Summer 2017

Optimal electric vehicle scheduling : A co-optimized system and customer perspective

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OPTIMAL ELECTRIC VEHICLE SCHEDULING : A CO-OPTIMIZED SYSTEM AND CUSTOMER PERSPECTIVE

by

MAIGHA

A DISSERTATION

Presented to the Graduate Faculty of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

in

ELECTRICAL ENGINEERING

2017

Approved by

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PUBLICATION DISSERTATION OPTION

This dissertation has been prepared using the Publication Option. Introduction and Conclusion chapters have been added for purposes normal to dissertation writing.

Paper I on pages 5 to 35, “Economic Scheduling of Residential Plug-In (Hybrid) Electric Vehicle (PHEV) Charging,” was published in *Energies*.

Paper II on pages 36 to 59, “Cost-Constrained Dynamic Optimal Electric Vehicle Charging,” was published in *IEEE Transactions in Sustainable Energy*.

Paper III on pages 60 to 85, “Electric Vehicle Scheduling Considering Co-optimized Customer and System Objectives”, has been submitted to *IEEE Transactions in Sustainable Energy*.

Paper IV on pages 86 to 111, “A Transactive Operating Model for Smart Airport Parking Lots”, will be submitted to *IEEE Transactions on Smart Grids*.

ABSTRACT

Electric vehicles provide a two pronged solution to the problems faced by the electricity and transportation sectors. They provide a green, highly efficient alternative to the internal combustion engine vehicles, thus reducing our dependence on fossil fuels. Secondly, they bear the potential of supporting the grid as energy storage devices while incentivising the customers through their participation in energy markets. Despite these advantages, widespread adoption of electric vehicles faces socio-technical and economic bottleneck. This dissertation seeks to provide solutions that balance system and customer objectives under present technological capabilities. The research uses electric vehicles as controllable loads and resources. The idea is to provide the customers with required tools to make an informed decision while considering the system conditions.

First, a genetic algorithm based optimal charging strategy to reduce the impact of aggregated electric vehicle load has been presented. A Monte Carlo based solution strategy studies change in the solution under different objective functions. This day-ahead scheduling is then extended to real-time coordination using a moving-horizon approach. Further, battery degradation costs have been explored with vehicle-to-grid implementations, thus accounting for customer net-revenue and vehicle utility for grid support. A Pareto front, thus obtained, provides the nexus between customer and system desired operating points. Finally, we propose a transactive business model for a smart airport parking facility. This model identifies various revenue streams and satisfaction indices that benefit the parking lot owner and the customer, thus adding value to the electric vehicle.

ACKNOWLEDGMENTS

This dissertation is dedicated to my advisor, Dr. Mariesa L. Crow and my mother.

I fall short of words to express my gratitude toward Dr. Crow whose guidance, support, motivation and words of wisdom have had a profound impact on me. Her sage advice to 'run this marathon with perseverance, confidence, conviction and hard work' helped me succeed. Not only has she influenced me as an outstanding academician, but also as a very strong woman. This work would not have been possible without her.

I would like to thank my committee members, Dr. Joo, Dr. Ferdowsi, Dr. Kimball and Dr. Long, for their patience and guidance. Dr. Joo always attended to my questions and extended a helpful hand in times of 'mathematical' distress. While Dr. Ferdowsi provided a warm, welcoming environment, conversations with Dr. Kimball helped me widen my perspective on various topics (academic and non-academic). My sincere thanks to Dr. Long who added a managerial outlook to the work presented here. A special thanks to Dr. Shamsi for his encouragement, thought-provoking questions and insights.

I will stay eternally grateful to my mother who taught me to face and survive all challenges. Her courage has always lit up my path and she will remain my personal 'yoda'. My special thanks to Abhishek with whom I share a special bond. Sidhartha has been a gracious gift whose friendship, love and care helped me smile and dance throughout. I have been blessed with the amazing friendships of Mohit, Prarit, Aman, Gunjan, Varun, Aastha, VRC, Rao, Krishnan and Manish. I will cherish the memories of my 'karm-bhoomi' in lab-108 with my colleagues Marfield, Tu, Qiu, Lisa, Mounika, Daru Shah and Phani. We drank to our sorrows and successes. I cannot thank enough each person I encountered whose presence touched me during this time.

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SECTION

1. INTRODUCTION

Environment sustainability has received tremendous attention in the past few decades through research investments, federal support and worldwide dialogue. Increasing concern over diminishing fossil fuel reserves, climatic changes due to greenhouse gas emissions and economic, social and political volatility due to energy surplus/deficit have been driving research and development into alternate energy resources like wind, solar, geothermal, etc. Researchers are continuously involved in finding economic ways of harnessing naturally available resources to fulfill the ever-increasing energy demands. Our industrial, social and economic structure depends heavily on energy consumption. Electric power industry and transportation sector lie at the core of this development and hence this change.

Aging power system infrastructure coupled with ever-increasing load demands have led to research in finding alternatives that would provide higher quality power with greater reliability. These, along-with advancements in renewable energy integration, transportation electrification and energy markets, have opened areas of research in demand-response (DR), coordination-control, and development of smart grids, microgrids and nanogrids. The self-reliant nature of smart grids is expected to make the future power system infrastructure more reliable, resilient and robust to external and internal failures.

Seamless integration of distributed renewable energy resources with power electronics assistance is still challenging. Some problems include intermittency leading to ramping requirements (Duck cruve), protection system with bi-directional power transfer, variable generation control and complicated market behaviors. In lieu of this, energy storage has been identified as a prospective solution. Extending the control to the load side, mandatory or voluntary load reductions through emergency or economic-based DR programs are being implemented. They require active customer involvement, development of attractive pricing structures and secure communication links. With the inception and design guidelines for transactive energy networks, the physical and cyber layers of the system are being integrated in the market environment. Furthermore, development of communication infrastructure and internet of things (IoT) lie at the core of smart grids and microgrids. This infrastructure can be used for creating dynamic markets.

Transportation electrification adds another component to the evolving grid. In the last decade, markets have witnessed a growth of electric vehicles (EVs) as alternatives to traditional internal combustion engine (ICE) vehicles due to their economic, financial benefits and increased customer awareness toward environment. On an average vehicles remain parked 85% of the time during a day, making them excellent candidates for demand-response and grid support as controllable energy storage resources.

The basic problem associated with any demand-response strategy is its acceptance by the customers. Presently, transportation is very convenient and cost effective. Convincing a customer to enroll in a vehicle-coordination or demand-response program is a challenge due to the inherent distrust and anxiety of being controlled. Thus, design of any demand-response algorithm has a socio-economic aspect crucial to its success. Many utilities, nationwide, have undertaken pilot programs to test the acceptance of demand-response algorithms with success. The key concerns of a consumer owning an electric vehicle could be its availability for the next day's trip or minimum charge in case of emergency. In this research we focus on understanding customers driving habits and using them to design effective and effcient coordination strategies that benefit the utility and the customer. The success of any technology depends on its acceptance by the customers. It needs to be easily understood and as less intruding as possible, thus giving a sense of control to the customer over her choices, habits and activities. Financial incentives play a key role in customer motivation. Some utilities have implemented special time-of-use structures for electric vehicle owners for charging, thus treating it as a special load that is easily deferrable to the valley-hours (night) of the day. Through these initiatives, it is evident that coordination strategies for vehicles are gaining momentum, especially in the evolving smart grids. It is to be noted that this load poses a problem at higher penetration levels.

Past literature has widely discussed the impacts of electric vehicles charging on the grid and coordination schemes for mitigating these effects. Given the intermittent nature of renewable energy resources, electric vehicles have been explored as grid-storage devices and sources of ancillary services through Vehicle-to-Grid (V2G) technology; its economic feasibility is yet to be determined in details. This is a future scenario, since the existing system is not designed for two-way transfer of power. This dissertation discusses coordination strategies that require less communication, are computationally efficient, and provide autonomy to the customers while making them an integral part of the system, satisfying constraints. The customer is provided with the tools to make an informed decision while considering the system conditions.

The first paper in this dissertation discusses a heuristic charge scheduling strategy for a large EV population. It identifies the impact of different fitness functions, pricing structures and seasonal variations on residential load profiles using Monte Carlo simulation. Further, the efficacy of the aggregating and charging algorithms is determined through ANOVA analysis. This framework is extended in the second paper to a real-time moving-horizon based mathematical optimization scheme. This paper implements customer and system objectives individually and jointly. Individual vs. system optimal are also compared for a sample vehicle population. The third paper adds V2G implementations to the existing portfolio and thus adds a battery degradation model to the customer incurred costs. A multi-objective optimization strategy is developed using augmented epsilon-constraint method. The trade-offs between customer revenues, battery degradation costs and valley filling are represented as Pareto fronts. Adding on to this foundation, a transactive business model for a smart airport parking facility has been proposed in the forth paper. The principal players, fee structures, control sequences and profit margins for the parking lot operator have been determined in this study. This dissertation concludes with the closing remarks and future research directions in Section 2.

PAPER

I. ECONOMIC SCHEDULING OF RESIDENTIAL PLUG-IN (HYBRID) ELECTRIC VEHICLE (PHEV) CHARGING

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ABSTRACT

In the past decade, plug-in (hybrid) electric vehicles (PHEVs) have been widely proposed as a viable alternative to internal combustion vehicles to reduce fossil fuel emissions and dependence on petroleum. Off-peak vehicle charging is frequently proposed to reduce the stress on the electric power grid by shaping the load curve. Time of use (TOU) rates have been recommended to incentivize PHEV owners to shift their charging patterns. Many utilities are not currently equipped to provide real-time use rates to their customers, but can provide two or three staggered rate levels. To date, an analysis of the optimal number of levels and rate-duration of TOU rates for a given consumer demographic *versus* utility generation mix has not been performed. In this paper, we propose to use the U.S. National Household Travel Survey (NHTS) database as a basis to analyze typical PHEV energy requirements. We use Monte Carlo methods to model the uncertainty inherent in battery state-of-charge and trip duration. We conclude the paper with an analysis of a different TOU rate schedule proposed by a mix of U.S. utilities. We introduce a centralized scheduling strategy for PHEV charging using a genetic algorithm to accommodate the size and complexity of the optimization.

Keywords: electric vehicles; economic dispatch; energy management

1. INTRODUCTION

Increasing fuel prices, diminishing fossil fuel reserves, rising greenhouse gas emissions and political unrest have made plug-in (hybrid) vehicles an attractive alternative to traditional internal combustion engine vehicles (ICEV). The growth of plug-in (hybrid) electric vehicles (PHEVs) as a clean, safe and economical transportation option to ICEVs can be promoted by extending driving range, improving battery health and life, increasing electric grid reliability and promoting acceptance of PHEVs by the consumer. The degree of penetration of PHEVs as a transportation option depends on a variety of factors, including charging technology, communication security, advanced metering infrastructure (AMI), incentives to customers, electricity pricing structures and standardization. The wide-spread adoption of electric vehicles will have many multi-faceted socio-economic impacts. Among these are increased system load, leading to stressed distribution systems and insufficient generation, power quality and reliability problems, degrading battery health, scheduling of vehicles as a potential power source in an ancillary market, costs incurred *versus* revenues earned by end user in offering such services, along-with the dependence on variable consumer behavior have been considered as hurdles to PHEV implementation [1, 2].

Insufficient battery state of charge has been cited as the primary consumer insecurity regarding PHEVs [3]. In this paper, we interpret this concern as the desire to have a fully-charged battery at the beginning of the daily commute. This consumer desire for daily full charge must be balanced against the desire on the part of the utility to shape its load curve and avoid a load spike due to concurrent vehicle charging. It is well-accepted that coordinated vehicle charging can be used to minimize the adverse effects of PHEVs on the electrical distribution grid [4, 5]. Coordination can be either centralized or decentralized. A centralized strategy is one in which a central operator (or aggregator [6]) dictates precisely when every individual PHEV will charge, but may not be attractive to consumers who prefer to have complete authority over their transportation availability and/or electricity usage. Typically, the objective of such strategies is “valley-filling” in which the nighttime drop in load demand is decreased, resulting in a more level load profile. However, other objectives, such as system loss reduction, greenhouse emission reduction, battery lifetime extension, *etc.*, can also be optimization factors [7–10]. A centralized control strategy will require a central repository that collects parameter information from all vehicles to provide an optimal charging profile. It has also been suggested that this might be taxing on communication channels and computation time [11]. However, we believe that a centralized solution is the preferred approach under current technological capabilities. Furthermore, since the control signal is sent by the aggregator, adaptation will be easier. Lastly, it can be contended that consumer confidence can be won through pricing incentives. Thus, in this paper, we expand on these earlier approaches and develop a centralized scheduling approach that balances the actual cost of generation, the levelized time of use rates and load demand.

Specifically, we propose an optimal approach to PHEV charging that:

- provides full charging to the maximum number of vehicles;
- shapes the load curve to avoid demand spikes and accomplish valley-filling;
- minimizes the cost to the customer; and
- uses the most economic forms of generation available.

The critical contribution is the selection of the most appropriate fitness function to optimally shape the load curve.

2. BACKGROUND

A regional load profile adapted from the California Independent System Operator (ISO) is shown in Figure 1. The top curve is a typical daily load demand; the lower trace is the associated residential load and is approximately 40% of the total demand. Each residential customer is assumed to have an average load of 4 kWh per day.

The 2009 U.S. National Household Travel Survey (NHTS) provides information regarding commuter behavior. The information pertinent to this paper is summarized in Figures 2 and 3.

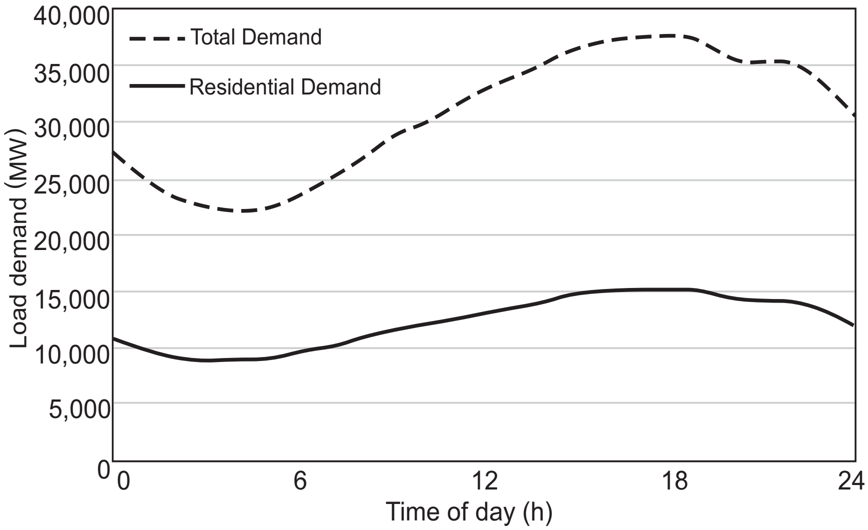

Figure 1. Load demand.

The salient details from these data are that:

- 66.5% of commuters have a daily commute of less than 30 mi (Figure 2); and
- 67.1% of commuters return home after 17:00 (Figure 3).

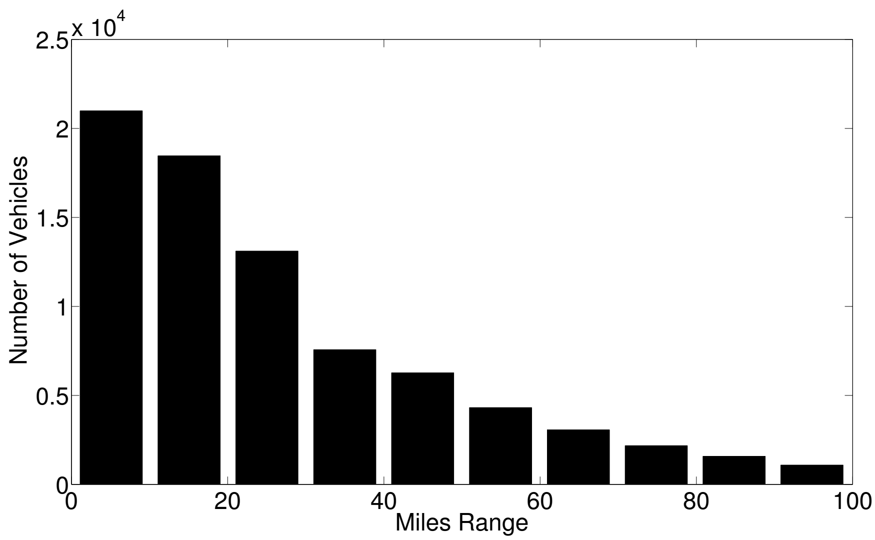

Figure 2. Number of vehicles per commute range.

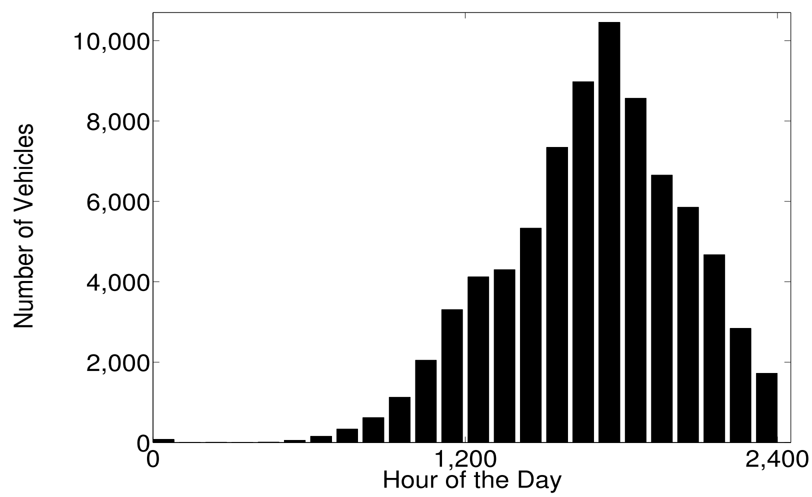

Figure 3. Number of vehicles returning per hour.

3. PROCESS

Throughout the analysis presented, the following parameters were assigned randomly to each commuter, and the results presented are the average of a Monte Carlo-based simulation with 1000 trials:

- battery size;
- commute length;
- return time;
- time available before next trip;
- charger type.

The commute length is randomly assigned to each household according to the distribution given in Figure 2. Based on the commute length, an appropriately-sized battery is then assigned.

Table 1 summarizes the batteries that are currently commercially available in the U.S. Based on these battery sizes, driver commute lengths (DCL) can be categorized and battery types associated, as shown in Table 2. Commuters in DCL20 are those that drive less than 20 mi daily, and their commute length can be adequately met by battery Types A–E, whereas a DCL100 commuter must have battery Type E.

Once the commute length and battery size have been assigned, then the return time is randomly assigned according to the distribution given in Figure 3. The time available before the next trip is also similarly assigned according to the distribution dictated by the NHTS. The chargers are assigned based on energy requirements. If the commute length and battery type require a Type II charger to fully charge, then a Type II charger is assigned;

Table 1. Commercially available battery sizes

Type	**Range (mi)**	**All electric range (mi)**	**Battery size (kWh)**	**Equivalent (mi/kWh)**
A	0–20	30	11	3.250
B	20–40	40	12	3.500
C	40–60	70	16	4.375
D	60–80	80	18	4.440
E	80–100	100	24	4.167

Table 2. Battery and commute length association. DCL, driver commute lengths

Category	**Commute length (mi)**	**Battery size (kWh)**
DCL20	0–20	(A, B, C, D, E)
DCL40	20–40	(B, C, D, E)
DCL60	40–60	(C, D, E)
DCL80	60–80	(D, E)
DCL100	80–100	(E)

otherwise, a charger type is randomly assigned. The default assignment was generated by MATLAB, which uses Bernoulli-distributed random binary numbers and probability of zero parameter $p = 0.5$. Two types of chargers were used:

Type I	120 Volts AC, 12 A, 1.44 kW
Type II	240 Volts AC, 32 A, 6.66–7.68 kW

Type III chargers (480 VAC) have not been considered, because they are not intended for residential use. If the commute length, battery size and the time available before the next trip necessitated a Type II charger, then it was deterministically assigned; otherwise, the charger type was also randomly assigned.

