours), once charger capacity exceeds a certain limit, increasing charger capacity is only useful if the energy price prediction is accurate and the battery capacity is sufficient to store energy when the electricity prices are relatively low. Per the RTP energy categories we introduced earlier, providing additional chargers to LR SAEVs will not reduce the average energy price when the electricity price is categorized as a spike (unpredictable event), due to the low price prediction accuracy.

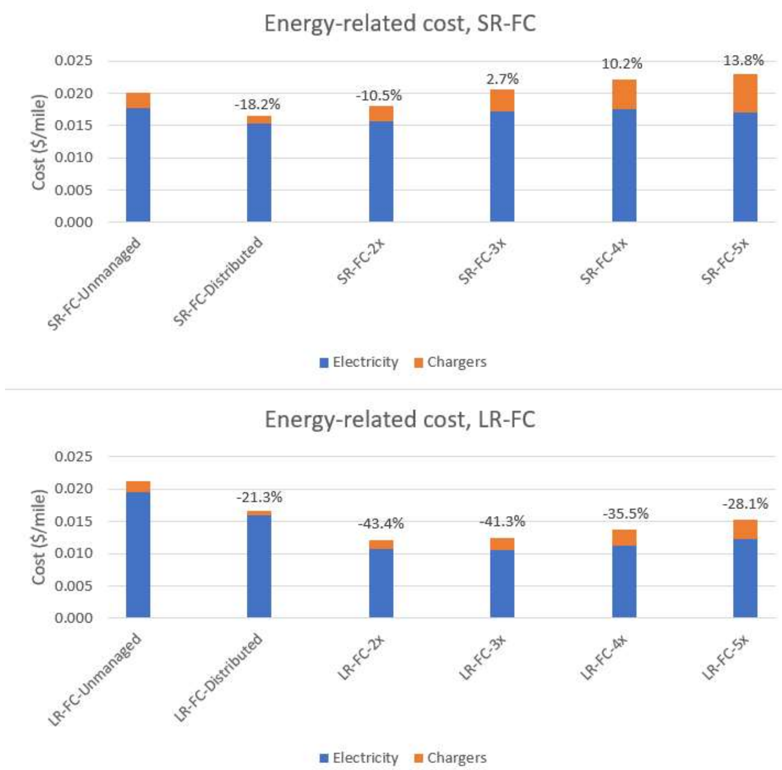


Figure 14: Per mile SAEV electricity and charger cost assuming RTP

7.6 Summary

Under the RTP structure, the SC performance is highly dependent on the battery capacity, prediction accuracy, and energy price fluctuation. With SR EVs, the additional energy cost savings are slim and the additional charging infrastructure are not cost-effective. On the other hand, SC is able to significantly reduce the SAEV energy costs for LR EVs, due to their large battery capacity. From the energy costs savings under each price fluctuation categories, the energy cost reductions are directly linked with price fluctuations, and the majorities of the savings are attributed to peak, off-peak and spike price categories.

Furthermore, the results show us the fleet operator should be focusing on both peak-shaving and valley filling, if the price is dynamic. Traditionally, these two concepts are used interchangeably for EVs with low utilization, because the EV range is sufficient to cover personal travel demand without intermediate battery recharge. For a shared EV, the range is no longer sufficient and may requires intermediate battery recharge, as the vehicle utilization is much higher and the vehicle utilization is non-uniformly distributed among the fleet SAEVs (some vehicles are driven more compared to others). On the other hand, electricity price spike in a RTP environment is the most difficult to predict, and often occurs around the late afternoon when the SAEV battery level is already low. Therefore, while having more chargers can potentially reduce the fleet energy costs, the risks from inaccurate prediction and the inherit constraint of battery capacity should also be considered in the charging decision process.

8 Renewable Energy Scheme

EV-RES coupling is considered desirable by many researchers because EV charging and discharging management can reduce the equivalent load and increase absorptive capacity of RES generation. Inspired by existing literature that focus on EV-wind coupling, we attempted to develop a wind energy generation model in the case study area. However, we found that the wind energy is highly volatile from day to day, and cannot guarantee meeting the daily energy demand from the SAEV fleet.