As a base case, this process was applied to the residential demand curve shown in Figure 1, and the average Monte Carlo simulation result (1000 trials) is shown in Figure 4. In this case, each commuter began the charging process immediately upon returning home. The base case residential load without any electric vehicle charging is shown as the bold trace. The load increases in all cases when there is electric vehicle charging. The worst case (highest peak) load occurs for Type II chargers. Since the Type II charger draws considerably more power than the Type I charger, the peak is higher immediately after the

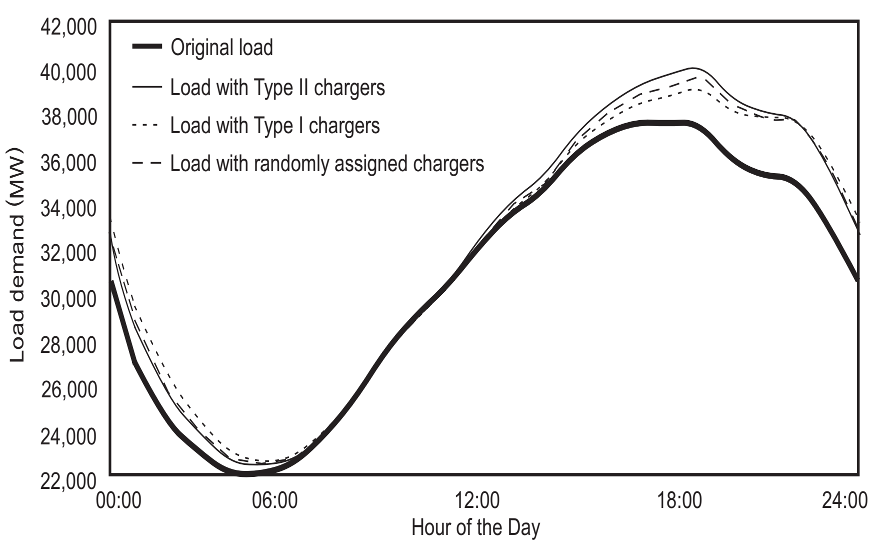

Figure 4. Residential load as a function of charger type.

return home (around 18:00). However, since the vehicle batteries charged from Type II will more rapidly reach their full state of charge, the Type II load will more rapidly fall off during the valley period from 04:00 to 05:00. The Type I charger load is the lowest demand curve, and the randomly-assigned-charger load lies between the Type I and Type II curves. Battery charging characteristics play an important role in the maintenance and lifetime of the battery. However, it is not possible to capture these aspects in the model used, due to the differences in time scale. It is assumed that a typical charge cycle of bulk-absorb-float with the proper charger settings is used to avoid overcharging.

As a comparison to time of arrival charging, a delayed charger assignment was also considered. In these cases, the charger types are assigned randomly (in 1000 Monte Carlo trials) and the vehicles began charging at a set time (assuming they had already returned home). This is analogous to the situation of having off-peak pricing with 100% participation from commuters. This case is shown in Figure 5. Note that the resulting peak load is higher than in the variable charging initiation times, even though the charger type is assigned randomly. Obviously, a delayed charging scheme must be implemented with care.

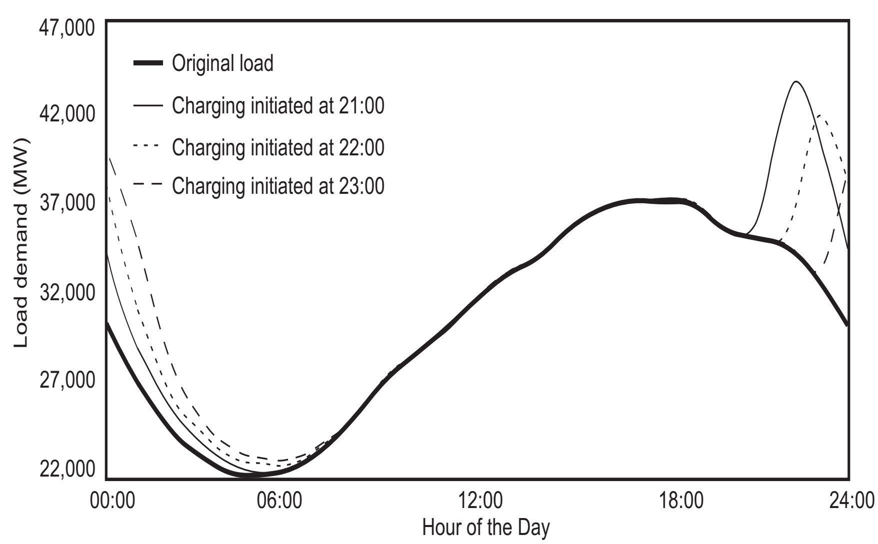

Figure 5. Residential load as a function of charger initiation.

4. VEHICLE AGGREGATION

As noted previously, a centralized control scheme will most probably require the aggregation of the vehicles to reduce the complexity of calculating the charging schemes of multitudes of individual vehicles. The aggregation of vehicles is typically accomplished by grouping the vehicles according to common parameters, such as:

- total charging time required (based on state of charge);
- network topology and physical geography;
- vehicle return time.

In this paper, we develop an aggregation scheme based on the total time required for charging, as illustrated in Figure 6. For simplicity, we also assume that the charging window is from 20:00 to 08:00, since the majority of vehicles are available for residential charging

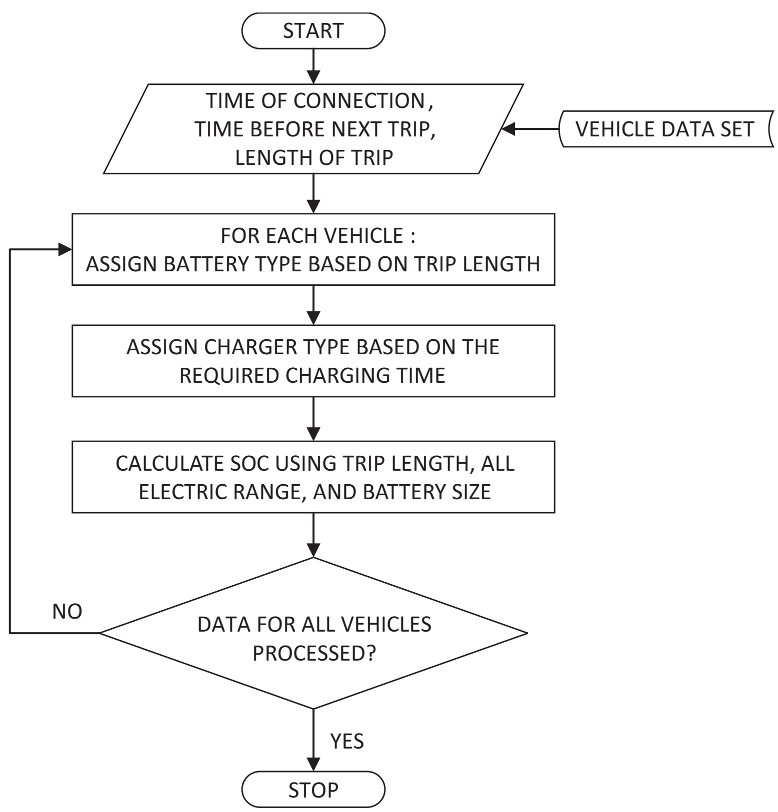

Figure 6. Vehicle assignment flow chart.

at this time. We assume that there are 12 possible connection times within the charging time frame (on the hour), but this can be expanded to any number of possible connection times without loss of generality (e.g., every 15 min), with added computational complexity. The vehicles are initially aggregated into equal sets that span the possible charging times. The illustration of the possible charging sets is shown in Figure 7.

Each possible charging set is called a “bin”: there are twelve one-hour charging bins, eleven two-hour charging bins, *etc.*, and only one twelve hour charging bin. The charging times are based on the randomly assigned vehicle travel data from the NHTS, which specifies the respective anticipated state of charge for each vehicle. It is assumed that once a vehicle starts charging, it will remain charging until it is fully charged (*i.e.*, no disconnect and reconnect). The required charging time for each vehicle in the study set is calculated. The number of vehicles requiring each length of charge time is shown in

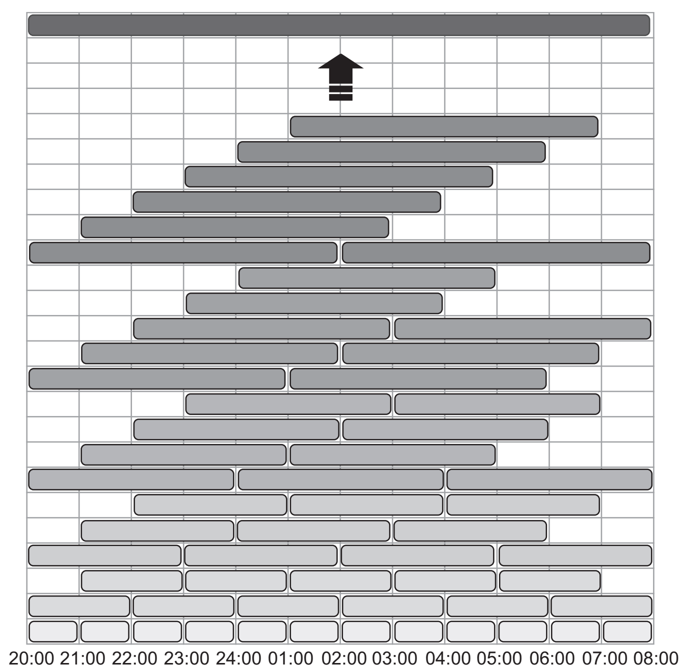

Figure 7. Aggregation of vehicles into bins.

Figure 8. Because the majority of drivers have a commute length less than 30 mi, there is a large number of vehicles requiring only 1–5 h of charging (based on battery type and charger type).

Once the vehicles have been assigned to their initial charging set, then the energy required for each charging set is calculated. The total energy required at each hour is the summation of all charging sets in that hour. A genetic algorithm is then used to assign the charging sets to the optimal connection times. In the genetic algorithm, each chromosome in the population represents a particular charging scheme in which each of the chromosome's genes represents the number of vehicles in the charging set. A fitness function is used to specify which chromosomes are retained in each generation. As the generations progress, the algorithm will reallocate the charging sets from Figure 7 across the time spectrum to optimize a given fitness function. Figure 9 describes the optimization process. The choice of fitness function can significantly impact the resulting load profile. As an example, a simple fitness function is chosen:

$$f_1 = \min\left(\max\left(P_{Load}\right)\right) \tag{1}$$

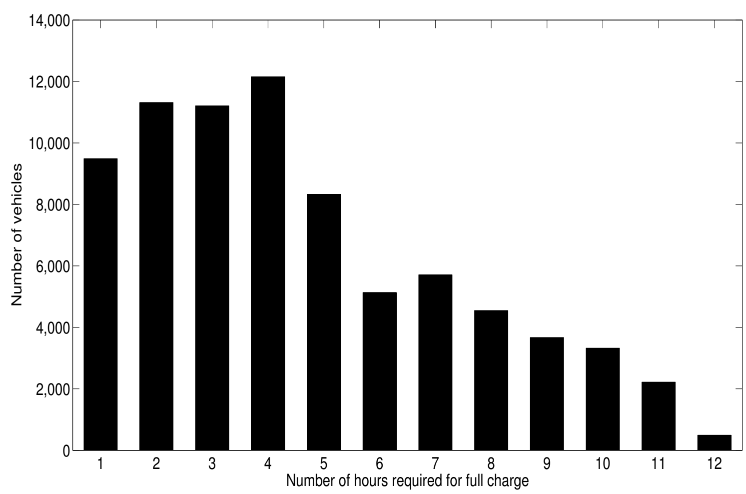

Figure 8. Number of cars in each charging window.

in which the maximum load at any time is minimized. This serves to reduce the maximum peak load. The results of these optimizations are shown in Figure 10 for 12 possible connection times (charging may commence once per hour). This approach is shown with respect to the uncoordinated charging load profile (also shown in Figure 4). Note that there is still a fairly sizable peak load around 22:00 hours. This is because there is little flexibility in scheduling the vehicles that require 10 or more hours of charging. These vehicles must

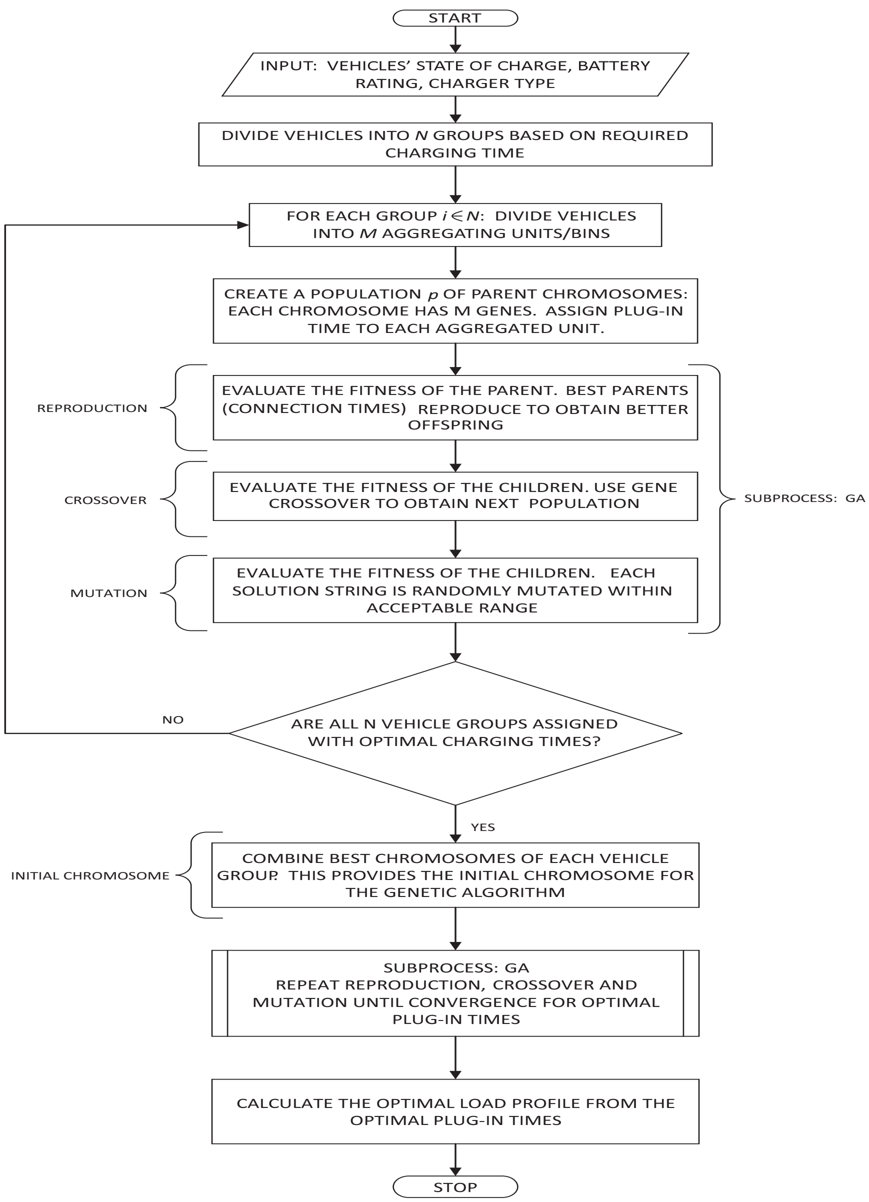

Figure 9. Optimization process.

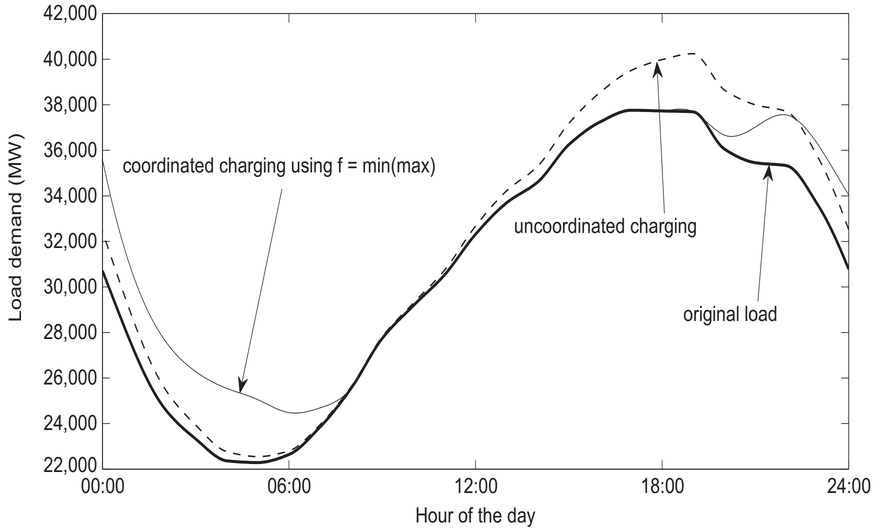

Figure 10. Optimized load profiles.

be connected no later than 22:00 hours to be fully charged by 08:00 the following morning; therefore, it is very difficult to significantly reduce the peak. However, it should be possible to achieve better valley filling by a better choice of fitness function.

Several different fitness functions are summarized in Table 3. The fitness functions are described:

1. The absolute difference between the system load and the projected average load is minimized.

Table 3. Fitness functions

Case	Fitness Function	Description
(A)	$\min\left(\sum_{i=1}^{12}\left\lvert P_i - P_{avg}\right\rvert\right)$	minimize deviation from system average load
(B)	$\min\left(\sum_{i=1}^{12}\left(P_i - P_{avg}\right)^2\right)$	minimize square of deviation
(C)	$\max\left(\sum_{i=1}^{\text{bins}} t_{\text{plug}}\right)$	move all plug in times to as late as possible
(D)	min(cost)	minimize system cost

2. The squared difference between the system load and the projected average load is minimized.

3. The plug-in time for each vehicle is delayed as long as possible based on vehicle state of charge (SOC) .

4. Total cost is minimized (described later).

Figures 11 and 12 show the optimization results for the algorithms in Table 3. Note that there is not one “best” algorithm. Each charging profile is optimal for the fitness function for which it was defined, but the notion of “best” depends on the user. For example, Profile (A) strives to minimize the absolute error between the total load and a pre-determined average. From the results shown in Figure 11, Profile (A) decreases more or less monotonically throughout the charging period. Similarly, Profile (B) minimizes the squared error between the total load and a pre-determined average. This results in a relatively flat load profile. The drawback to Algorithms (A) and (B) is that the algorithms require an estimate of an average load. This may not be feasible if the overall load profile is changing rapidly. The min-max algorithm initially presented was not pursued further, because it performed poorly when compared with the algorithms presented in Table 3. The min-max algorithm considers only the maximum load for a day, which does not capture the complete behavior of the system during off-peak hours. The other fitness functions use a collective system behavior rather than a point behavior to address the problem of load scheduling. The system cost provides for a better fitness function that is capable of giving better results along with a well justified objective for any real-world problem.

Profile (C) assigns vehicle charging as late in the charging window as possible and, therefore, skews all of the load towards 8:00 am. Obviously, this approach is not “optimal” in terms of practicality, since this causes a second (but lower) peak in earlier morning which, leads to difficult load following by generation.

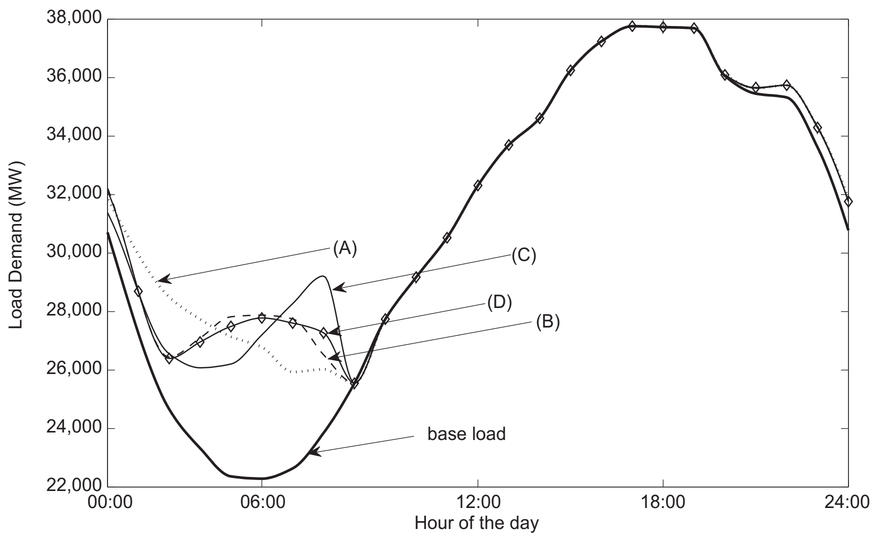

Figure 11. Load profiles for Table 3 algorithms.

One or more of these algorithms may not be considered suitable for practical implementation. Every utility or aggregator may have their own notion of an optimal practical profile. One obvious approach is to optimize vehicle charging based on cost, but cost is

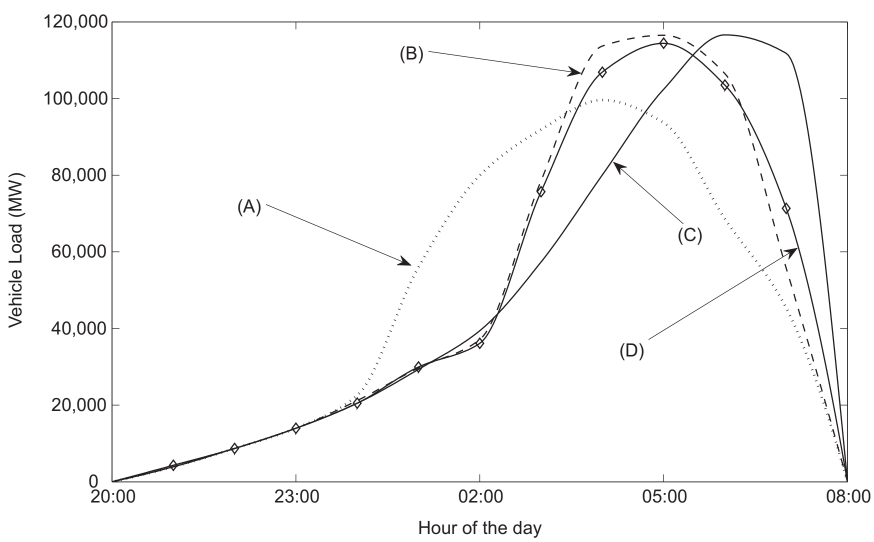

Figure 12. Optimized charging profiles for Table 3 algorithms.

not necessarily a straightforward function. The cost to the customer is not necessarily the cost to the utility. Customers typically want to minimize their cost of electricity, whereas utilities want to maximize their profits.