Unlike wind generation, PV generation pattern is more consistent and stable. Therefore, we dedicate this Chapter to describe the unique SAEV-PV direct couping opportunity. The most challenging part of large-scale PV integration is the excessive energy generation at peak, and neither battery energy storage nor demand side management is effective in solving this problem. Thus, it is difficult to design a high-rated PV system that is able to meet the total energy demand. Luthander et al.[41] reviewed a body of existing literature that study this particular scenario in building energy consumption, and found the average PV self-consumption rate is 50% in such settings. Here, we examine whether SAEV SC can be more effective at absorbing solar energy compared to traditional demand side management solutions and battery storage solutions, especially at peak PV generation (with ideal weather condition and solar penal angle).

8.1 Renewable Energy Data

NREL Wind integration data sets [37] and solar integration data sets [36] are used to model RES generation patterns within the study area. These datasets provide simulated energy generation data for a period of one year. Sites are randomly selected within the case study area to form a network of renewable generation sources that supply energy to power the SAEV fleet. For the case study, the solar integration data sets are used to obtain a generalized PV generation curve by averaging generations from all selected sites within one year, at 5-minute interval. The final PV system to supply energy to the SAEV fleet is 980 MW in the case study. The site capacity range between 0.2 MW and 22MW (no utility scale PV generation within the case study area). Approximately 100 PV generation sites were selected.

8.2 Charging vehicle assignment function

Similar to the vehicle assignment method used in the TOU scheme where the energy off-peak hours are predetermined, a generalized PV generation curve can be obtained from historical PV generation data. Because peak generation is a natural constraint on the maximum number of concurrently charging vehicles, the charging infrastructure constraint is not specified in this scenario. Instead, we specify the PV system that is capable of supplying the amount of energy needed for the SAEV operation. Therefore, the first step is to determine the ideal number of charging vehicles and the amount of new vehicles that should charge (Equation 8.9) and (Equation 8.10). Finally, the fleet operator assigns individual EV that are low in battery to charging stations (Equation 8.11). The set of available SAEVs are sorted by their SOC and the SOC of the $N_n th$ vehicle becomes the recharge threshold (if N_n is greater than the total number of available vehicles then all the available vehicles will be sent to charge). Additionally, a minimum charging constraint of 80% SOC is imposed to avoid consecutive charging activities in a short period of time.

$$N_t = C \times \frac{G_t}{R_{charging}},\ s.t.\ \sum_{t=0}^{288} G_t = D_d \tag{9}$$

$$N_n = N_t - N_e \tag{10}$$

For all available SAEVs, the vehicles that satisfy the following conditions will be sent to charge:

$$SOC_{ev} \leq SOC_{N_n},\ s.t.\ SOC_{ev} < 80\% \tag{11}$$

where:

t is the simulation time step that represents 5 minutes in real time, $t \in [0, 288)$;
N_t is the ideal number of charging vehicles at time step t;
C is a constant to ensure correct unit conversion;
G_t is the PV generation at time step t (kWh);
D_d is the total daily SAEV fleet energy demand in kWh;
$R_{charging}$ is the SAEV recharge rate (mile/time step/veh), recharge rates can be found in section 4.3;
N_n is the number of new SAEVs sent to charge at time step t;
N_e is the number of currently charging SAEVs at time step t;
SOC_{ev} represents the battery level in percentage of each individual SAEV;
SOC_{N_n} represents the charging threshold (the SOC of the N_nth available SAEV sorted in ascending order).

8.3 System Performance

For price-based charging assignment schemes, we evaluate the system performance using average energy price. However, in the PV generation case, the optimization goal changes from reducing price to increase the utilization of renewable energy generation. Therefore, we replace the average energy price with self-consumption, which is defined as the amount of PV generation consumed by SAEV fleet without the need for intermediate energy storage, as the primary performance index:

$$Self\_Consumption = \frac{\sum_{t=0}^{288} D_t}{\sum_{t=0}^{288} G_t} \tag{12}$$

8.4 Fleet Charging Behavior

Unlike charging using the main grid, where SC implies overnight valley-filling, PV generation are only available during the day and peaks at solar noon. As a result, existing SAEV charging demand without charging management already overlaps with PV generation by 40% to 60%. From the simulated SC behavior with PV generation, we found that LR-FC is the only scenario where the SAEV fleet can match the PV generation at peak. SR EVs show the largest gap between the generation and charging demand. As a result, these demand are shifted towards hours where PV generation is not available, thus requiring additional generation sources to supplement PV generation (Fig. 15).