To better understand the impact of vehicle charging loads on utility cost, the set of incremental costs shown in Figure 13 are applied to the load profile. These incremental costs have been scaled and adapted from [12]. The horizontal lines indicate the incremental costs that are superimposed on the load profiles in Figure 14. The optimization algorithm is then used to identify a vehicle charging profile that minimizes the overall cost of generation during the charging window. These results are indicated as Profile (4) in Figures 11 and 12. This approach moves the vehicle charging away from the peak load, but since the incremental cost is constant between 24,000 and 26,000 MWh, there is not a significant shifting of load during the valley period. The minimum cost profile is very similar to Profile (B), which is the minimum squared error. Therefore, Algorithm (B) could be used as a computationally efficient approximation for finding the minimum cost. Algorithm (D) is the most computationally-intensive method, because it requires that the cost be evaluated

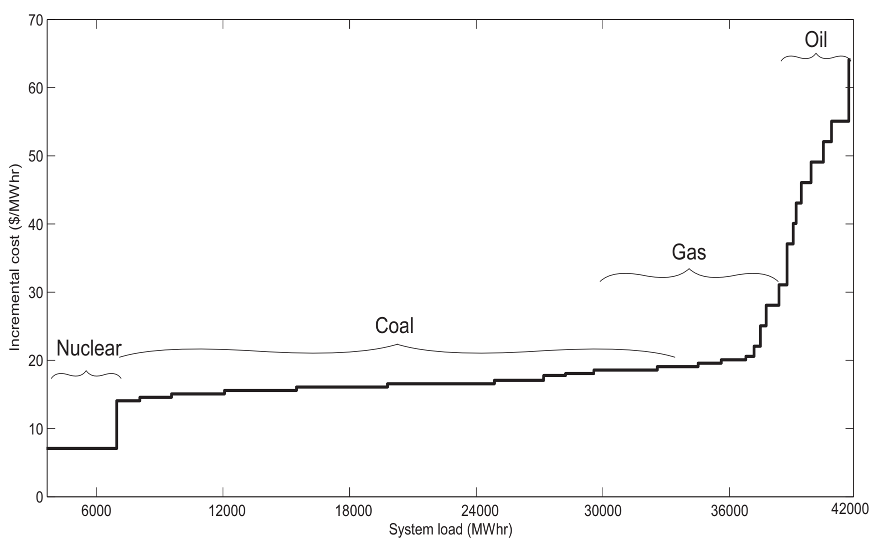

Figure 13. Incremental costs.

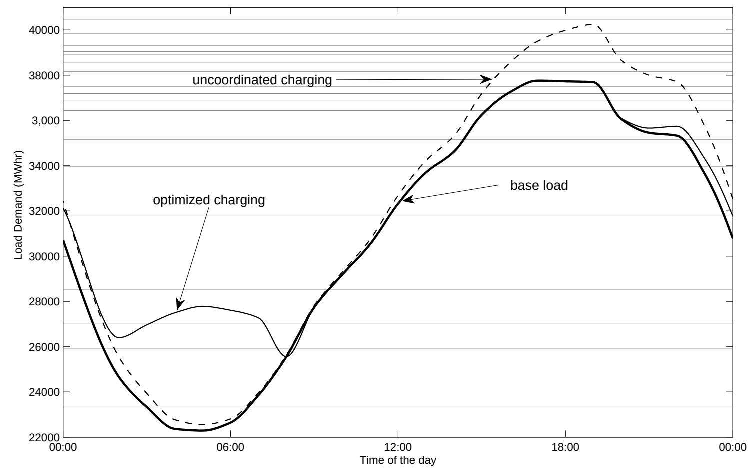

Figure 14. Load demand superimposed on incremental cost.

for every chromosome at every iteration. The other fitness functions only require the actual power resulting from the chromosome. Table 4 summarizes the costs of the different algorithms with respect to the base load over the eight-hour charging period.

5. TIME OF USE RATES

The load shapes presented in the preceding section were developed to minimize the impact on the utility system. There is, however, currently little or no incentive for vehicle owners to allow the utility to control their charging times to produce these optimized load

Table 4. Costs of the algorithms from Table 3

Algorithm	Cost ($)
(A)	716,410
(B)	708,071
(C)	714,910
(D)	707,962

shapes, since they are not typically charged real-time prices that correspond to the actual load. In fact, the most probable situation is one in which the owners start charging their vehicles immediately upon returning home (which results in the uncoordinated charging profile of Figure 4). Many utilities have considered implementing a tiered time of use (TOU) structure to encourage owners to defer charging to non-peak times.

Utilities across the U.S. have adopted different time of use rates to incentivize customers to better manage their energy use. Most TOU rates are two (on-peak and off-peak) or three different rates (on-peak, part-peak, off-peak). Figure 15 shows the TOU rates for several U.S. utilities, and Table 15 gives representative rates [13–19].

To compare the impact of the various charging profiles on the cost to the customer, these cost structures are applied to the load profiles of the various charging algorithms and plotted in Figure 16. These rate structures are used for example purposes only; it should be noted that the actual cost per kilowatt hour for each utility may be different than the rates given in Table 15. An analysis of Figure 16 yields several trends. Utility B is the most expensive, since their on-peak rates are the longest. Utility D has the shortest on-peak hours, but is more expensive than Utility C and Utility E, because the on-peak rates extend later into the evening and pick up the large load. Utility G is also relatively expensive, because their off-peak rates are the shortest and their partial peak hours start at 07:00 hours.

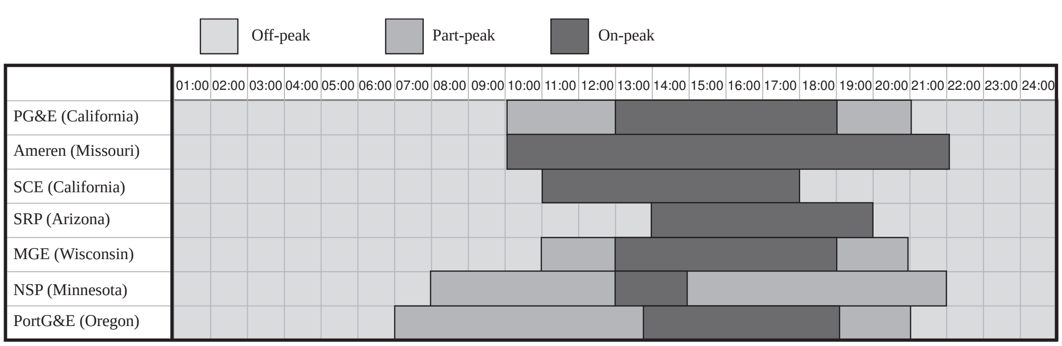

Figure 15. Tiered time of use (TOU) structures for several U.S. utilities.

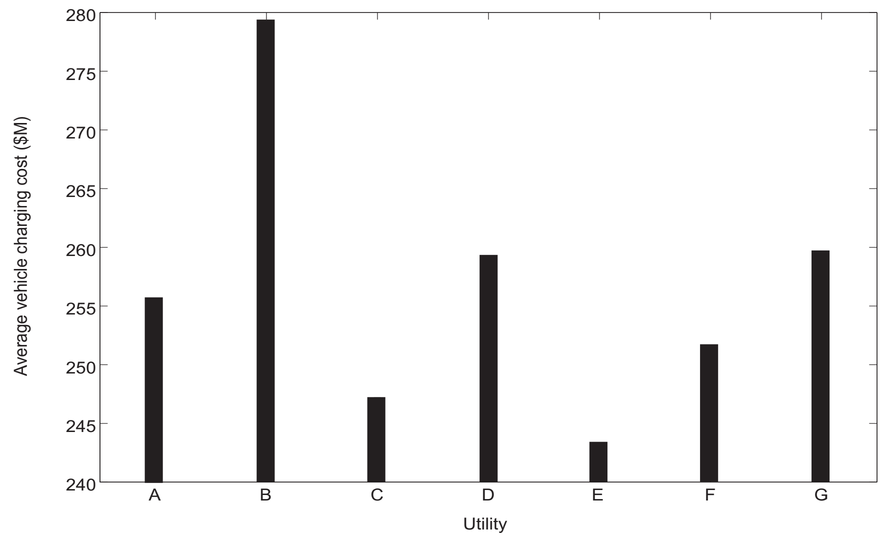

Figure 16. Customer costs associated with load profiles.

6. ALGORITHM INTEGRITY

To test the integrity of the optimization algorithm, several benchmarks were analyzed. Since at the heart of the algorithm is a random assignment of vehicles, a metric was needed to measure the possible deviation in results and their impact on the load profiles. To measure the statistical deviation, the algorithm was run 50 times using Algorithm (C). The cumulative results are shown in Figure 17. The horizontal line represents the mean value of the data. The rectangles (when included) give the 25% and 75% percentiles with the upper and lower bars giving the maximum and minimum values. The stars ($*$) indicate statistical outliers. Note that at the beginning of the charging interval, the load values across all runs are tightly coupled. This is due to lack of flexibility in scheduling the long charge/low state-of-charge vehicles. However, as the charging window progresses, there is more possibilities for scheduling the one- and two-hour charging vehicles; thus, there is greater deviation. However, even considering the spread of values obtained, the load shape still remains relatively consistent; thus, the algorithm produces statistically similar results from run to run. This validates the optimization approach and algorithm.

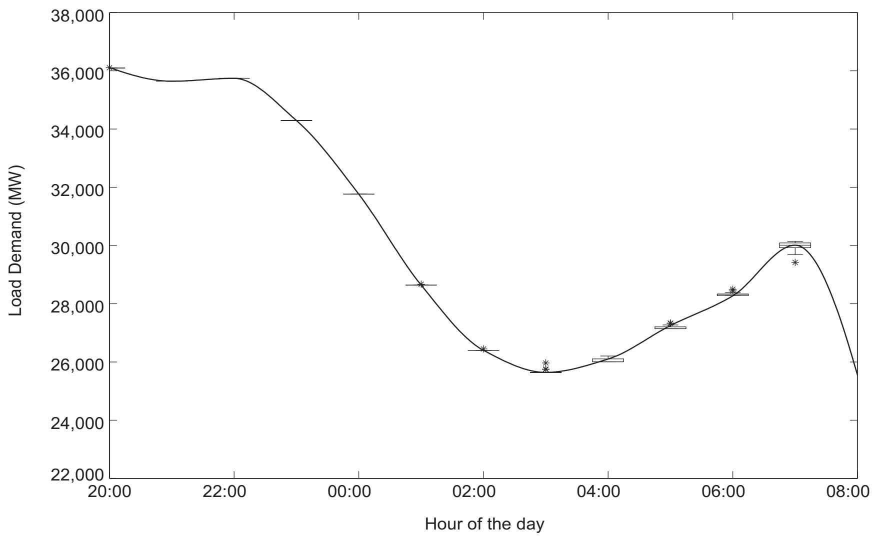

Figure 17. Data deviation in Algorithm (C).

Another method of testing algorithm integrity is to apply it to other load profiles. Figures 18 and 19 are two seasonal profiles adapted from ERCOT (Electric Reliability Council of Texas). Figure 18 represents a typical work day in January, and Figure 19 represents a typical work day in June. The January profile is similar to the California ISO (CAISO) load profile, but with a higher load factor (the ratio of the average load to the maximum load). The charging profiles are qualitatively similar to those obtained in Figure 11. As with the CAISO load profile, Algorithm (C) (scheduling charging as late as possible in the charging window) gives poor results and, in this case, actually causes an early morning peak. Algorithm (D) (minimum cost) once again provides the best outcome, but still results in a second, late evening peak. One possible method of improving the load characteristics is to allow charging to start earlier (at 17:00 instead of 20:00, as is currently used). The ERCOT June profile is quite interesting. The demand factor is very high; therefore, there is little valley to "fill", nor is the cost differential between minimum and maximum significant. The minimum cost algorithm still provides the best results, but the resulting charging load is still unwieldy. In

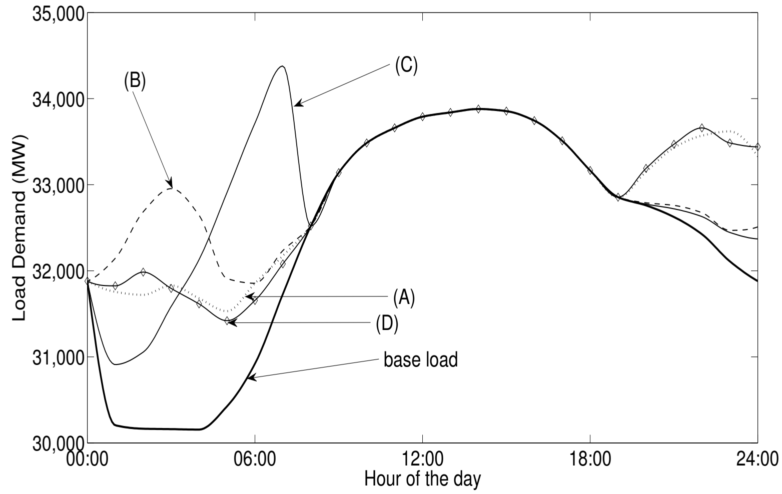

Figure 18. ERCOT January profile.

this case, a different charging policy would serve the ERCOT region better, such as providing charging access during the day at places of employment, shopping centers, parking garages, *etc*.

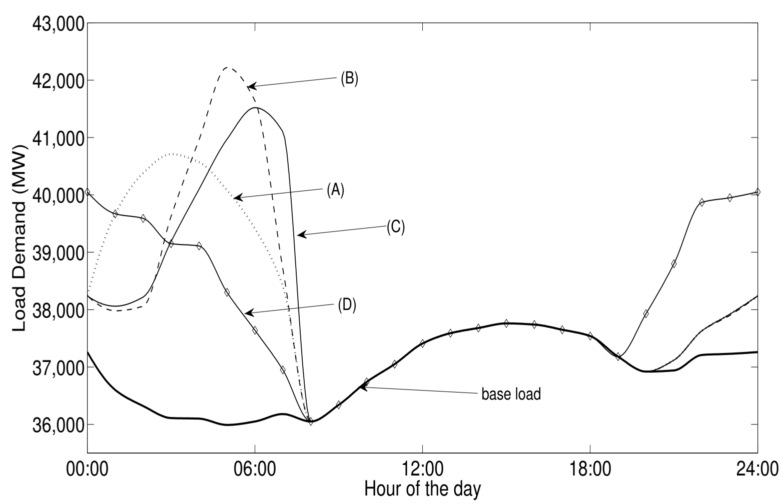

Figure 19. ERCOT June profile.

7. TEST SYSTEM FORMULATION AND ALGORITHM APPLICATION

The coordination scheme is applied to a test system, and the results are thus quantified by means of load profile and voltage variations of the system.

7.1. System Specification. A three-phase balanced system, modified from the Institute of Electrical and Electronics Engineers (IEEE) 34 bus system [20], was formulated to test the impact of the algorithm (Figure 20). A daily load profile for the test system and also for the individual nodes was made to match the initial load profile studied. The approximate number of houses at each node was calculated assuming 4 kW of maximum load per house. Considering one electric vehicle per household as a 100% penetration on the system for the worst case scenario, the number of vehicles equals the number of houses at each node.

7.2. Vehicle Load on the Test System. A total of 147 houses, and, thus, vehicles, were selected for the test system. A set of vehicles was randomly selected from the NHTS dataset, which were randomly assigned to 11 nodes. Only eleven nodes of the test system had loads. The total number of houses on the system is 147. Since 100% penetration of vehicles is considered, each house is assigned one electric vehicle randomly from a pool of

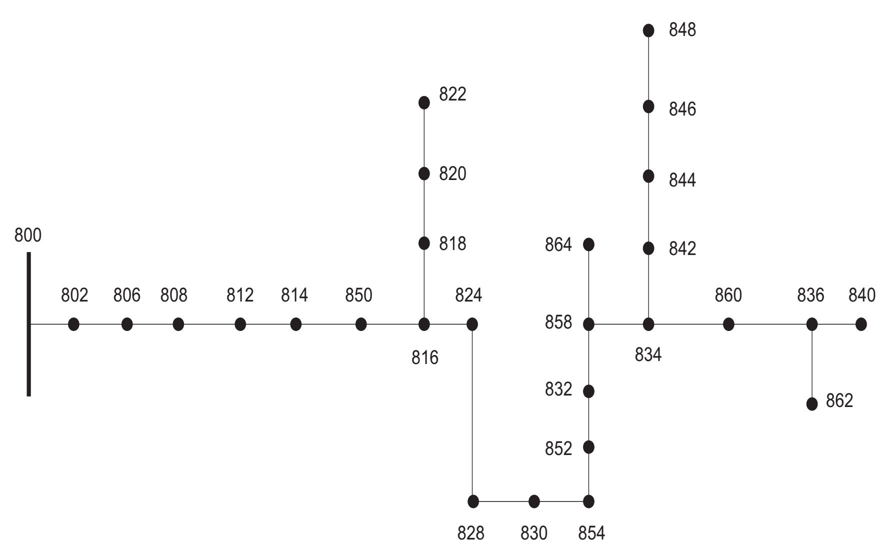

Figure 20. System specification.

vehicles selected from the NHTS database. The vehicles are distributed in proportion to the load at each node. The vehicles were selected in the same ratio as in the NHTS database with regards to the time required for charging. This selection is attributed to the general driving patterns from the NHTS database. Once assigned to a node, it is assumed that the vehicle load would be observed at the same node, which is representative of the ownership of a vehicle and Type I charging at home.

7.3. Load Profiles. Having obtained the vehicle characteristics at each node, three other profiles were obtained, namely:

- Load under uncoordinated vehicle connection: The vehicles are connected whenever the driver arrives home. Charging is completely under the control of the customer.
- Load under global coordinated vehicle connection: The vehicles are assigned charging times between 20:00 and 08:00, depending on the SOC of the battery. The control is at the substation (Node 800), which coordinates all the 147 vehicles together.
- Load under local coordinated vehicle connection: This is very similar to the global scheme with the exception that each node uses its respective load profile to coordinate the vehicles connected to that node.

The coordination schemes were run 50 times each, in order to obtain a range of load profiles.

7.4. Fitness Function. Minimizing the total sum of the deviation of instantaneous load from the average residential load was used as the optimization objective. It was found that this average value when varied over a range gives slight changes in the profile. The P_{avg} of the total load profile (residential + vehicle) gives better results than the P_{avg} of the residential load profile alone. This signifies the importance of the prediction of the vehicle load in the efficacy of the algorithm.

7.5. Results for the Test System.

- The load (Figure 21) and voltage profiles (Figure 22) show significant improvement from the uncoordinated profiles. The high voltage in the uncoordinated case during hours 01:00–08:00 is due to fewer loads on the system. The global and local load profiles give similar load profiles. These profiles are similar for all nodes in the system.

- In addition to differences in load, the impact on feeder voltage is also an important consideration. It can be observed in Figure 23 that uncoordinated charging leads to large deviations in voltages, but global and local coordination results in far less deviation in voltage.

- The analysis of variance (ANOVA) on the deviation of the daily voltage shows that the coordinated cases have a total deviation much lower than the deviation obtained for the uncoordinated case and are, thus, a better choice of coordination scheme. Figure 24 shows the mean deviation of daily voltage in case the coordinated load is less than that for the residential and the uncoordinated load profile cases. The voltage variation

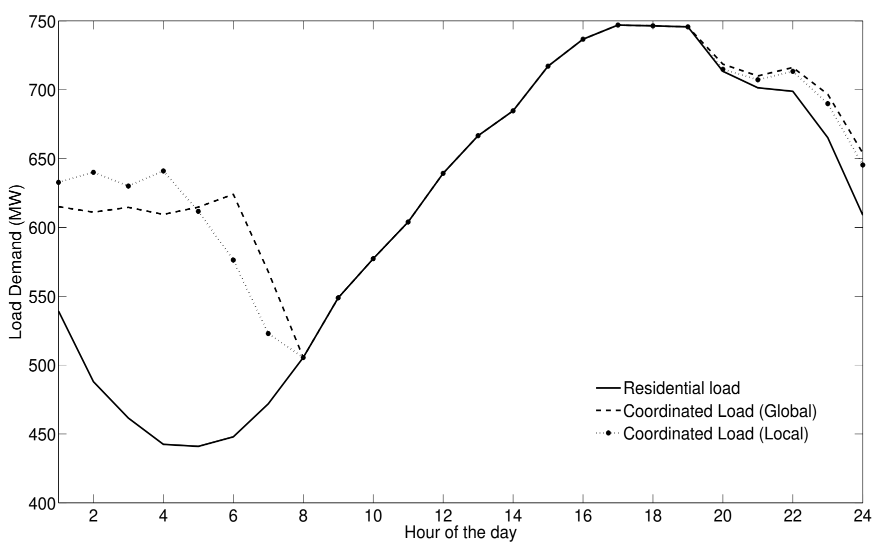

Figure 21. Load with coordinated charging.

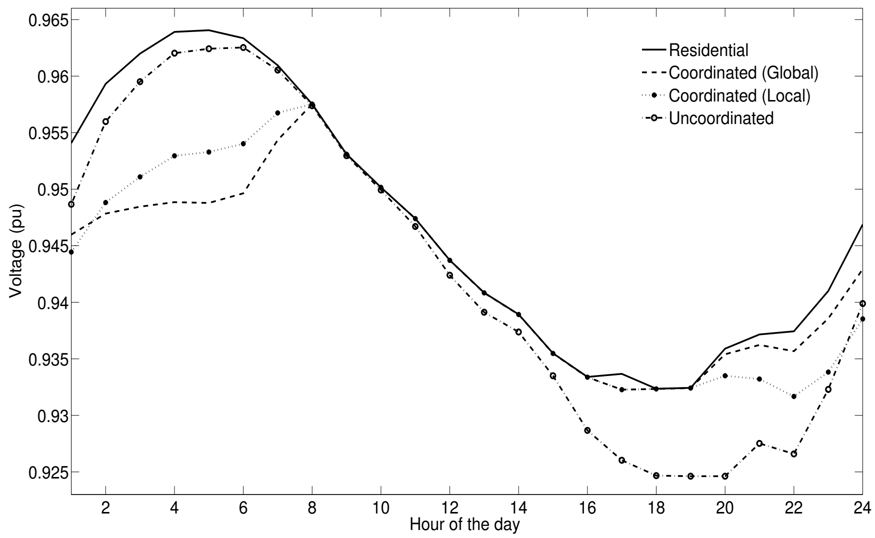

Figure 22. Voltage profiles for Node 840 under coordinated and uncoordinated charging.

at each node for the coordination schemes (100 runs) is also shown in the box plot in Figure 25. The nodes closer to the substation (Node 800) show far less variation than the nodes further along the feeder.

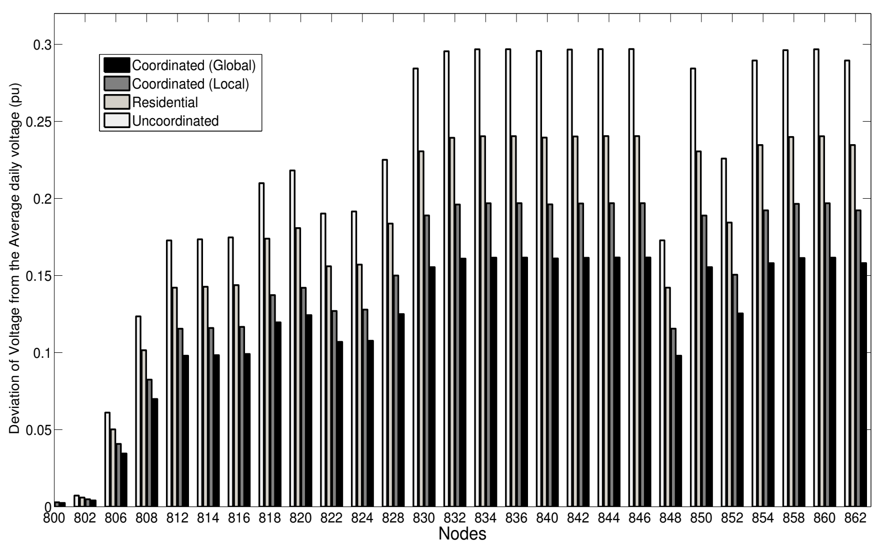

Figure 23. Deviation of voltage from average voltage.

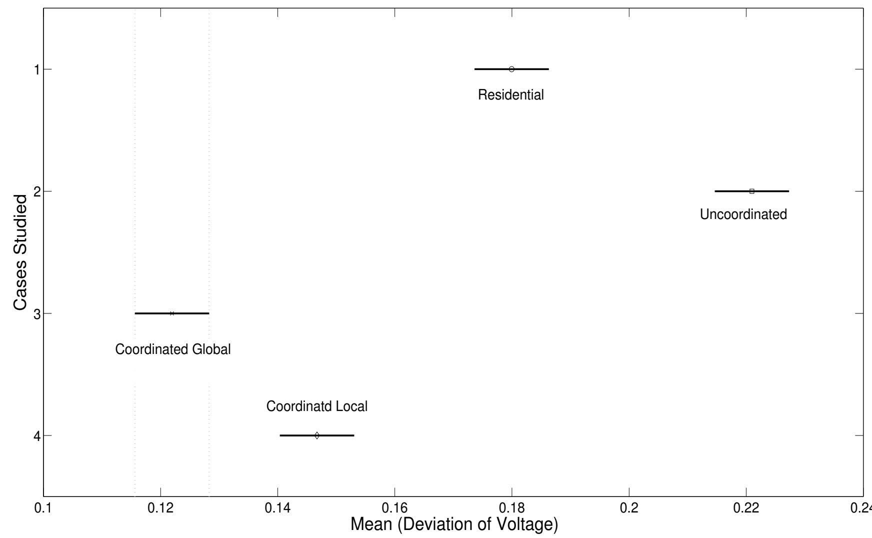

Figure 24. ANOVA results on the deviation of voltage from average daily voltage for the system.

- Given that voltages were obtained from 50 runs each of global and local coordination schemes, a probability density function (pdf) of the voltage variation along with a box plot was obtained for each node. The pdf at each node is similar to that obtained for node 840 (Figure 26). This gives us a range within which voltage at that node will vary given the vehicle set connected according to either the local or global coordination schemes. The x-axis gives the node voltage and the y-axis indicates the percentage of time that particular voltage was obtained.

The improvement and minimal deviation in voltage is the motivation behind the application of the algorithm for vehicle connection.

8. GLOBAL VERSUS LOCAL COORDINATION

The global and local schemes differ in decision-making policies with regards to responsibility and authority. The global scheme works with a central authority that makes the decision for the system, given the system condition. The local scheduling scheme provides greater autonomy to the nodes to handle their individual loads, hence a decentralized

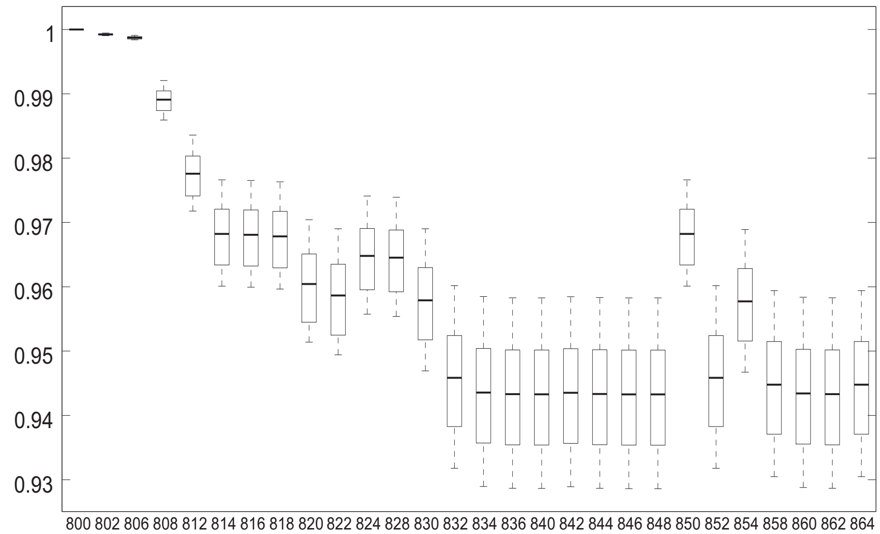

Figure 25. Box plot with the maximum, minimum and mean voltage at each node for 100 coordination cases.

responsibility structure and a probable less overhead on the central unit. The idea behind global optimization is to use the complete system information, while the local scheme uses the local load profiles and information specific to the respective nodes. The lack of system information might lead to erroneous results in case of faults or unforeseen load deviations that might change the shape of the local load profiles, which are the basis of the proposed

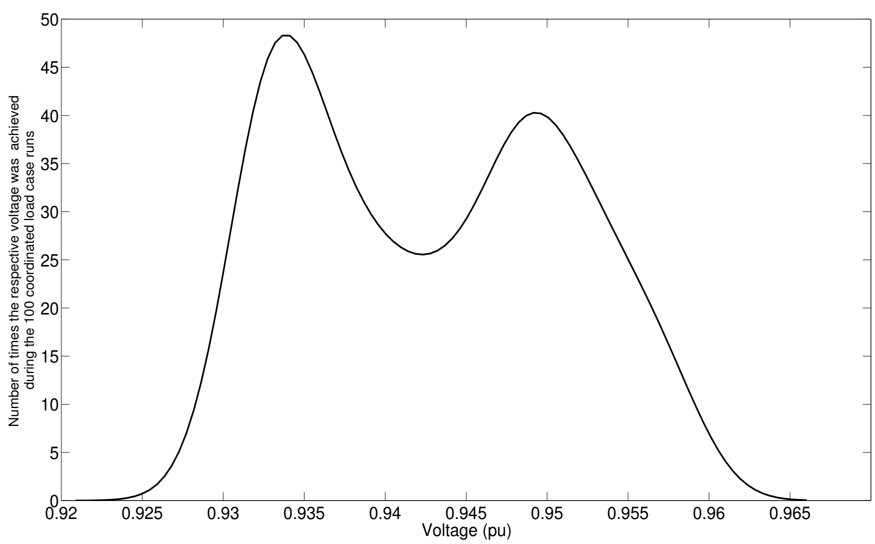

Figure 26. Probability density function of coordinated voltage on Node 840.

optimization schemes. The global scheme might turn out to be more resilient in such situations. Communication is much higher in the case of a global scheme than in that of a local scheme. Each node sends a 'tuple' of information to the central unit, which is then processed at the central unit, and the resulting control signals are sent back to the nodes for optimal scheduling. The local scheme, on the other hand, makes decisions using the local information, thus reducing the communication overhead. Here, the increased cost of communication in the case of the global scheme would have to be compared with that of the installation cost of the smart control capability at each node in the case of the local scheme. Secure transfer of information is also of crucial importance in either scheme, which would incur extra costs.

Given the pros and cons of either scheme, different structural and functional decision policies can be proposed:

- A hybrid, two-tiered structure can be implemented, where the authority and the responsibilities can be shared at the global and local levels. Probably, a local optimal scenario can be generated and sent to the central unit, which can then finally approve the schedule in view of the system condition. In case of a communication break between any node and the central unit, the local scheme can be implemented at the node.

- The local structure proposed in the paper provides complete autonomy to the nodes in a complete non-cooperative environment. A cooperative scheme can be discussed wherein the neighboring nodes share local information and cooperatively decide on their scheduling schemes. This would be classified as a cooperative decentralized scheme.

- A distributed scheme can also be implemented, where the central authority designates the responsibility of scheduling to the nodes. This can be done in a cooperative or non-cooperative manner at the nodes. A cooperative dynamic structure might be the best fit in a real-time scenario.

The above discussion is focused on static scheduling schemes. Dynamic scheduling or real-time scheduling would be the next step in this direction, due to the additional complexities of individual driving patterns.

9. CONCLUSIONS

This paper describes an aggregation method that can be used for scheduling plug-in vehicles for charging. A series of fitness functions are proposed and tested to illustrate the effect of different charging schemes on the total load as a function of charging load. Time-of-use rates are also analyzed to indicate which scenarios lead to the least customer and utility cost. Better voltage profiles and lower voltage deviations were obtained for the test system, followed by ANOVA analysis, showing the effectiveness of the coordination scheme. Future work will consider different charging policies, different rate structures and load demand profiles.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the financial support of the National Science Foundation under projects EFRI-0835995 and ECCS-1068996.

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II. COST-CONSTRAINED DYNAMIC OPTIMAL ELECTRIC VEHICLE CHARGING

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ABSTRACT

Electric vehicles are an integral component of an environmentally sustainable and resilient infrastructure. Successful penetration of electric vehicles requires close coupling between the customers and load serving entities, adaptive energy markets and technological advancements. In this paper, distribution line over-loading due to vehicle charging has been mitigated using both day-ahead (static) and real-time (dynamic) frameworks, using continuous and discrete charging rates. The proposed solution focuses on valley filling (system perspective) and charging cost reduction (customer perspective). The real-time solution was achieved using a moving horizon optimization technique. In addition to providing charging coordination, the impacts of two different pricing structures were analyzed to ascertain the customer's individual cost optima with respect to the system optima. The results presented strongly indicate that a global pricing structure will not be optimal for all consumers due to their diverse driving habits.

Keywords: electric vehicles, demand-response, moving horizon optimization, energy management

1. INTRODUCTION

Increasingly stringent clean air standards and fuel price volatility has driven expanded interest in transportation electrification [1] [2]. Successful electric vehicles (EV) deployment depends on various technological, social, and economic factors on both the demand and the supply side. Chief among these are well designed financial incentives, utility pricing programs, demand-response pilots, and research and development in batteries, fuel cells, and vehicle systems. Battery cost has significantly decreased over the past decade [3], consequently reducing the cost difference between conventional internal combustion engine (ICE) vehicles and the electric vehicles.

Plug-in electric vehicles (PEVs) have several attractive features including a lower carbon footprint, reduced dependence on oil, and an ability to provide ancillary services (e.g. frequency regulation, voltage support) through vehicle-to-grid (V2G) [4][5]. As aggregated energy storage, they have the potential to support intermittent, distributed renewable energy generation (DREG) [6]. Also, at the end of transportation lifetime, batteries unfit for use in the vehicles can be repurposed for grid support as storage devices [7]. Despite their advantages, there are several possible socio-technical barriers to the commercial success of EVs including [8]:

- the high cost of EVs due to expensive battery packs,
- the limited availability of fast charging infrastructure, and
- range anxiety due to battery size.

Furthermore, the high penetration of PEVs will have a significant impact on the electric grid. Uncoordinated PEV charging can cause an increase in peak-time demand, stress on system components, and hasten the need for replacement and reinforcement of the existing aging network [9]. A higher peak will require the deployment of costly peaking generators to meet the charging load. This can also lead to over-heating of system components such as distribution lines and transformers, resulting in reduced life expectancy. Uncoordinated charging may also cause congestion on the network, thus affecting the quality and reliability of the power supplied [10]-[11]. For these reasons, it is imperative to provide incentives to vehicle owners to participate in scheduled (or 'coordinated') charging to benefit the system performance, but without adversely impacting PEV owner willingness and satisfaction.

We propose an approach for the optimal scheduling of electric vehicles that improves the system load factor while simultaneously maximizing customer satisfaction by minimizing the electricity costs required for charging. This approach accomplishes charging load shaping through implementation of voluntary, economic-based demand response (DR). This mixed-objective optimization problem is formulated in day-ahead and real-time scenarios as a constrained quadratic optimization problem. The main contribution of this paper lies in coupling customer and grid based objectives in real-time under different pricing structures and system capacity constraints. The results are validated using actual driving behavior from the National Household Travel Survey (NHTS) [12], thereby considering practical aspects such as variation in time of arrival, time of departure, and energy needs of a diverse population. The specific contributions of this paper include:

- Introducing a mixed-objective formulation that simultaneously addresses customer charging cost and valley filling to address grid-operator and customer requirements jointly,

- Incorporating discrete and continuous variables to describe intermittent PEV charging,

- Introducing a fast responding and scalable real-time algorithm based on a moving-horizon optimization for vehicle scheduling along-with static day-ahead scheduling for performance evaluation, and

- Using fixed and time-of-use (TOU) pricing schemes to identify the most suitable rate structure for each customer.

Treating PEVs as controllable loads in DR applications for transactive energy markets [13]-[14], or for improvement in network health, including thermal loading of network components, reduction in feeder losses, voltage deviations, congestion, or load factor improvement has been previously proposed [15]-[16]. We build on these earlier works by introducing a mixed-objective formulation and intermittent PEV charging to provide a more flexible approach for optimal scheduling. We then validate our proposed method using a large database of actual driving behaviors to identify the best rate structures for pricing PEV charging usage.

2. PROBLEM DEFINITION

The proposed methodology provides an optimal charging schedule for each vehicle on the network for residential-based charging. While inter-trip charging at the workplace may be available to some PEV owners, this is not a widespread trend. Therefore, it is assumed that the majority of vehicles will be charged at home. A central control unit (CCU) collects the 'vehicle state information' (VSI) of all vehicles. The VSI-tuple for each vehicle i contains $\langle t_{i,arr}, t_{i,dep}, SOC_i \rangle$ that correspond to arrival time, expected departure time, and the SOC of the battery on arrival, respectively. It is assumed that the vehicle has the capability to determine the SOC of its battery. The time window between arrival and departure times is t_{avail} and is the period in which the battery is available for charging. The controller also has prior information about each vehicle's battery capacity ($B_{i,cap}$), maximum (P_{max}) and minimum (P_{min}) charger limits, charging efficiency (η) and power factor (pf). This information can be collected at the time of purchase or program enrollment and stored by the CCU for future use. After finding an optimal charging scheme Ω, as per the objectives and constraints, the charge schedule $\{\Omega_i : i \in \{1, 2, ..., nVeh\}, \forall t \in t_{avail}\}$ is sent from the controller to each vehicle (Fig. 1).

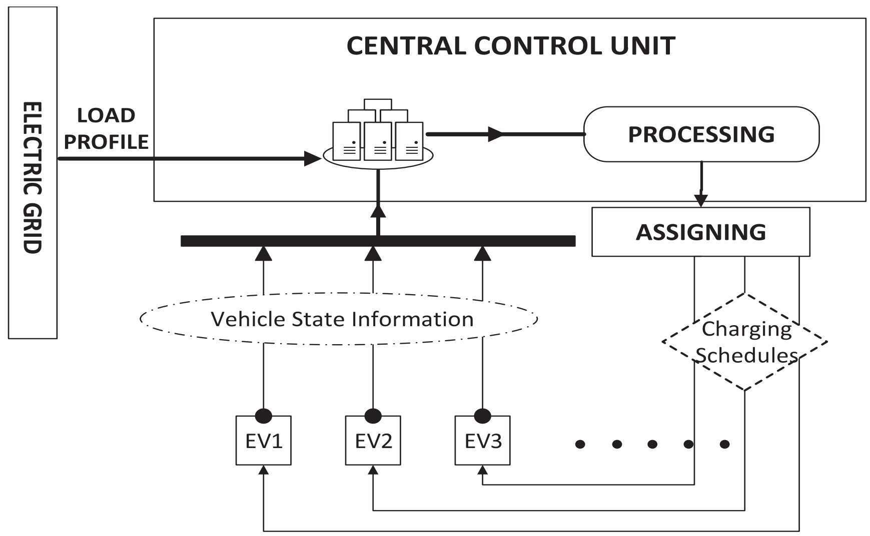

Figure 1. Centralized control scheme for static charging algorithms.

The charging rate of the battery is considered either continuous or discrete. A continuous charging rate may vary anywhere between zero and maximum limit of the charger. A discrete (on/off) rate, on the other hand, refers to a scheme in which the charging occurs at either full power or zero. Most of the literature promotes using a continuous variable even though it may not be easily applicable under present technological capabilities [16]. Both discrete and continuous charging variables are discussed in this paper, in linear and quadratic formulations respectively.

Coordinated charging approaches can be categorized into two categories: centralized and decentralized. In centralized coordination techniques, an aggregator-like entity is responsible for sending control signals to the consumers. Thus, the information of all vehicles is centrally available. A decentralized scheme uses distributed EV-level information to devise optimal charging plans. Although decentralized or distributed techniques are attractive choices for large networks, centralized schemes require less sophisticated control architecture and can be implemented with ease using current technological capabilities. Despite the cost of the communication overhead, centralized controls are economically feasible for distribution networks and microgrids and can provide maximum coordination potential between the EV and the grid. For these reasons, a centralized coordination algorithm is proposed in this paper.

2.1. Static Charging Scheme (SCS). In a static day-ahead scenario, the controller uses the forecasted load and the VSI to find the charging schedules for each vehicle. These schedules are then sent to the customers. Since the controller has complete knowledge of the system, this is treated as the best-case solution in this study. However, due to uncertainty, this approach suffers from the following inherent problems:

- The customer might not follow the expected driving characteristics. It is not possible to predict all trip lengths and arrival times in advance. Vehicles might arrive/depart sooner or later than specified or might travel variable distances.
- EV unavailability due to pre-determined charging schedules may adversely impact customer acceptance and comfort.
- The actual load during the day might not follow the forecasted day-ahead load-profile. Since the load profile is central to the optimization problem, this can lead to sub-optimal charging of vehicles and it lacks adaptation.