8.5 SAEV Simulation Results

In all PV SC scenarios, SAEVs can achieve a self-consumption above 80%, suggesting that SC is effective at allowing the SAEV charging behavior to adapt to the PV generation pattern. Among the scenarios

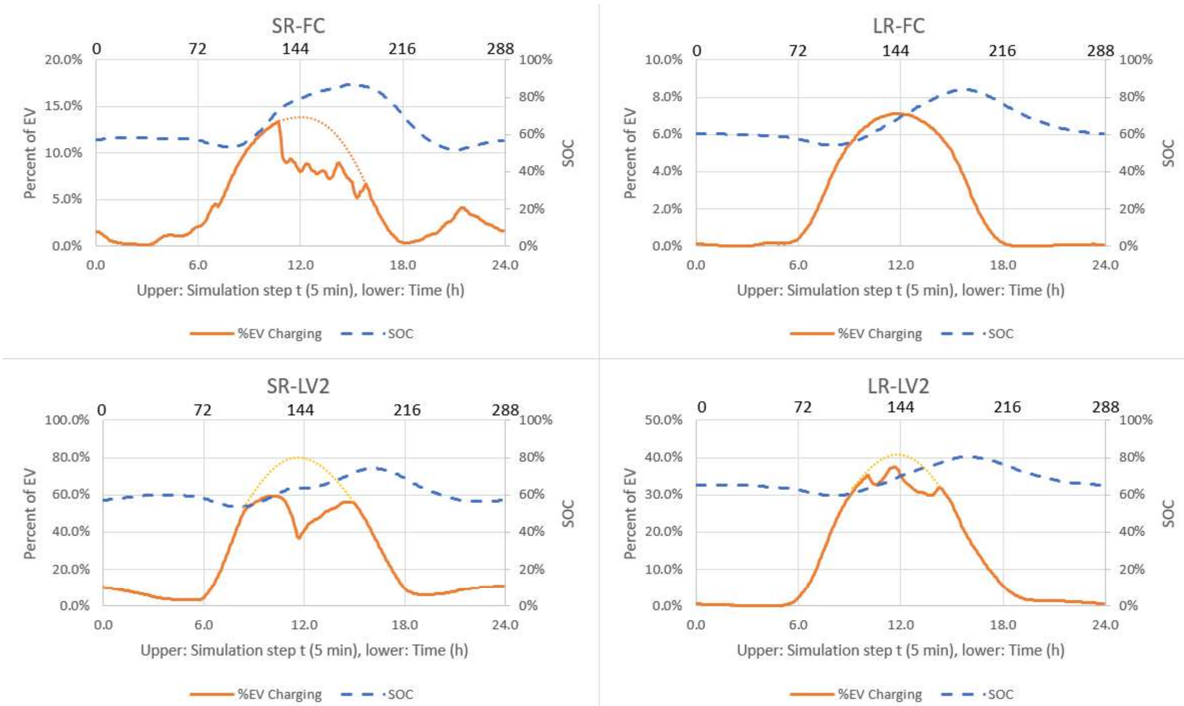


Figure 15: Fleet charging behavior based on PV generation

Table 5: Simulation Result, PV

	SR-FC UMG	SR-FC PV	LR-FC UMG	LR-FC PV	SR-LV2 UMG	SR-LV2 PV	LR-LV2 UMG	LR-LV2 PV
Total trips	1288099							
% unserved trips	0.01%							
Fleet size	50,295	50,295	49,644	49,644	69,217	69,217	49,639	49,639
Number of chargers	4,446	6,710	2,852	3,542	33,211	41,207	11,980	18,602
Daily VMT per veh (mi.)	168.5	171.0	167.8	168.7	121.3	123.4	168.3	170.4
Avg % unoccupied VMT	9.8%	10.7%	8.7%	9.1%	9.1%	10.3%	9.3%	10.0%
Avg % VMT for charging	2.1%	2.7%	1.1%	1.2%	1.7%	2.4%	0.9%	1.3%
Average wait time (min)	2.05	2.08	1.87	1.89	1.88	2.90	2.33	2.64
PV Self consumption (%)	61.2%	81.4%	58.3%	98.6%	38.0%	81.4%	45.2%	93.4%

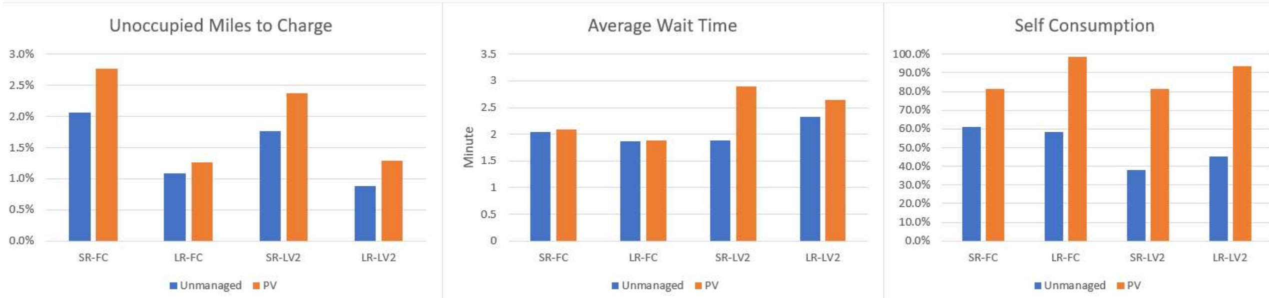


Figure 16: Performance of PV SC

simulated, LR EVs are able to reach higher self-consumption (from 93% to 99%); while SR EVs are only able to reach a self-consumption up to 81.4%, due to their limited battery capacity. The results also show that Level 2 chargers cause additional wait time for passengers. Meanwhile, trip wait time is not affected when DC fast charger is deployed. This is due to low charging rate of Level 2 chargers, which forces the fleet operator to send a large percentage of fleet to charge in order to absorb PV generation at peak. In the SR-LV2 scenario, the fleet operator needs to dispatch up to 60% of the SAEV to charge. As a result of the 60% reduction in effective fleet size for transportation service, the average passenger wait time increase by 54% compared to the unmanaged scenario. Lastly, all SC scenarios require additional unoccupied miles for charging and an additional 24% to 55% charging infrastructure, compared to unmanaged scenario (Fig. 16).

8.6 Summary

EV charging management is naturally a combination of demand side management and energy storage, because both charging schedule and charging intensity can be controlled. Due to this unique characteristic, SAEV charging can be managed to effectively absorb PV generation. The findings are consistent with existing literatures on EV-PV coupling. It is important to keep in mind that the case study area is not suitable for utility-scale PV development due to the high latitude, and an further study might be needed to better understand the long term energy impacts for EV integration.

Because the sizing of renewable infrastructure is based on the total transportation energy demand, the results provide a guideline for the maximum PV capacity the SAEV fleet can take advantage of: 81% for SR EVs and 99% for LR EVs, both assuming FC. Generation capacity beyond the maximum capacity will result in excessive generation waste and lower the self-consumption rates. As expected, PV charging increases the unoccupied miles to charge regardless of EV range or charger type.

By comparing scenarios with different battery capacities, we found that SR vehicles do not possess the storage capacity to adhere to the charging schedule. Meanwhile, LV2 chargers are resulting significant increase on passenger wait times. Overall, only long range vehicles with DC fast charger (LR-FC) demonstrate the ability to rely on PV generation to serve regional transportation demand while maintaining the same level of transportation service.

9 Conclusion

Experts predict ar-sharing, mobility on demand services, and autonomous vehicles will be integrated into the transportation system in the near future. Meanwhile, future smart grids are expected to incorporate dynamic pricing for effective Demand Side Management. In the present work we proposed SC strategies for a SAEV fleet and demonstrated the operation scenarios for TOU pricing, real-time pricing and PV generation. The findings suggest that (smart) grid operators need to design effective pricing strategies and use the price signal to balance real-time SAEV charging energy supply and demand, otherwise peak energy demand will increase. The same energy pricing strategy can be applied to allow large-scale renewable generations to be integrated to the grid and reduce RES curtailment. Meanwhile, the SAEV fleet operator need to consider vehicle range, charging infrastructure and charging strategy that correspond to the energy pricing structure to improve mobility operation and reduce total costs. We found that SC strategy might not be best when all operational costs are considered, even the average energy price paid by the fleet is reduced.