2.2. Dynamic Charging Scheme (DCS). A dynamic charging scheme is a real-time charge scheduling algorithm based on the moving horizon principle, also referred to as receding horizon control. According to the moving horizon principle, an optimal control sequence Ω_k is computed at time t_k. The first control signal is implemented, the time horizon is shifted, and a new optimization is performed at time t_{k+1} incorporating new information, thus accounting for the change in the state of the system. This results in a new control sequence Ω_{k+1}. The flowchart for implementing moving horizon for vehicle scheduling is shown in Fig.2, where k refers to the current time instant and N is the time-horizon for scheduling. On the arrival of new vehicles or change in the departure time of connected vehicles, VSI is updated. On receiving the updated information, the CCU runs the optimization under the selected policy and generates new charging schedules for connected vehicles. In essence, as one moves forward in time, the horizon is shifted, vehicle information is updated, and new schedules are generated. This method has the following application advantages:

- Customers do not need to predict or declare their information in advance.
- The controller can use the latest available system load forecast for scheduling.
- Uncertainty in driving behavior can be handled.
- The algorithm can easily adapt and scale if new vehicles are added or removed from the network or need urgent attention.

3. PROPOSED EV CHARGING POLICIES

According to the driving habits captured in the NHTS database, 66.5% of commuters drive less than 30 miles per day and 67.1% of commuters return home after 17:00 hours [12]. Moreover, the residential electric load profile is typically lower during the night, resulting in a valley. These statistics indicate the possibility of load leveling through coordinated charging during the valley hours. Based on these circumstances, the following assumptions are made:

- The residential load profile is known to the central control unit. The CCU may be implemented by a third party (e.g. aggregator or the distribution system operator (DSO)).
- A communication architecture and advanced metering infrastructure is in place for sending information and receiving control signals.
- Vehicles are charged after they arrive home after completing the day-trip. No inter-trip charging is considered.

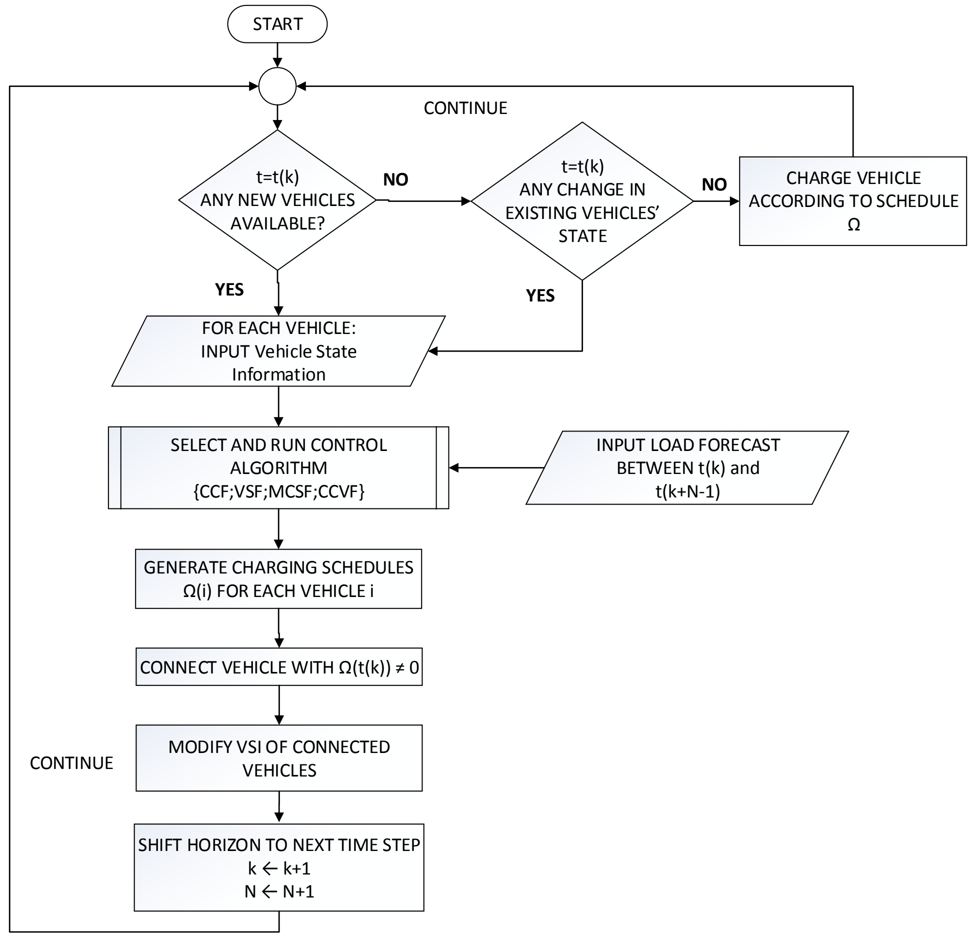

Figure 2. Moving horizon optimization process flow.

- A type-1 charger is a single-phase 120V, 12A charger with a maximum power limit of 1.44 kW [17]. A type-2 charger has a maximum power rating of 6.66 kW. Unless a vehicle specifically requires a type-2 charger, a type-1 charger is used to charge the vehicles.
- Each customer provides their VSI to the central controller.
- The charger is lossless and has unity power factor.

- Battery technology that supports intermittent charging is available. Intermittent charging is defined as one or more charge-idle periods during the entire charging window.

The optimal charging scheme for each vehicle depends on the outcome desired (customer's or utility's perspective) and different objectives may yield significantly different charging schemes. Four different possible charging policies are presented in this section.

3.1. Capacity-constrained Cost-based Customer Focus (CCF). In a customer focused approach, customer acceptance levels are instrumental to the success of the charging program. Recent pilot programs have addressed optional time-of-use pricing, critical peak pricing, real-time pricing, and tiered rates in attempts to increase consumer involvement [18]. However, relinquishing control of vehicle charge to the aggregator, cost of electricity, and impact on battery health are concerns for consumers. Battery health optimization is out of the scope of this paper, therefore precedence is given to the first two concerns by optimally charging the vehicles to minimize the total charging cost [15]. The total charging cost is defined as the sum of the product of energy demand during a time slot ($P_i^t \Delta t$) and the electricity price during that slot (R^t). In this study, a 1 hour time slot is used (i.e. $\Delta t = 1hr$). The linear programming formulation to minimize the total cost of charging the vehicles connected to the network is:

$$\min_{P_i^t} \quad f_1 = \sum_{t=1}^{t_{i,avail}} \left(\sum_{i=1}^{nVeh} P_i^t \Delta t \right) \left(R^t \right) \tag{1}$$

subject to

$$P_{min} \leq P_i^t \leq P_{max} \qquad \forall i, t \tag{2}$$

$$SoC_{i,min} \leq x_i^t \leq SoC_{i,max} \qquad \forall i, t \tag{3}$$

$$x_i^{t+1} = x_i^t + \frac{\eta_i \Delta t}{B_i} P_i^t \qquad \forall i, t \tag{4}$$

$$\sum_{t=1}^{t_{i,avail}} P_i^t \Delta t = E_{i,req} \qquad \forall i \tag{5}$$

$$\sum_{i=1}^{nVeh} P_i^t \leq \left(P_{peak} - P_{res}^t\right) \qquad \forall t \tag{6}$$

where

P_i^t: power delivered to each vehicle i at time instant t

R^t: electricity rate at time instant t

$nVeh$: total number of vehicles connected to the network

$t_{i,avail}$: time available for charging vehicle i

x_i^t: SOC of vehicle i during time instant t

B_i: Battery capacity for vehicle i

η: Charging efficiency for vehicle i

$E_{i,req}$: total energy requirement of vehicle i

P_{peak}: forecasted peak load demand

P_{res}^t: residential load demand at time t

$SoC_{i,min}$, $SoC_{i,max}$: Maximum and minimum SOC of vehicle battery, respectively

P_{max}, P_{min}: Maximum and minimum power ratings of vehicle charger, respectively

The limit on the charging power assigned to vehicle i at time instant t is given by constraint (2). Since V2G is not considered in this optimization, P_{min} is 0 and P_{max} is 1.44 kW for a type-1 home charger. A linear battery charging model for each EV i is given by (4). The SOC of the battery is constrained by (3). The total energy supplied to vehicle i during its charging window is equal to its requirement $E_{i,req}$, represented in constraint (16). Finally, (17) enforces that vehicle charging lies within system capacity limits, thus avoiding overloading condition. Equations (2)–(16) pertain to customer convenience, whereas (17) takes the distribution system capacity into consideration.

3.2. Valley-filling System Focus (VSF). In valley-filling, the charging objective is to improve the load factor by shifting peak load to times of light load. Since most vehicles are available for charging throughout the night, a fitness function is developed to promote load leveling. (7) minimizes the deviation between the instantaneous load at any time instant t and the average load during the day. This would try to schedule vehicles during the valley period and thus minimize the gap between instantaneous and average load [19]. The constraints in (8)-(9) are used in conjunction with the following fitness function via a quadratic formulation:

$$\min_{P_i^t} \quad f_2 = \sum_{t=1}^{24} \left(P^t - P_{avg}\right)^2 \tag{7}$$

where P^t is the total load of the system (with a residential load average P_{avg}) at time instant t. This includes the load of all the available vehicles and the residential load and is defined as:

$$P^t = \left(\sum_{i=1}^{nVeh} P_i^t\right) + P_{res}^t \tag{8}$$

$$P_{avg} = \frac{\sum_{t=1}^{24} P_{res}^t}{24} \tag{9}$$

It should be noted that by varying P_{avg} over time, demand profile tracking can be achieved with ease [14].

3.3. Mixed-Objective Customer-System Focus (MCSF). In this approach, the dual objectives of valley-filling and minimized customer charging cost for the customers are coupled in a quadratic multi-objective problem. The objective function for the MCSF is:

$$\min_{P_i^t} \quad f_3 = w_1\,(f_1/f_1^*) + w_2\,(f_2/f_2^*) \tag{10}$$

where w_1 and w_2 are the weights for functions f_1 (CCF) and f_2 (VSF) respectively and $w_1 + w_2 = 1$. The functions f_1 and f_2 have been normalized using their optimal values f_1^* and f_2^*, obtained individually from the CCF and VSF optimizations respectively. The mixed-objective problem also uses the set of constraints (8)-(9). The MCSF policy is a compromise between the CCF and the VSF policies. As the weights of the individual objectives change, so does the total charging cost. the total charging cost in the MCSF policy will lie between the costs obtained for the CCF and VSF schemes under both the TOU and Fixed pricing structures.

3.4. Cost-Constrained Valley-filling Focus (CCVF). In [19], the authors investigated different fitness functions using a heuristic algorithm and determined that valley filling and charging cost related fitness functions gave promising results. Based on this, the fourth problem formulation attempts the valley filling optimization using customer charging cost as a constraint. This problem design extends mutual benefits to both the DSO and the customer. The objective function used is f_2 of (7), with an additional constraint given as:

$$\sum_{t=1}^{t_{i,avail}} R^t \left(\sum_{i=1}^{nVeh} P_i^t \right) \leq C_{final} \tag{11}$$

In (11), C_{final} is the total charging cost obtained using fitness function f_1, which is then used as a constraint along with (8-9) to solve f_2.

4. TEST SYSTEM MODELING

A modified IEEE-34 bus test system shown in Fig. 3 has been used to demonstrate the results and efficacy of the proposed charging policies in both static and dynamic environments. Each phase has 147 residences with a 4kW maximum load per household, exclusive of the EV load [19]. A generic, summer day load profile obtained from a service region of Pacific Gas and Electric has been scaled to fit the system under consideration [20]. The central control unit is placed at the substation (Node 800) of the system. For illustrative purposes, a randomly chosen dataset selected from the NHTS database was assigned to the nodes of the test system in accordance with the number of houses on each node. In order to preserve the driving pattern of the NHTS database, the population in the test system was assumed to follow similar characteristics. Thus, vehicles were selected in the same ratio, in accordance with their driving distance, as they appear in the database. Vehicle arrival and departure times were obtained directly for the selected sample from the NHTS database. Accordingly, in the dynamic scheme, the vehicles were made available as and when they arrived. The battery size was selected randomly depending on the commute length (Table 2) from Table 1.

Table 1. Commercially available battery sizes [19]

	Range (miles)	All Electric Range (miles)	Battery Size (kWhr)	Equivalent Miles/kWHr
A	0-20	30	11	3.250
B	20-40	40	12	3.500
C	40-60	70	16	4.375
D	60-80	80	18	4.440
D	80-100	100	24	4.167

Table 2. Battery and commute length association [19]

Category	Commute Length (miles)	Battery Size (kWhR)
DCL20	0-20	[A, B, C, D, E]
DCL40	20-40	[B, C, D, E]
DCL60	40-60	[C, D, E]
DCL80	60-80	[D, E]
DCL100	80-100	[E]

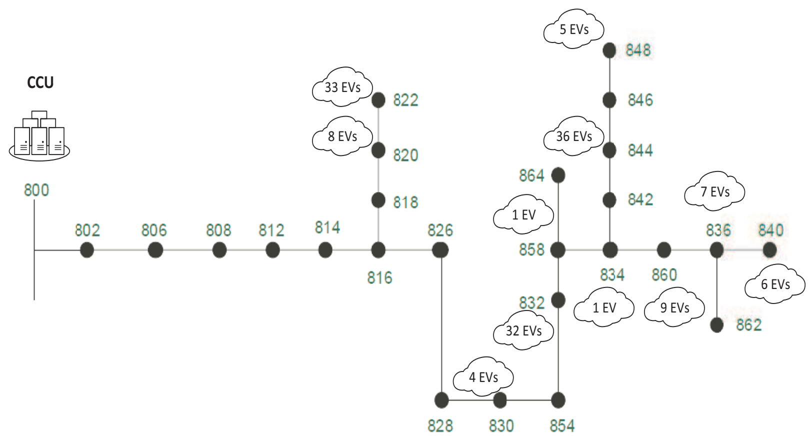

Figure 3. Test System with vehicle-node information.

5. SIMULATION RESULTS

The different charging policies described in Section 3 are illustrated using the test system in Section 4 for a typical summer load profile using both static (SCS) and dynamic charging schemes (DCS). The optimal schedules are generated by running the optimization under the policy selected and using the pricing structure of the individual vehicles. Each policy follows the same principle of moving-horizon for scheduling the vehicles in real-time. It is up-to the DSO or aggregator to choose the best policy as per their needs. The optimization software package CPLEX [21] was used to solve the linear, quadratic, and quadratic constrained formulations. Both fixed and 3-tier TOU [20] pricing structures (Table 3) have been compared. The duration of each tier for the TOU structure was obtained using a Gaussian-mixture model-based clustering technique [22]. The rates used in this paper have been derived from residential TOU data [20]. A clustering technique was used to derive on-peak, mid-peak and off-peak periods for the specific load profile used in this study. The forecasted residential load is assumed to be unaffected by the TOU structure; only the EV charging load is impacted. The same load profile has been used in both the static and dynamic schemes.

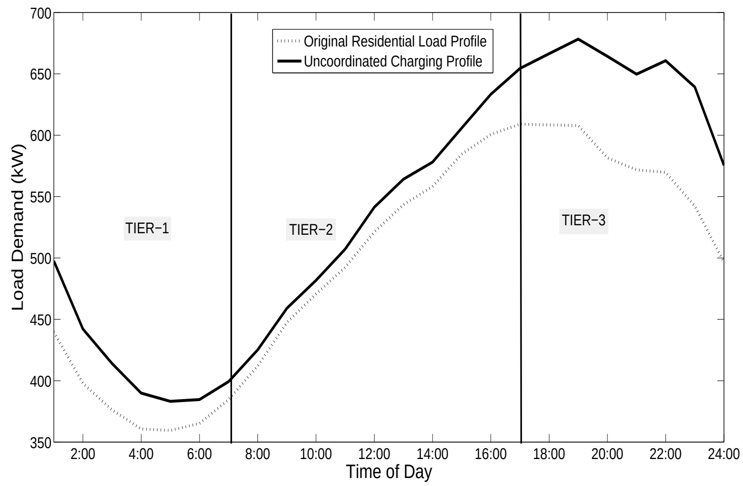

Figure 4. Uncoordinated electric vehicle load demand.

Figure 4 shows the base case ("original") residential load profile and the "uncoordinated charging" profile which corresponds to immediate charging upon return home. The uncoordinated charging trace indicates that without controlled charging, a much larger load peak may occur. For the test system, this corresponded to an 11.4% increase. Note that the valley period remains underutilized without charge coordination.

5.1. Case Study 1: CCF. In case study 1, the CCF policy (Section 3.1) is implemented in day-ahead and real-time for the two afore-mentioned pricing structures. This policy is implemented as a linear optimization problem with discrete charging variables. Fig. 5 shows that even though the system constraint on peak load is not violated, this policy results in secondary peaks during the valley. The dynamic charging scheme (DCS) results

Table 3. Rate structures [20]

Rate Type	Energy Charge (¢/kWh)		
Fixed	16.803		
TOU 3-tier	13.101	20.779	32.306
	1:00-8:00	9:00-16:00	17:00-24:00

in lower peaks when compared to the static charge scheme (SCS). Both fixed and TOU rates resulted in intermittent charge assignments within the charging window. It was also observed that for the majority of vehicles (but not all), the TOU rates resulted in a lower charging cost and the total optimal cost was lower for TOU structure. The charging costs are summarized in Fig. 9 as CCF (Fixed/TOU).

Since some customers were actually subjected to higher costs with a TOU structure, these customers (only) were then retroactively assigned to a fixed rate structure. On selectively assigning fixed rates to these customers, a lower system optimal was achieved. The charging costs are summarized in Fig. 9 as CCF (Combined).

In order to determine the impact of a combination of different rate structures on the sample population, we vary the customer enrollment in the rate plans randomly. This random sampling is expected to remove any bias due to selective application of rate structures to specific customers. By varying the ratio of the two rate structures within the population using a uniform distribution, a system optimal cost was achieved that remained between the individual optima obtained for the TOU and the fixed rates. This range within which the total charging cost of the population varies is referred as the maximum (cost) limit and

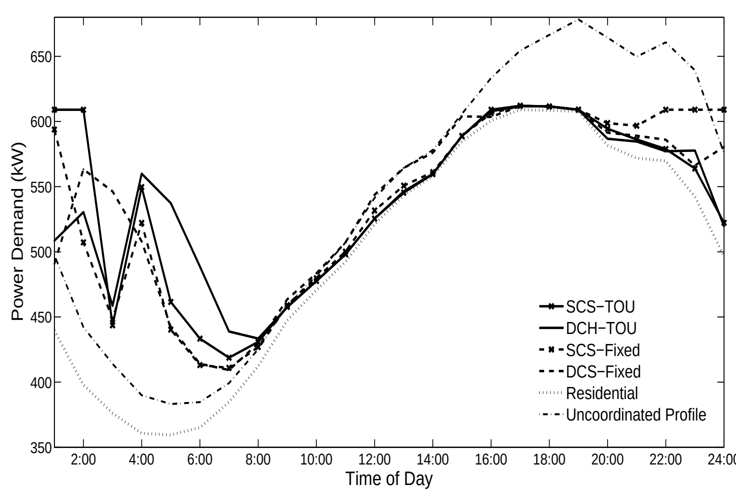

Figure 5. Coordinated load profile for Cost-based Customer Focus.

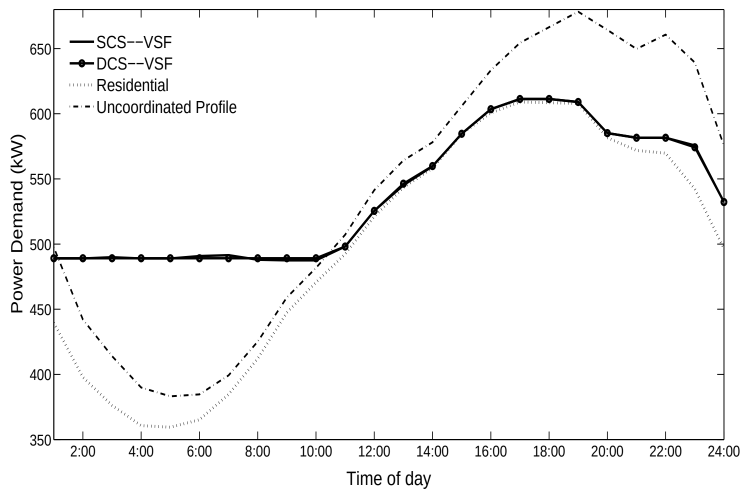

Figure 6. Coordinated load profile for Valley-filling System Focus (QP).

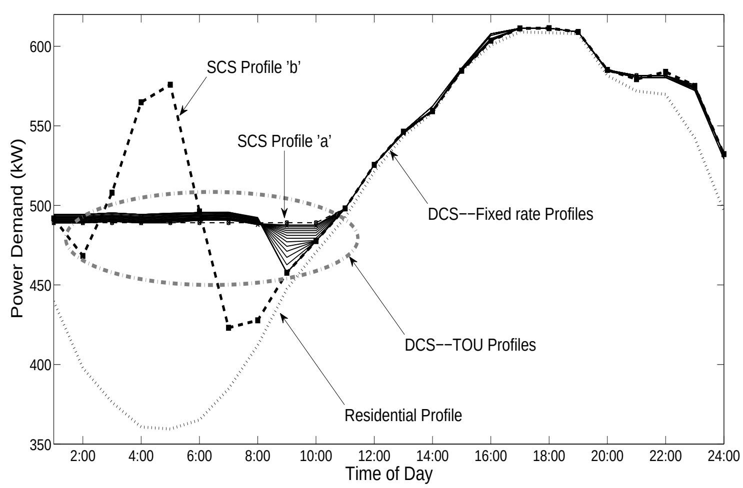

Figure 7. Coordinated load profile for Multi-objective Customer System Focus.

the minimum (cost) limit in Fig. 9. Intuitively, it means that the total charging cost for the sample population remains within these maximum and minimum limits, obtained using random sampling. The dynamic charging scheme resulted in the same optimal cost as did the static charging scheme for both rate structures.