Based on simulated SAEV travel and charging behavior, the SAEV unmanaged charging peak occurs between 6 pm and 8 pm, which correspond to the end of PM transportation peak. In the same time period (6 pm to 8 pm), the real-time electricity price suggests that the grid is expected to experience the most energy demand under the regional energy use pattern. As such, the addition of the SAEV charging demand will worsen the grid strain and requires additional energy capacity to accommodate such increase in energy demand. Unless the energy rate is flat, the SAEV fleet operator will be paying high energy price and the cost of mobility service will increase.

With the assumption of smart grid and dynamic energy prices, the cost analysis suggests that the maximum savings from energy costs is 42%, which is higher than the maximum savings from TOU rates at 34%, suggesting the RTP is more effective in incentivizing EV charging management for LR EVs. On the other hand, SR EVs still straggle due to their limited battery capacity and the SC is less successful and only able to achieve a energy cost saving of 15%, regardless of electricity pricing structure. We found that the performance of price-based SC is largely governed by limited battery capacity and the discordance between charging opportunity and transportation demand. Additionally, prediction accuracy is the key to both maximizing the potential energy cost savings by increasing charging intensity and minimizing on-peak charging as a result of prediction error in a RTP environment.

Assuming SAEVs will take advantage of PV generation, we found that EV charging management is naturally a combination of demand side management and energy storage to allow PV generation to be absorbed by SAEVs. The rated PV self consumption ranges from 81% to 99%, which is much higher compared to PV being utilized in a building setting. However, LV2 charger are unsuitable for such scheme because it implies a large percentage of the fleet will be charging at generation peak (solar noon) and transportation service will be impaired during that time.

Overall, we discovered that it is important to understand the high utilization of a SAEV and design the SC strategies that are capable of benefiting both transportation system and energy system. Battery capacity plays the essential role in the EV-grid interaction. Without sufficient battery capacity, the battery tend to act as a mobile energy source and the energy demand can hardly be shifted during hours with high trip demand (8 am to 6 pm), because charging activities are necessary for the fleet to remain operational. With a expanded battery capacity, however, the battery acts as both mobile energy source and energy storage, thus improving the charging flexibility and allowing the SAEV charging demand to be managed for different energy scenarios. Another aspect of active charging management strategies is the impact on additional vehicle-mile travel that occurs. Fleet operator should pay close attention the additional miles traveled because not only do they contribute to SAEV wear and tear but also might contribute to roadway congestion and impact the transportation system. Finally, PV generation and SAEV can benefit from each other to accelerate transportation sustainability, as the presence of SAEV reduces PV curtailment and the presence of PV generation give SAEVs much needed intermediate recharge opportunity outside of traditional overnight energy valley.

9.1 Limitations and Future Research

In the case study, the estimated usefulness of SC in reducing fleet energy costs may be conservative. This is a result of both regional energy profile and price prediction error (RTP assumption only). As described in section 4.2, the case study region has low energy costs and energy volatility, which made SC less significant, especially when other costs factors are considered. In other states where the energy price are higher and more volatile, charging management can provide additional energy cost savings for SAEV fleet operator and environmental and infrastructural savings at the system level. A example would be the duck curve scenario, where SAEV can take advantage of excessive solar generation to reduce energy costs and to increase the system capacity for renewable energy. For dynamic pricing, the prediction model are simplified and cannot accurately predict the magnitude and duration of energy spike, thus feeding SAEV fleet inaccurate information regarding future energy price. Incorporating a robust energy simulation/prediction model will produce a more accurate energy savings estimation, and also model the impact of changes in the energy structure.

At the early state, we assume the additional energy demand from transportation (2% compared to current regional energy demand) will have negligible impact on the real-time energy price. However, as SAEV market share grows, the energy demand will influence the energy price, thus requiring a feedback loop to update price with real-time SAEV charging demand. This is another reason for a more robust energy model is needed. With a detailed energy model, we can model the impact of SAEV charging demand on the real-time energy prices. In such process, the SAEV fleet and the utility provider and negotiate via the smart grid to establish the up-coming charging consumption at the next hourly block and the corresponding price. Such modeling approach can reflect the true energy savings under market equilibrium for fleet operators while reflecting the operation costs for utility providers.

Even with active charging management, we still require the EV to be fully charged before released for service. In theory, a EV can maintain available status while charging and accept trips (assuming the remaining range in the battery is sufficient). However, such approach will result in even more unoccupied mile to charge and might accelerate battery degradation (by increasing charging frequency). Additionally, allowing SAEVs to terminate charging without reaching full charge may affect the transportation service and increase the amount of unserved trips. Further research is needed to investigate the effect of releasing vehicle before fully charged.

The simulation results with SC implemented show that involuntary charging occurs when the fleet SOC is at or below 40%. We already explained the non-uniform distributed of EV utilization is the reason why fleet SOC cannot be pushed down further. This finding inspired us to consider the possibility to integrate SC into the vehicle-trip matching process. Unlike current selection algorithm which randomly select vehicle to serve trip, a trip-vehicle matching process considering SOC will allow the fleet operator to control the SOC heterogeneity and to manipulate the fleet charging profile at a higher level. By altering the distribution of vehicle utilization (either in favor of high-SOC or low-SOC vehicles), it is possible to better utilize the EV battery and reduce charging frequency and the amount of involuntary charging, without the need to increase battery capacity. Similarly, there is another opportunity for SC to be integrated into the vehicle-charging station matching process. By prioritizing opportunistic charging (when a vehicle is close to a charging station), SC may be effective but requires less travel for charging activities. This will be a future research topic of interest.

We found that peak-shaving is critical to achieve high energy cost savings under the RTP settings. Therefore we suggest an operational strategies for peak-shaving under RTP for future studies. Peak-shaving can be achieved by increasing the charging sensitivity on SOC and taking a more conservative SC strategy, thus ensure the fleet are always sufficiently charged. The concept of smart trip matching in the previous paragraph will also benefit the SAEV fleet and allow peak-shaving.

It is very likely that smart charging can allow the SAEV fleet operator to reduce the fleet size and and the operation costs. In the current iteration of the SAEV simulation model, such potential benefit of smart charging cannot be reflected since charging management kicks in after warm run is complete and the fleet size is determined. Future research should consider methods to reflect such opportunity in SAEV fleet operation.

Within the same grid, LMPs are often higher near load centers like cities, where demand for electric power is concentrated. Similar to the spacial energy imbalance problem, SAEVs often faces spatial imbalances that might damage mobility service and adds congestion at charging stations. In future research, we would like to add a spatial component to the SC framework, that recognize the spatial energy imbalance and vehicle position imbalance.

Even though the wind generation pattern are less desirable for SAEV charging, we believe that more research is needed to understand the implications of EV-wind coupling within the private EV ownership context.

In the case study, we use regional travel demand model to model SAEV travel behavior. While it can accurately reflect the current regional travel pattern, other Mobility-on-Demand datasets can better reflect future SAEV travel pattern and provide details on passenger demographics and trip characteristics. Future studies should consider such datasets to calibrate the results from SAEV simulation model. Finally, it is likely that a SAEV fleet will be a mixed fleet consist of different vehicle types and charger types. We are interested to see how a mixed fleet performs compared to monotonic fleet as this is still a research gap to be filled.

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Note

1/24/18

Previously we thought using a Microgrid can provide a better definition of system boundary, which is essential to the integration of Renewable energy sources (due to the uncertainty of RES) and energy independence and reliability for the SAEV fleet (to provide reliable transportation services). However, we found that the main power grid dynamics is more important in the management of SAEV, because such fleet will consume a considerable amount of energy in the future in the metropolitan areas. Therefore, we shift the focus from a Microgrid setting to the design of a generic EV SC framework on the main grid that can better reflect the energy system dynamics (supply, demand, peak etc.).

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Appendix

List of Tables in Appendix:

Table 6: 10 Locational Marginal Price Samples ($/MWh)