5.2. Case Study 2: VSF. Due to the secondary peaks observed in case study 1, it can be reasonably concluded that minimizing charging cost alone is not necessarily optimal for the system. To counteract the secondary peak, a valley-filling optimization (VSF) is examined. Figure 6 shows the results of the VSF policy. The dynamic charge scheduling profile follows the static solution closely and results in load leveling. The cost of charging using the optimal charging schedules were generally the same for DCS and SCS schemes when fixed rate was applied; the SCS resulted in lower costs than DCS when TOU rates were applied (Fig. 9). This difference could be attributed to limited system-state information in the case of DCS. On an individual basis, only a small number of customers benefited from the fixed rate structure. Once these customers were identified, they were explicitly assigned to a fixed pricing schedule and the remaining customers were on TOU rates. Therefore all customers were scheduled using the rate structure that benefited them the most. Therefore, similar to case study 1 (except for the few Fixed rate vehicles), the TOU rates were found to be more economical than the fixed rates. The charging variable in the quadratic formulation is continuous in nature.

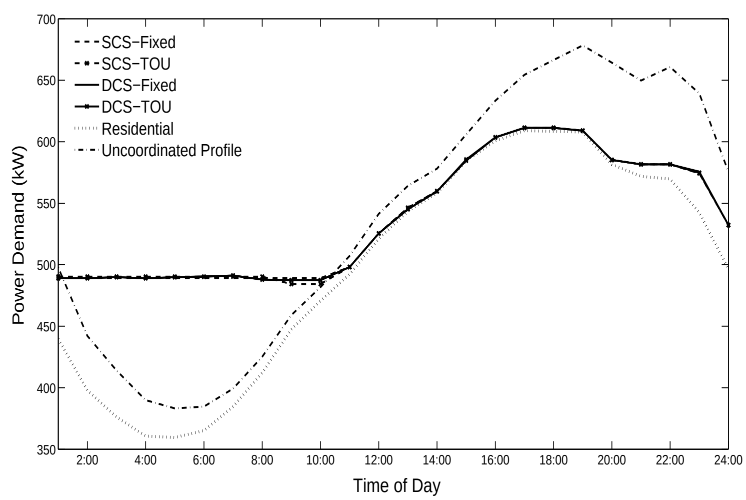

Figure 8. Coordinated load profile for Cost-Constrained Valley Filling (CCVF).

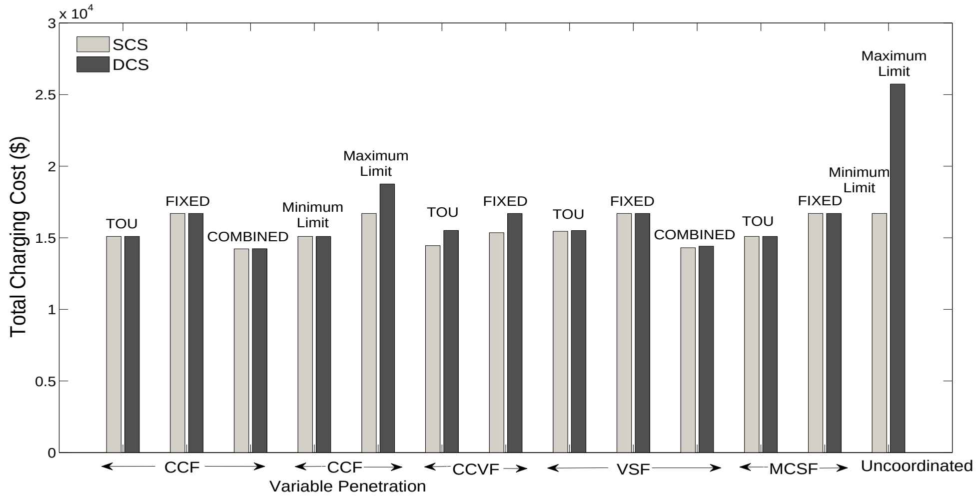

Figure 9. Total charging cost under different policies.

5.3. Case Study 3: MCSF. The CCF considers only the customer perspective (charging cost) under system capacity constraint, whereas VSF considers only the utility perspective (valley-filling). In the mixed-objective customer-system approach, both objectives are considered simultaneously as a weighted mixed-objective quadratic problem. The weights of each objective function were varied with a step size of ±0.05, giving twenty-one solutions. In the static case (SCS), these solutions followed one of two schemes with only slight variation. These charging schemes are shown in Fig. 7 as profiles ‘a’ or ‘b’. These solutions remain bounded with slight variation between 7:00 and 11:00 hours for the DCS. The total charging cost varied between the maximum and minimum costs obtained in cases 1 and 2 (shown as CCF and VSF blocks in Fig. 9). Varying the number of customers on fixed rate and time-of-use schedules did not result in a better optimal scheduling.

5.4. Case Study 4: CCVF. In this case, the objective is to directly minimize charging costs while valley filling. Fig. 8 shows the results of applying SCS and DCS to the constrained quadratic optimization problem with a continuous charging variable. The final load profile is similar for different rate structures and schemes. On varying the number of customers under the two rate structures, we obtain Figure 10, with only slight variation in the load profile between 8:00 and 11:00 hours. This indicates that mutually beneficial optimal solutions for both the utility and customer can be obtained using this policy.

5.5. Analysis and Discussion. In the case studies presented above, it can be observed that there is a small increase in load during the peak hours. This is due to vehicles that need to be connected during those hours as per their driving profile. In most cases and especially when implementing DCS, intermittent charging schedules are obtained for most vehicles (Fig. 11). This paradigm, with either discrete or continuous charging variables, can be attractive in a number of ways:

1. In emergency situations where some vehicles needs urgent attention, other vehicles can stop charging for short periods.

2. Market-dynamics and demand-response through V2G services can be rendered via discontinuous charging.

3. Vehicles can utilize the most economical hours for charging.

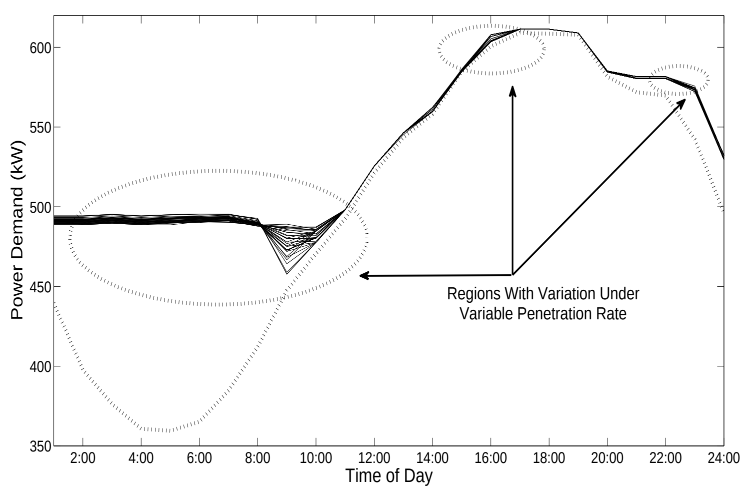

Figure 10. Coordinated load profile for variable rate penetration in CCVF.

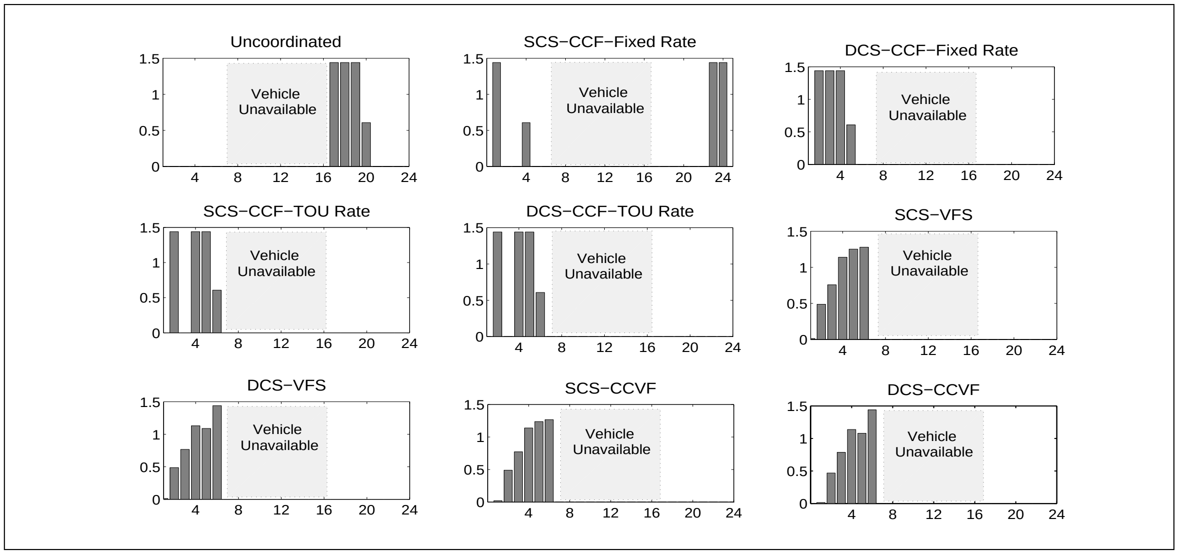

Figure 11. Charging schedules for a sample vehicle under different policies.

4. Provides support to grids with high penetration of renewable generation, by catering to their intermittent nature.

Charging schedules under the different policies are depicted for a sample vehicle in Figure 11. It is assumed that this vehicle is not at home between 7:00 and 17:00 hours. Each policy, when implemented, provides a different schedule for the vehicle.

Figure 9 depicts the total cost of charging using different policies. Some salient attributes of these policies are:

- Day-ahead charging schemes resulted in slightly lower costs than real-time schemes, probably due to the availability of complete system information.

- A TOU rate structure costs less than the fixed pricing for most customers, with a few exceptions. This deviation from a general trend could be attributed to the peculiar driving needs of those consumers. Alternately the optimization requires that an individual vehicle incurs higher costs to balance out a group of vehicles with lower charging costs. Such customers may be better off with fixed rates. Thus, no single pricing structure is beneficial for the whole population.

- The lowest costs were obtained when the two pricing schemes were used in combination for the CCF policy. But since the CCF results in secondary peaks, the VSF or CCVF can be used with variable rate combinations based on individual driving profiles.

- The random assignment of different pricing structures does not produce minimum costs because a special set of customers require deterministically chosen fixed rates to achieve a minimum.

Dynamic schemes closely follow the results of the static schemes in which all system information is known a priori. Therefore, it can be concluded that even without full information, the DCS scheme is effective in achieving optimal solutions. The existing grid communication networks can be used for the transfer of information using broadband, Zigbee, ZWave, or cellular network protocols. The CCU performs the optimization which is run using CPLEX that is fast, scalable, and capable of handling large number of variables. The CCU needs to send control signals to the vehicles once on arrival and then only if the original schedule changes as more vehicles arrive or system conditions change, thus limited communication is required in dynamic scheme. Interference issues, power consumption and security concerns are beyond the current scope of this paper.

6. CONCLUSION

In this paper, four optimization policies were discussed in static and dynamic framework, with consideration to the benefits of intermittent charging. Distribution system overloading is avoided by constraining the total load demand below the residential peak as much as possible. It is shown that best results can be achieved by coupling system and customer objectives. Customer convenience was addressed along-with system constraints and network health pertaining to peak demand. Moving horizon based real-time charging schemes can provide promising solution to dynamic coordination of vehicles. The impact of two pricing schemes on system and individual optima have been discussed. It can be concluded that a proper mix of electricity rates may ascertain benefits to all customers. Best results can be achieved by combining most appropriate pricing structures as per customer driving needs. Future work will consider stochastic behavior, vehicle-to-grid and renewable energy penetration.

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III. ELECTRIC VEHICLE SCHEDULING CONSIDERING CO-OPTIMIZED CUSTOMER AND SYSTEM OBJECTIVES

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ABSTRACT

Efficient electric vehicle scheduling is a multi-objective optimization problem with conflicting customer and system operator interests, especially during vehicle-to-grid implementations. Economic charging while minimizing battery degradation and maintaining system load profiles couple the interests of these two entities under consideration. This paper focuses on identifying the relationships between these objectives and proposes to use augmented epsilon-constrain (AUGMECON) based technique to implement two-way and three-way multi-objective optimization. The importance of using the afore-mentioned objectives in peak-shaving and valley-filling for an aggregated (residential) EV fleet have been discussed. The proposed solution will provide a look-ahead strategy into effective electric vehicle scheduling by co-optimizing multiple objectives. An optimal solution from those represented by the Pareto fronts may be chosen as per the specific requirements of utility and customer.

Keywords: AUGMECON, battery degradation, electric vehicles, multi-objective optimization, V2G

NOMENCLATURE

$B_{cap,i}$ Battery capacity of vehicle i.

$B_{i,cap}$ Battery capacity of vehicle i.

CF_{max} Capacity fade (20% of usable battery life).

C_{batdeg} Total battery degradatiion costs

C_{bat} Battery cost in \$ $(\$300/kWh)$.

$C_{i,rate}$ Charger selection for vehicle i

C_{labor} Labor cost for battery replacement $(\$240)$.

DOD Depth of discharge (80%) of battery at end of life.

$E^{dch}_{\Delta t}$ Energy discharged in Δt.

E^{t}_{bat} Energy stored in the battery at time t.

$E_{i,req}$ Energy required for full charge for vehicle i.

E_{sup} Total energy supplied to vehicle dusing parking duration

N_{veh} Total number of vehicles.

P_{avg} Average load demand = $\sum_{t=1}^{24} P^{t}_{res}/24$.

$P_{ch,max}$ Maximum charging power rating $\in \{1.44, 6.66\}$.

$P_{ch,min}$ Minimum charging power rating $\in \{0\}$.

$P_{dch,max}$ Maximum discharging power rating $\in \{0\}$.

$P_{dch,min}$ Minimum discharging power rating $\in \{-1.44, -6.66\}$.

$P^{t}_{i,veh}$ Vehicle i load demand at time t.

P_{peak} Forecasted peak load demand.

P^{t}_{res} Residential load demand at time t.

P^{t}_{sys} Total system load demand at time t.

S Solution space for variable x.

$SoC_{i,arr}^{t}$ SOC of battery at time of arrival of vehicle i .

$SoC_{i,avg}^{t}$ Average SOC of battery of vehicle i at time t.

$SoC_{i,max}$ Maximum SOC of battery of vehicle i (100%).

$SoC_{i,min}$ Minimum SOC of battery of vehicle i (20%).

Ψ_{i}^{deg} Battery degradation costs for vehicle i during the day.

Ψ_{i}^{rev} Total revenue of vehicle i during the day.

$\Psi_{i,t}^{DOD}$ DOD related battery degradation for vehicle i at time t.

$\Psi_{i,t}^{SOC}$ SOC related battery degradation for vehicle i at time t.

η_{ch} Battery charging efficiency (0.92).

η_{dch} Battery discharging efficiency (0.90).

λ^{t} Electricity rate at time instant t.

υ_{i}^{t} Binary optimization variable.

ε Positive constant of AUGMECON $\in \left[10^{-6}10^{-3}\right]$

bat_{life} Battery lifetime in years = 10 years or 5000 cycles.

d Linear battery degradation cost-intercept = 6.41×10^{-6}

$d_{i,arr}$ Arrival day of vehicle i

$d_{i,dep}$ Day of departure of vehicle i

$d_{i,park}$ Number of parking days for vehicle i

e_{j} Equality constraint parameter.

f_j Objective function j.

$grid_j$ Number of gridpoints of objective.

$iter_j$ Iteration parameter.

m Linear battery degradation cost-slope parameter = 1.59×10^{-5}.

$range_j$ Range of objective function.

s_j Positive slack variable.

t Time instant.,

t_{delay} Delay in providing service to a vehicle

$t_{i,avail}$ Time available before vehicle departure i.

$t_{i,avail}$ Time available for charging vehicle i.

$t_{i,req}$ Time required for full charge for i.

t_{park} Total parking hours for a vehicle

ub_j Upper bound of objective.

x Optimization variable.

$x^t_{i,ch}$ Charging power of vehicle i at time t.

$x^t_{i,dch}$ Discharging power of vehicle i at time t.

1. INTRODUCTION

Commercialization and adoption of electric vehicles (EV) in the automobile market has raised concerns over their uncontrolled charging demands, exposing the inadequacy of the present power system to serve the increasing load demand efficiently. Increase in EV load might lead to network congestion, losses, thermal stresses and network reinforcements in addition to higher operating costs at peak demands. Therefore, scheduling and control of EV load is essential for economic operation of the system. Vehicle-to-grid (V2G) operations of the EVs impose additional problems due to power injection into the electric grid traditionally designed for one-way power flow. Apart from the technical challenges, well designed financial models and transactive energy frameworks would be required to make V2G a feasible and lucrative option [1] -[2].

Unavailability of fast charging infrastructure, range anxiety and higher costs of EVs weigh heavily on customer choice. Additionally, relinquishing charging control to an external entity is undesirable by the customer unless on-demand availability and adequacy of the vehicle is ensured. Hence, there is a need for well-designed control and scheduling techniques that cater to customer comfort, financially motivate them and provide incentives for V2G without compromising network or battery health. This also underlines the need for using a multi-pronged approach to problem solution.

Past literature has studied various aspect of multi-objective optimization of electric vehicles [3]-[4] from the perspective of customer vs. system operator. In [5], annual traffic at fast charging stations was maximized while minimizing distribution system energy losses and annual investments. In general, artificial intelligence based methods like genetic algorithms (NSGA-II) or particle swarm optimization (ESPSO) have been used for determination of efficient solutions in multi-objective optimization (MOO) problems. By far, a three-way MOO combining customer and system objectives has not been studied in detail. This paper intends to bridge this gap and proposes to use a mathematical programming technique for the same, thereby extending the work in [5]-[6].

The authors in [7] included a depreciation term to account for battery degradation in a weighted objective function. An event driven, model predictive control method has been proposed in this work to minimize user costs and to track a reference profile. Similar approach was followed in [4] to optimize a weighted sum of four objectives using particle swarm optimization technique. The objectives included minimizing system losses, frequency of OLTC transformer tap changing, deviation from the daily load profile and maximizing customer satisfaction. In these studies a fixed set of weights were used for analysis, thus Pareto solutions were not obtained.

In [8] and [6], 2-way multi-objective problem considering operating load variance vs. charging costs and costs vs. emissions have been solved using the weighted-sum methods and augmented ϵ-constraint respectively. The authors established the conflicting nature of the objectives under consideration. The former designed local control scheme while the latter used a centralized control approach for EV scheduling. [8] used a normalizing factor based on the Nadir and Utopia points of each objective function. Despite the consideration of V2G, battery degradation was not considered in either study. This study extends these frameworks and scheduling paradigm developed in [9] to solve 2-way and 3-way optimization problems considering customer and system perspectives, and compares weighted-sum with augmented ϵ-constraint approach.

Most literature on multi-objective optimization study this problem from the power management perspective [10]-[11]. [10] and [12] use an electrochemical battery model to determine optimal, battery health conscious power management strategies for EVs. The detailed impacts and dynamics on load profiles and customer charging costs have not been discussed in these studies.

In this paper, a centralized EV control, optimization and scheduling (COS) scheme is discussed based on multi-objective optimization approach that aims at co-optimizing customer's and system operator's (SO) objectives. It addresses the needs of the system operator to control the peak load and that of the customer who is financially motivated while being concerned with battery life during V2G operations. The COS scheme is expected to provide a look ahead into the optimal solution choices for the available vehicle set. In real time, this may be used to guide EV scheduling directly or indirectly through change in

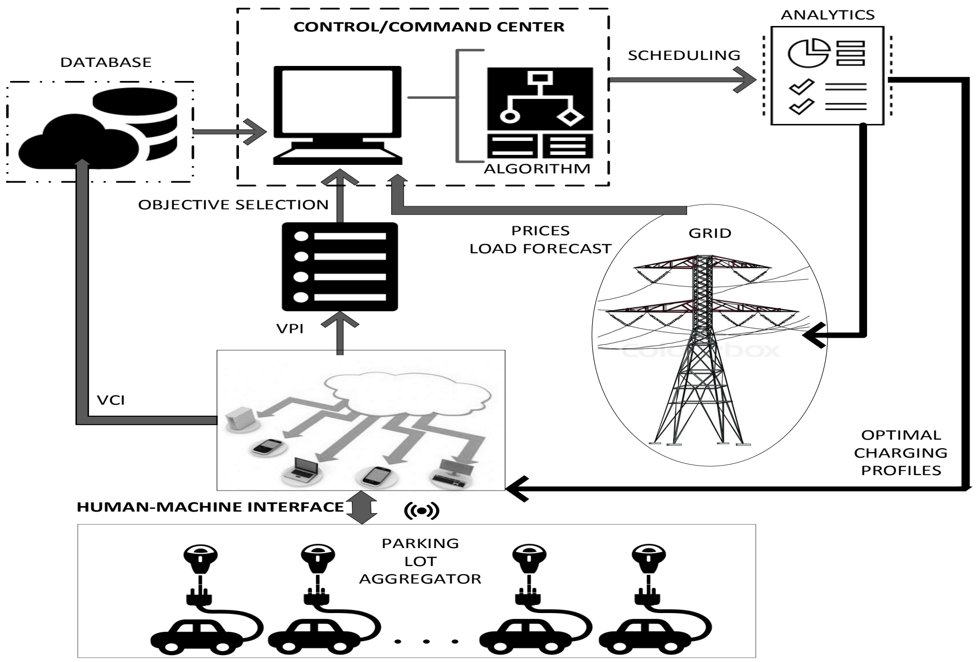

Figure 1. Control Optimization and Scheduling Architecture for PLC.

pricing schemes or by providing charging choices to customers. With the development of transactive business models, parking lot could participate as an independent actor in energy markets.

The contributions of this paper include:

1. Identification of conflicting and in-line objectives for efficient EV charging.
2. Implementation of 2-way and 3-way multi-objective optimization for EV scheduling for a residential parking lot using augmented ϵ-constraint optimization ($AUGMECON$).
3. Co-optimization of customer and utility objectives.
4. Comparison between $AUGMECON$ and weighted sum approach in determining efficient Pareto fronts.

2. PROBLEM FORMULATION AND METHODOLOGY

The centralized COS scheme is implemented by the parking lot controller (PLC). The PLC receives vehicle characteristic information (VCI) and vehicle profile information (VPI) from each vehicle as tuples: $\langle B_{i,cap}, SOC_{i,min}, SOC_{i,max}\rangle$, and $\langle t_{i,avail}, SOC^{0}_{i,avg}\rangle$ respectively. This is followed by running the optimization. Finally, the resulting schedule and additional cost information is sent to each vehicle and the system operator. Depending on the objectives used during the optimization, information regarding cost/revenues earned during scheduling, battery degradation costs incurred and impact on the system may be sent to the customer. The system operator may be informed of the energy available for transaction at each hour and the impacts of different schemes on the system load profiles. Therefore, the COS scheme implemented by PLC acts as a mid-layer between the customer and system operator.

2.1. Objective Function Modeling. This section defines the objective functions corresponding to battery degradation, customer costs/revenues and system load profiles.

2.1.1. Battery Degradation Cost Model (BDCM). Cyclic charging and discharging during V2G implementations affect the automotive life of EV battery adversely, thus incurring costs to the customers [13]. Battery, being one of the most expensive components of the EV needs special consideration to provide best return on investment to the customer. Battery power fade and capacity fade have been found to be influenced by temperature, open-circuit voltage, C-rate and depth-of-discharge (DOD) of the battery [14]. Often the effect of power fade is very small in comparison to capacity fade. Since battery degradation costs are highly non-linear functions, a simplified lifetime battery degradation cost (BDC) model has been adopted from [15] and [14]. For each vehicle i at time instant t, BDC (Ψ^{t}_{i}) is composed of two components: 1) SOC related cost $\Psi^{SOC}_{i,t}$ and 2) DOD related cost $\Psi^{DOD}_{i,t}$ (2). These components are defined in (3) and (4) for all $x \in X$ where $x = \{\{x^{t}_{ch,i}, x^{t}_{dch,i}\} : i \in [1, N_{veh}], t \in [1, t_{avail}]\}$. A capacity fade of 20% at the end of a ten year lifetime of a Li-ion battery has been assumed in this study.

$$\Psi_i^{deg}(x) = \sum_{t=1}^{t_{i,avail}} \Psi_i^t = \sum_{t=1}^{t_{i,avail}} \Psi_{i,t}^{SOC} + \sum_{t=1}^{t_{i,avail}} \Psi_{i,t}^{DOD} \tag{1}$$

$$\Psi_{i,t}^{SOC} = C_{bat} \frac{m \cdot SOC_{avg,t} - d}{CF_{max} \cdot bat_{life} \cdot 8760} \tag{2}$$

$$\Psi_{i,t}^{DOD} = \frac{C_{bat} \cdot B_{cap} + C_{labor}}{bat_{life} \cdot B_{cap} \cdot DOD} E_{\Delta t}^{dch} \tag{3}$$

$$x = \begin{cases} x_{ch,i}^t, & \text{if} \quad \upsilon_i^t = 1 \quad \text{(charging mode)} \\ x_{dch,i}^t, & \text{if} \quad \upsilon_i^t = 0 \quad \text{(discharging mode)} \end{cases} \tag{4}$$

where

$$SOC_{i,avg}^{t+1} = SOC_{i,avg}^t + \frac{x_{i,ch}^t + x_{i,dch}^t}{B_{cap}} \tag{5}$$

$$E_{\Delta t}^{dch} = E_{t-1}^{bat} - E_t^{bat} \tag{6}$$

A binary variable υ_i^t is introduced in the computations to ascertain either charging or discharging mode at each time instance t for each vehicle i (4). $SOC_{i,avg}^{t+1}$ is calculated using the net energy added to the battery during that time interval (5). Since degradation cost due to DOD is associated with V2G mode, (6) is true only for discharging operations.

The first objective function is defined as:

$$\arg\min_x f_1(x) = \sum_{i=1}^{N_{veh}} \Psi_i(x) \tag{7}$$

2.1.2. Customer Charging-Discharging Cost Model (CCDM). Time-of-use (TOU) rates are being offered by the utilities as a part of the demand-response initiative to motivate load shifting by customers. EV owners are being provided with special TOU rates to schedule vehicle charging during the un-tapped valley period [16]. The resulting decrease in electric bills serves as financial incentive to the customers. Similarly, a customer might earn higher revenues by participating in V2G energy transactions by selling energy during peak hours. In this study we assume a net-metering policy for charging and discharging the

EV at the time-of-use prices offered by the utility (λ_t). The total costs incurred/revenues earned by the customer are represented by Ψ_i^{rev}. (1) and (9) provide the mathematical formulation and definition of the objective respectively.

$$\Psi_i^{rev}(x) = \sum_{t=1}^{t_{i,avail}} \left(\frac{x_{ch,i}^t}{\eta_{ch}} - x_{dch,i}^t \cdot \eta_{dch} \right) \left(\lambda^t \right) \tag{8}$$

$$\arg\min_x \; f_2(x) = \sum_{i=1}^{N_{veh}} \Psi_i^{rev}(x) \tag{9}$$

2.1.3. Valley-filling Model (VFM). Uncoordinated EV charging may cause substantial increase in peak demand. This is economically undesirable due to 1) bringing up of costly generators to serve the load and 2) increase in network stresses leading toward infrastructural reinforcements. Valley-filling leads to shifting of load demand to create a more level profile without increasing the peak demand, thus serving the interests of the SO. Valley filling minimizes the deviation between instantaneous and the average load. Scheduling during lightly loaded valley period is expected to improve the load factor of the system. It is defined as:

$$\arg\min_x \; f_3(x) = \sum_{t=1}^{24} \left(P(x)_{sys}^t - P_{avg} \right)^2 \tag{10}$$

$$P(x)_{sys}^t = P_{res}^t + \sum_{i=1}^{nVeh} P_{i,veh}^t \cdot \Delta t \qquad \forall t \tag{11}$$

where

$$P_{i,veh}^t = \frac{x_{ch,i}^t}{\eta_{ch}} - x_{dch,i}^t \cdot \eta_{dch} \tag{12}$$

The total system load at time t is calculated in (11) as the sum of residential load and total vehicle load at that time. The total vehicle load is the net EV demand ($charging - discharging$) on the system at time t (12). A 1 hour time step (Δt) has been considered in this study.

2.2. Vehicle and System Constraints. Vehicle scheduling is a constrained optimization problem. Due consideration must be given to customer convenience (vehicle arrival and departure times, SOC requirements), charger limitations (maximum power input/output), battery dynamics (minimum/maximum SOC) and system peak loads. The following constraints complete the problem definition.

Equations (13) and (14) define the minimum and maximum charging and discharging power limits respectively. $SOC_{i,avg}^{t}$ defined in (5) is constrained as per (15). Constraint (16) ensures that the battery is fully charged at the end of the charging period. In order to constraint the peak load to its original value (residential peak load demand), (17) may be used. For each vehicle i and time instant t, the following constraints hold:

$$P_{ch,min} \leq x_{i,ch}^{t} \leq P_{ch,max} \tag{13}$$

$$P_{dch,min} \leq x_{i,dch}^{t} \leq P_{dch,max} \tag{14}$$

$$SoC_{i,min} \leq SOC_{i,avg}^{t} \leq SoC_{i,max} \tag{15}$$

$$\sum_{t=1}^{t_{i,avail}} \left(x_{i,ch}^{t} - x_{i,dch}^{t} \right) \Delta t = E_{i,req} \tag{16}$$

$$\sum_{i=1}^{nVeh} \left(\frac{x_{ch,i}^{t}}{\eta_{ch}} - x_{dch,i}^{t} \cdot \eta_{dch} \right) \leq \left(P_{peak} - P_{res}^{t} \right) \tag{17}$$

It is worth noting that any change in the driving or parking patterns would affect the scheduling schemes and would require a stochastic analysis. Eventually, with higher penetrations of EVs their impact on real-time pricing and market dynamics would also become prominent. These factors would affect the charging paradigm but are currently out of scope of this study.

2.3. Multi-objective Optimization Procedure. Unlike mathematical programming in single objective, the objectives in multi-objective optimization may not be optimized simultaneously. The concept of optimal solution is thus replaced by the most preferred solution under Pareto optimality or efficiency conditions. A solution is called Pareto optimal if its improvement cannot be accomplished without deteriorating the performance of at least one of the other objectives. An effective MOO technique seeks to find these multiple trade-off solutions from which one may be chosen based on some higher-level information (Fig. 2). Two classical methods for solving MOO have been discussed in the following sections.

Original MOO problem:

$$\min \left(f_1(x), f_2(x), \cdots, f_p(x) \right)$$
$$\text{subject to} \quad x \in S$$

2.3.1. Weighted Sum Method. In the weighted-sum method, problem is designed as an aggregated convex combination of the objectives. Each objective is multiplied by a weighting factor and added to transform the multi-objective problem into a single objective. In order to account for the bias due to the scale of one objective over the other, the objective functions may be normalized. Generally, this normalizing factor is the corresponding optimum function value (f_i^*). The aggregated function is given as:

$$\min_x \quad f_{weighted} = w_1 \left(f_1(x)/f_1^* \right) + w_2 \left(f_2(x)/f_2^* \right) \tag{18}$$

where w_1 and w_2 are the weights for functions f_1 and f_2 respectively and $w_1 + w_2 = 1$. The functions f_1 and f_2 have been normalized using their optimal values f_1^* and f_2^*, obtained by performing the optimizations individually. Despite its simplicity in solving

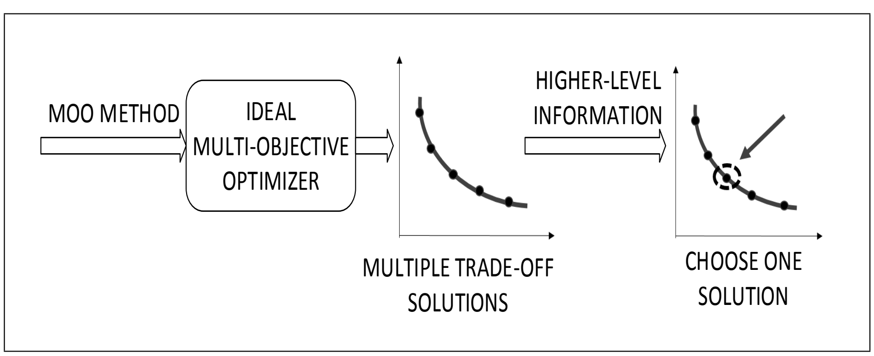

Figure 2. Illustration of multi-objective optimization method.

convex problems, the weighted-sum method does not guarantee a uniformly distributed set of Pareto-optimal solutions for a uniformly distributed set of weights. Secondly, it cannot find solutions in the non-convex solution space. These drawbacks can be overcome by using the AUGMECON method.

2.3.2. Augmented ϵ-Constraint Method. ϵ-constraint method seeks to optimize one of the objectives while varying the others within a restricted range specified by the pay-off table. $AUGMECON$ method is an improvement on the traditional ϵ-constrain method [17] for performing multi-objective optimization. The advantage of AUGMECON over the classical weighted-sum approach is 1) its capability to find solutions in non-convex regions and 2) finding different Pareto-optimal solutions by varying the value of ϵ, which thus dictates the solution set to some extent. As the number of objectives increase, user is required to provide more information. AUGMENCON method for solving MOO for vehicle scheduling is described below:

$$\underset{x,s_2,s_3}{\arg\min}\left(\underbrace{f_3(x)}_{\text{term-1}} - \underbrace{\varepsilon\,(s_2 + s_3)}_{\text{term-2}}\right) \qquad x \in S \tag{19}$$

subject to :

$$f_j(x) + s_j = e_j \qquad \forall j \in [1,2] \tag{20}$$

where

$$e_j = ub_j - \frac{\left(iter_j \times range_j\right)}{grid_j} \tag{21}$$

A payoff table (POT) $(p \times p)$ defining the range of each objective is introduced using the lexicographic method described in [17]. Each row j of the payoff table corresponds to objective f_j with its optimal value f_j^* as the j^{th} column entry and values of all other $p-1$ objectives calculated at x^{j*} at each corresponding column. One of the p objectives is then used as the optimization function (key objective or KOF) along-with the other $p-1$ functions introduced as equality constraints, varied within the maximum and minimum range defined by the payoff table (Fig. 3).

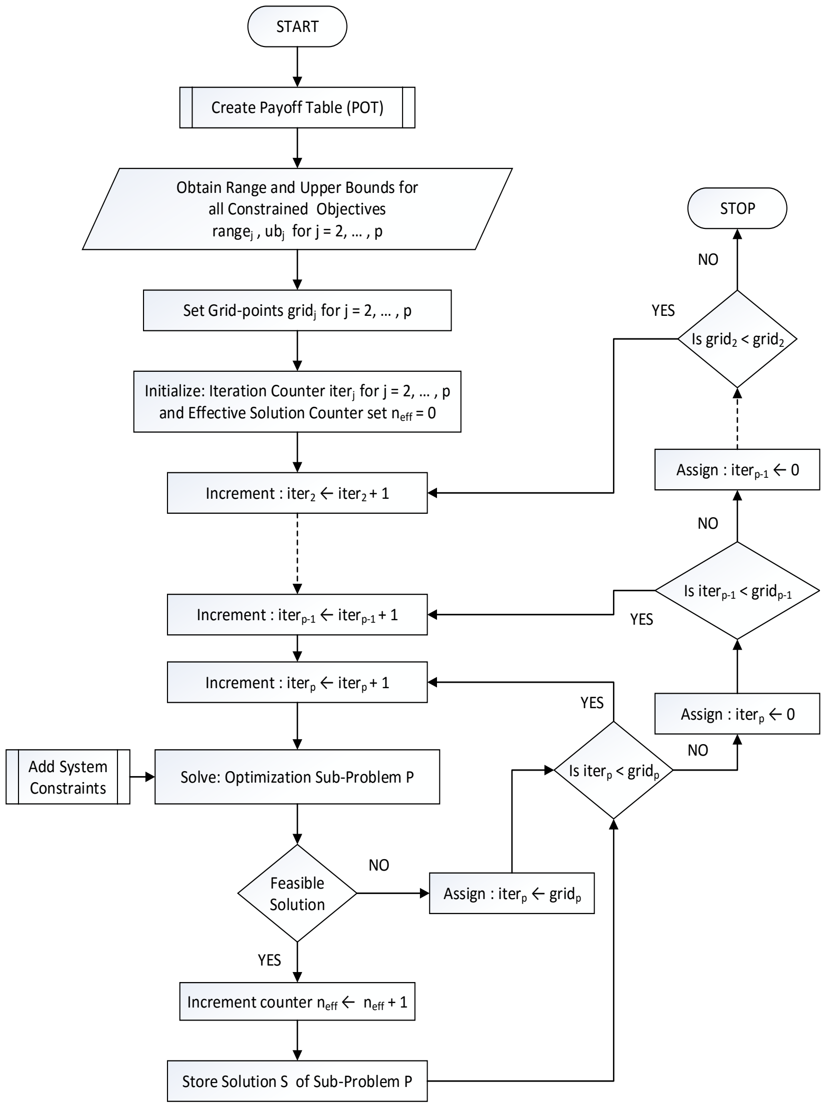

Figure 3. Flowchart for the AUGMECON method for MOO.

In table 1, row 1 corresponds to the result of optimizing battery degradation costs with its optimal value in column 1. The values of charging cost and valley filling, calculated at its minimum argument 'x', are then entered in columns 2 and 3 respectively. The range of each objective is calculated as the difference between its maximum and minimum values. Once the range is defined, the gridpoints ($grid_j$) give the number of sections/blocks this range is divided into. $^{range_j}/_{grid_j}$ defines the step size through which e_j decrements at every

Table 1. Payoff table for the objective functions

	f_1 (\$) (BDCM)	f_2 (\$) (CCDM)	f_3 (VFM)
f_1^*	0.1634109	156.2275	1.516×10^4
f_2^*	282.8085	20.53755	1.7002×10^5
f_3^*	295.7163	86.6299	4.0314×10^4
Range	295.553	135.6899	15.486×10^4

iteration as each constrained objective moves from its maximum value to its minimum value. Therefore, a sub-problem P is defined corresponding to each value of parameter e_j (19)-(21).

In 3-way MOO using AUGMECON method, valley filling (f_3) was chosen as the key objective (KOF) with the addition of term-2 (19) for two reasons:

1. It results in a flat load profile
2. It is computationally easier to handle linear functions as constraints as opposed to quadratic functions

Objectives f_1 and f_2 are then entered as equality constraints according to (20) and (21). The value of ε in (19) is set at 10^{-6}. 20 and 5 gridpoints ($grid_j$) are considered in 2-way and 3-way MOO cases respectively. In the 2-way case, the iterate $iter_j$ varies between 1 and 20 leading to 20 sub-problems. A step size of 0.05 was used in the weighted-sum approach for updating the weights, thus resulting in 20 weight combinations. In the 3-way case 5 gridpoints for each of the $p-1=2$ objectives, resulted in $5\times5=25$ subproblems to be solved. An increase in computational complexity is encountered with increase in the number of gridpoints in solving the sub-problems. Here, a parallel programming approach could provide better computational speeds.

3. SIMULATION RESULTS AND OBSERVATIONS

A typical summer day load profile and 3-tier time-of-use pricing (table 2) were obtained from PGE and subsequently scaled up for simulating the residential parking lot [18]. Even though the rates used were those proposed by PGE, for better accuracy the design of tiers followed the clustering method proposed in [19]. A 60% EV penetration in a 245 house residential complex is assumed for which the driving profiles were obtained from the NHTS database [20]. Further, the methodology proposed in [21] was adopted for battery and charger assignments which included 5 battery sizes and type I and II chargers [22]. Aggregated effect of vehicles on the system is considered due to the absence of geo-spatial distribution of the vehicles in the distribution system.

BDCM and CCDM have been solved as mixed integer linear programs (MILP). Due to the quadratic nature of the valley filling objective, VFM and AUGMECON models have been solved as quadratic mixed integer programs (QIP). IBM-ILOG CPLEX [23] was used to generate the initial guess for the relaxed version of each problem (LP and QP respectively) followed by final solution using GUROBI optimization package [24].

3.1. Case Definitions. The following cases have been used to test the viability of MOO approach:

- *Base Case:* G2V mode - Uncoordinated EV charging immediately upon arrival
- *Case-1 :* Customer focused : Minimizing customer charging cost (or maximizing revenues) in V2G/G2V modes (CCDM)

Table 2. TOU rate structure [18]

<table>
<tr><th>Rate Type</th><th colspan="3">Energy Charge (¢/kWh)</th></tr>
<tr><td rowspan="2">TOU 3-tier</td><td>13.101</td><td>20.779</td><td>32.306</td></tr>
<tr><td>2:00-10:00</td><td>11:00-13:00
21:00-1:00</td><td>14:00-20:00</td></tr>
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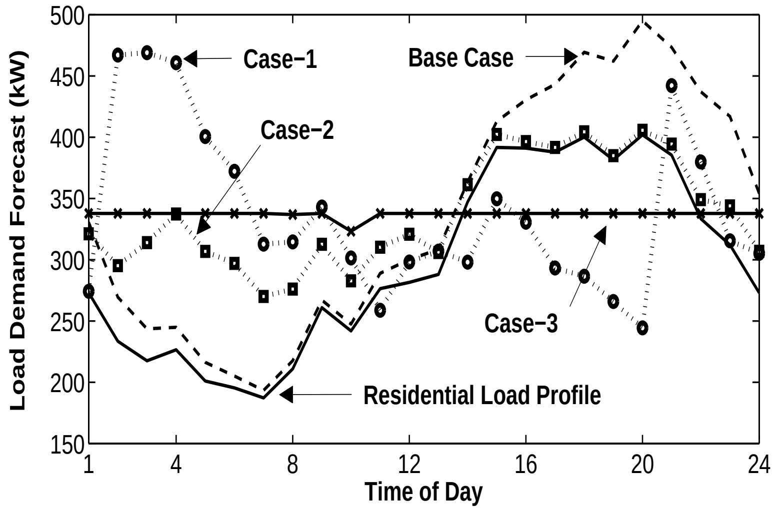

Figure 4. Optimal load demand forecast under individual objectives.