Hour	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
0	35.6	33.3	37.7	25.0	19.5	14.6	24.6	28.7	28.0	32.0
1	31.7	29.5	36.0	22.7	1.6	14.5	20.6	26.8	26.8	30.1
2	28.9	30.0	35.1	20.8	0.9	10.4	17.6	26.2	25.2	28.8
3	28.9	28.7	35.1	24.4	0.9	3.5	19.2	26.4	26.1	29.6
4	29.6	30.0	35.7	23.1	0.9	3.5	18.9	25.1	27.6	30.5
5	31.2	32.9	38.6	24.8	3.3	5.4	17.2	27.2	30.2	31.7
6	35.2	37.2	47.1	26.9	7.6	13.6	17.0	28.7	32.8	31.6
7	36.3	43.6	75.8	28.6	21.5	13.4	25.8	29.7	35.7	33.0
8	37.4	44.5	48.3	27.7	23.1	17.2	27.9	31.0	35.9	34.9
9	37.4	44.2	48.6	27.4	24.0	21.5	30.6	31.8	40.6	32.9
10	37.9	44.3	46.8	26.8	27.2	28.7	33.3	30.7	33.5	35.8
11	38.6	44.4	45.3	26.2	29.4	31.1	37.0	31.2	32.9	32.1
12	39.3	43.5	45.2	25.7	30.0	32.4	52.6	32.3	32.3	32.7
13	39.6	43.5	45.9	27.0	30.3	33.1	54.1	34.0	32.0	36.8
14	35.3	43.8	44.9	30.4	29.9	33.6	77.8	40.4	32.0	37.0
15	35.7	43.6	40.9	29.5	30.1	35.9	79.0	51.6	32.3	33.4
16	44.8	43.4	44.7	27.8	29.5	36.6	33.3	126.0	32.3	34.4
17	78.6	43.2	50.9	29.1	28.9	38.0	35.6	2655.8	32.6	35.1
18	45.1	47.3	176.7	30.5	30.2	35.6	35.2	205.6	32.5	39.2
19	45.0	49.3	180.8	30.8	28.5	34.8	30.4	145.9	35.1	40.2
20	40.6	48.4	228.9	29.7	28.8	34.3	30.8	48.9	36.3	38.3
21	38.9	44.6	182.5	32.1	27.8	34.3	30.0	45.0	34.6	35.2
22	35.3	44.6	49.8	32.3	25.9	31.4	28.6	40.4	32.7	36.6
23	33.9	37.0	43.8	29.4	23.1	24.5	27.0	34.7	30.9	32.8

Table 7: Daily Weighted Average Energy Price, RTP-LR-FC ($/MWh)

	umg	dis	2X	3X	4X	5X
Day 1	41.6	38.4	35.6	34.7	35.3	35.8
Day 2	44.3	40.7	37.3	36.2	36.5	36.5
Day 3	87.3	69.6	64.7	67.9	79.5	88.3
Day 4	28.6	27.5	25.8	25.1	24.7	24.8
Day 5	27.0	21.1	14.7	10.5	8.3	7.7
Day 6	30.3	24.4	16.4	14.3	14.1	15.0
Day 7	39.9	33.6	25.9	23.5	22.7	22.8
Day 8	220.2	159.8	39.1	43.7	54.2	72.7
Day 9	33.6	32.1	30.2	29.1	28.8	28.7
Day 10	35.5	34.0	32.9	32.4	32.1	31.9
Peak (2)	40.7	36.0	30.7	29.1	29.0	29.3
Off-peak (3)	33.9	28.7	22.8	20.3	19.6	19.7
Spike (2)	153.8	114.7	51.9	55.8	66.9	80.5
No peak (3)	32.6	31.2	29.6	28.9	28.5	28.5
All Sample (10)	58.8	48.1	32.3	31.7	33.6	36.4
Projected Annual	54.6	45.4	32.0	31.4	32.8	35.1

Table 8: Daily Weighted Average Energy Price, RTP-LR-FC ($/MWh)

	umg	dis	2X	3X	4X	5X
Day 1	41.3	38.6	39.4	39.9	40.4	40.3
Day 2	44.1	40.9	41.1	42.0	42.5	42.4
Day 3	83.4	72.1	73.6	79.8	87.0	91.4
Day 4	28.4	27.5	26.9	26.7	26.8	26.7
Day 5	26.6	21.4	22.0	20.7	19.4	19.3
Day 6	29.6	24.7	24.9	25.0	25.1	25.3
Day 7	38.8	33.8	31.0	32.2	35.1	36.2
Day 8	211.3	161.9	180.4	226.1	225.6	202.6
Day 9	33.7	32.2	31.3	31.7	31.6	31.2
Day 10	35.3	34.1	34.2	34.1	34.1	34.0
Peak (2)	40.0	36.2	35.2	36.1	37.7	38.2
Off-peak (3)	33.4	29.0	29.3	29.2	29.0	29.0
Spike (2)	147.4	117.0	127.0	153.0	156.3	147.0
No peak (3)	32.5	31.3	30.8	30.8	30.8	30.6
All Sample (10)	57.3	48.7	50.5	55.8	56.7	54.9
Projected Annual	53.3	45.9	47.1	51.5	52.5	51.1