- *Case-2 :* Customer focused : Minimizing battery degradation cost in V2G/G2V modes (BDCM)
- *Case-3 :* System focused: Valley filling in V2G/G2V modes (VFM)
- *MOO-1 :* Battery degradation vs. Customer cost/revenues
- *MOO-2 :* Valley filling vs. Customer cost/revenues
- *MOO-3 :* Valley filling vs. Battery degradation
- *MOO-4 :* Battery degradation vs. Customer cost/revenues vs. Valley filling

Figure 4 shows the resulting load profiles for cases 1-3 with independent implementation of the three objective functions. The following observations can be made:

- *O1:* (Base case) Uncoordinated charging results in an inadvertent increase in peak demand and leaves the valley period un-tapped.

- *O2:* (Case 1) Implementation of time-of-use rates (without imposing any system-level constraints) leads to creation of two additional peaks. The peaks were found to be higher than the original system peak demand. This is highly undesirable and offsets the desired benefits of time-of-use rates that are intended to shift load to the valley period. In such situations, an adaptive real-time pricing strategy would be required.

- *O3:* (Case 2) Avoiding battery degradation costs results in limited V2G operations. Thus, peak shaving is not observed. Vehicles charge during the valley period. The load profile closely follows the residential load demand during peak hours.

- *O5:* It can be hypothesized that it might be possible to achieve a trade-off between the battery degradation costs and the charging costs/revenues. This is investigated in section 3.2.

- *O4:* V2G and G2V operations in the valley filling mode result in a flat load profile. This is the most desirable load profile and is independent of the effect of pricing structure.

3.2. Two-way Multi-objective Optimization. Figures 6-11 show the load profiles and Pareto fronts for cases $MOO-1$, $MOO-2$ and $MOO-3$. The results depicting system load profiles provide an insight into the variation of load demand forecast under optimal conditions. Fig. 5 shows the customer charging/discharging costs/revenues and battery degradation costs for a sample set of vehicles. Results of the two MOO methods discussed in section 2.3 have been shown in the Pareto fronts (Figs. 7, 9 and 11). The following observations can be made:

- *O5 (MOO-1):* Customer incurred costs and battery degradation costs are approximate mirror images of each other. An increase in revenues earned through V2G operations (through cyclic charging/discharging of battery) results is higher battery degradation costs and vice-versa (Fig. 5).

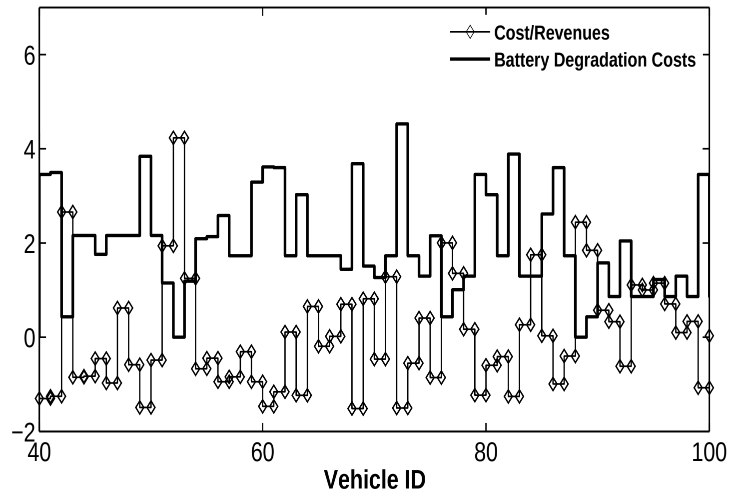

Figure 5. Comparison of battery degradation costs vs Charging Costs/Revenues for a sample set.

- *O6 (MOO-1):* BDCM and CCDM are in conflict with each other (Figs. 6-7). Therefore, the Pareto front provides the customer with a choice to operate at an optimal point weighing financial profits against losses attributed to battery health.

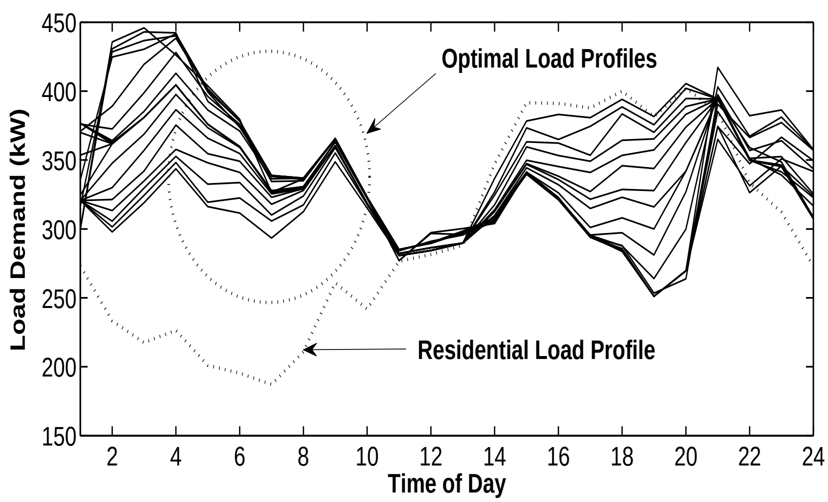

Figure 6. Load profiles for 2-way MOO with charging cost vs. battery degradation.

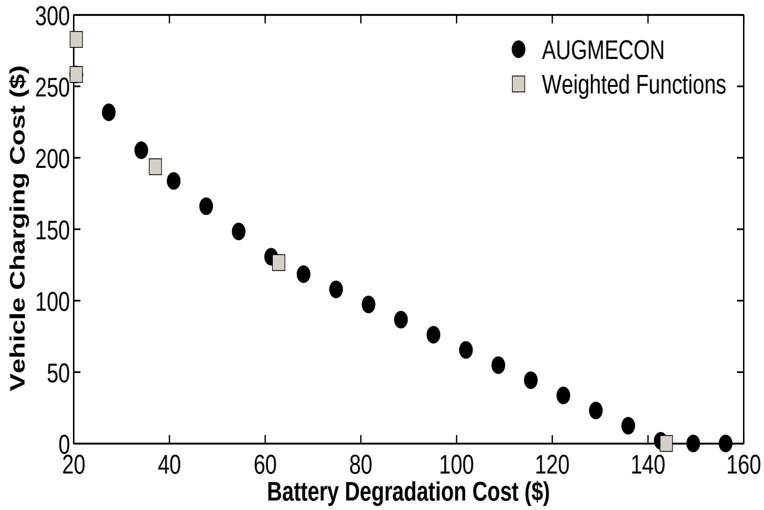

Figure 7. Pareto front (customer charging cost/revenue vs. battery degradation cost).

- *O7 (MOO-2):* Minimizing charging cost uses the low price tier to charge most vehicles and uses the high price tier to earn profits through V2G operation. This distorts the load profile as shown in case-3 in Fig. 4. Since this is undesirable by the system operator, valley filling objective tries to balance the charge/discharge operations. Therefore, customer charging cost/revenues and valley filling conflict each other (Fig. 8). The Pareto front in Fig. 9 provides the system operator and customer with the capability to reach a mutual consensus by selection of optimal operating criteria.

- *O8 (MOO-3):* Valley filling (VFM) and battery degradation (BDCM) both limit the V2G operations. While the former levelizes the load profile, the latter follows the initial residential load profile during peak hours. Thus, they are not in conflict with each other (Fig. 10) and cannot provide a Pareto front. Fig. 11 shows the optimal operating points as battery degradation costs are varied within the *POT* range.

- *O9 (MOO-3):* Battery degradation costs were found to be higher when valley filling was implemented alone. Cyclic discharging during peak hours to flatten the load profile results in an increase in battery degradation costs comparatively.

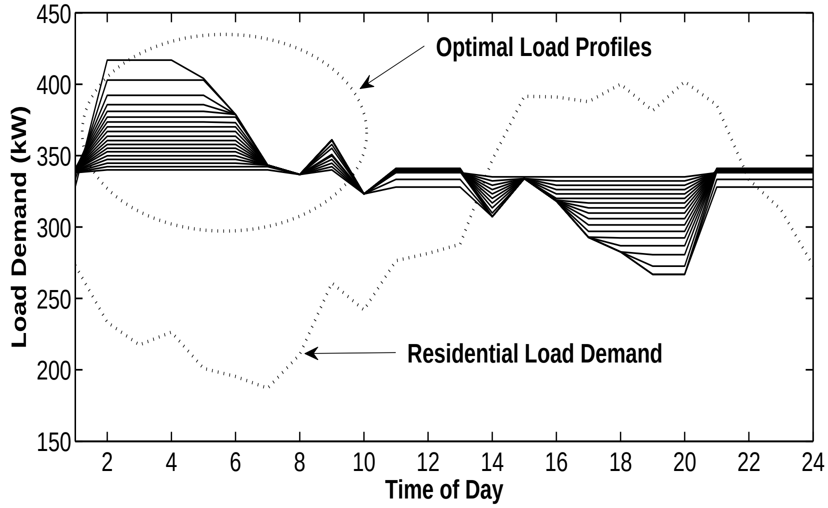

Figure 8. Load profiles for 2-way MOO with charging cost vs. valley filling.

- *O10:* The weighted-sum method does not provide uniformly distributed solutions for any of the cases discussed above. But, it can be observed that the solutions for both techniques lie within the same range. *AUGMECON* provides a uniform Pareto front.

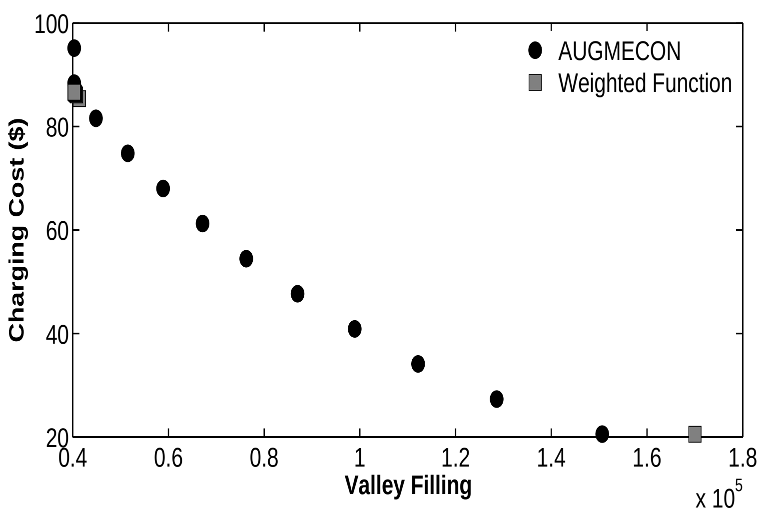

Figure 9. Pareto front (customer charging cost/revenue vs. battery degradation cost).

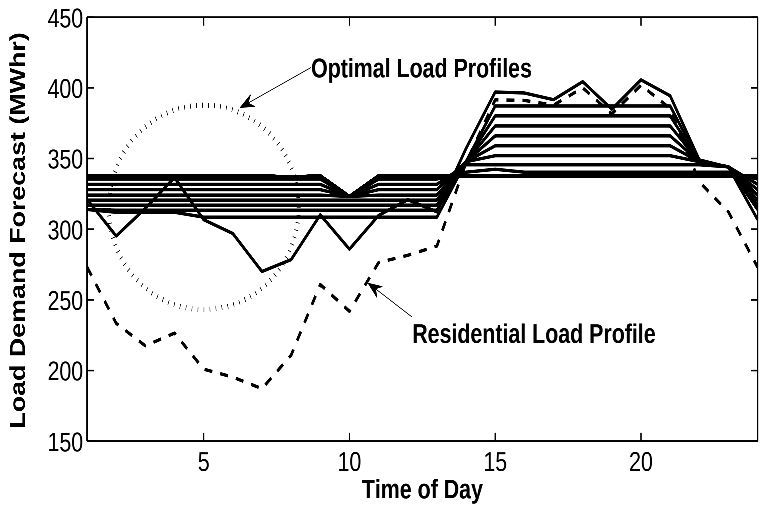

Figure 10. Load profiles for 2-way MOO with battery degradation vs. valley filling.

3.3. Three-way Multi-objective Optimization. The results in section 3.2 show that there are two pairs of conflicting objectives and one pair of in-line objectives. As valley filling and battery degradation increase, customer charging costs decrease. Figs. 12 and 13 show the load profile and Pareto front as a result of performing a 3-way MOO on battery degradation costs, customer charging costs and valley filling objectives.

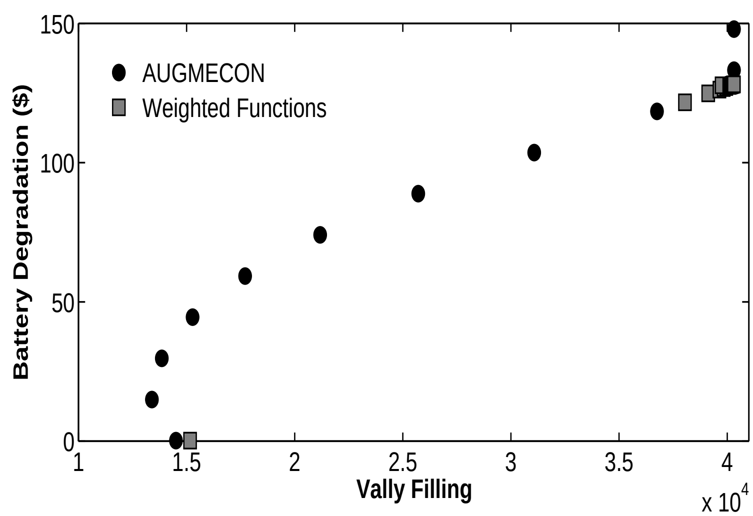

Figure 11. Optimal solutions for battery degradation costs vs. valley filling.

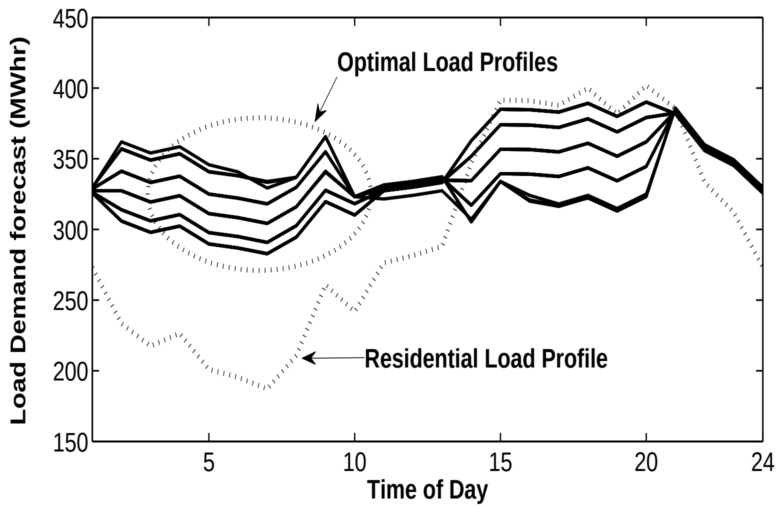

Figure 12. Load profiles for 2-way MOO with battery degradation vs. valley filling.

The information in the Pareto front can provide the system operator with the tools to design effective incentive plans to motivate the customers. Consequently, the system integrity may be preserved while providing financial benefits to the customers through V2G operations. Weighing customer benefits against the system requirements can provide better solutions to the EV scheduling problem. Moreover, the impacts of different pricing

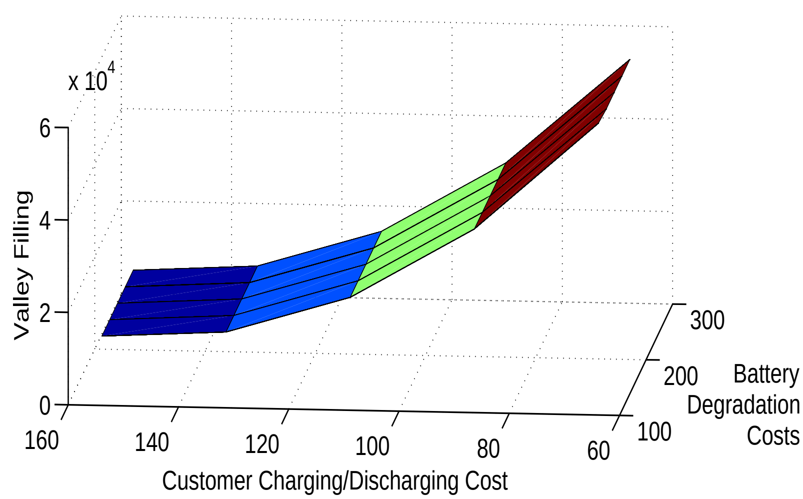

Figure 13. Optimal solutions for battery degradation costs vs. valley filling.

structures and driving profiles on customer profits and battery health may be used to educate the customer. Furthermore, efficient charging practices may be suggested for their benefit, thus improving customer engagement. A MOO approach, as the one discussed above, provides an efficient technique to understand these dynamics and formulate plans accordingly.

4. CONCLUSION

In this paper, the dynamics between customer and system objectives have been identified and investigated. An $AUGMECON$ based multi-objective optimization methodology has been implemented to identify co-optimal solutions for the benefit of these two entities. A customer's financial motives and a system operator's network-based concerns have been leveraged for this purpose. A comparison between $AUGMECON$ and weighted-sum approach establishes the superiority of the former in finding uniformly distributed solutions. The day-ahead centralized scheduling scheme would provide information to the customer and system operator to make informed decisions. The inadequacy of single objectives in proposing mutually beneficial and efficient MOO based control and scheduling schemes has been explored. Computational improvements and real-time implementations of this work will be investigated in future.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the financial support of the National Science Foundation under the project ECCS-1068996.

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IV. A TRANSACTIVE OPERATING MODEL FOR SMART AIRPORT PARKING LOTS

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ABSTRACT

Successful adoption of electric vehicles requires adequate and widespread public charging infrastructure to increase customer comfort. Technological advancements in smart parking infrastructures and vehicle-to-grid energy transfer bear the capability of adding value to the vehicle, grid and electricity markets. As a deferrable load and flexible source, an aggregate electric vehicle fleet can enhance system resilience. In this paper, the idea of using long-term parking at airports to develop a transactive business model for electric vehicles has been explored. Different cost components were tested and compared under profit maximization with due consideration to battery degradation costs. Technical details coupled with business propositions have been explored in this study using a mixed integer optimization implementation. A day-ahead energy transaction portfolio was created considering customer convenience. Results indicate that long-term smart parking can be profitable to all entities while providing significant benefits to the grid.

Keywords: electric vehicles, SMART parking, transactive business model, vehicle-to-grid (V2G)

NOMENCLATURE

$B_{cap,i}$ Battery capacity of vehicle i.

$B_{i,cap}$ Battery capacity of vehicle i.

CF_{max} Capacity fade (20% of usable battery life).

C_{batdeg} Total battery degradatiion costs

C_{bat} Battery cost in \$ (\$300/kWh).

$C_{i,rate}$ Charger selection for vehicle i

C_{labor} Labor cost for battery replacement (\$240).

DOD Depth of discharge (80%) of battery at end of life.

$E^{dch}_{\Delta t}$ Energy discharged in Δt.

E^{t}_{bat} Energy stored in the battery at time t.

$E_{i,req}$ Energy required for full charge for vehicle i.

E_{sup} Total energy supplied to vehicle dusing parking duration

N_{veh} Total number of vehicles.

P_{avg} Average load demand $= \sum_{t=1}^{24} P^{t}_{res}/24$.

$P_{ch,max}$ Maximum charging power rating $\in \{1.44, 6.66\}$.

$P_{ch,min}$ Minimum charging power rating $\in \{0\}$.

$P_{dch,max}$ Maximum discharging power rating $\in \{0\}$.

$P_{dch,min}$ Minimum discharging power rating $\in \{-1.44, -6.66\}$.

$P^{t}_{i,veh}$ Vehicle i load demand at time t.

P_{peak} Forecasted peak load demand.

P^{t}_{res} Residential load demand at time t.

P^{t}_{sys} Total system load demand at time t.

S Solution space for variable x.

$SoC_{i,arr}^{t}$ SOC of battery at time of arrival of vehicle i .

$SoC_{i,avg}^{t}$ Average SOC of battery of vehicle i at time t.

$SoC_{i,max}$ Maximum SOC of battery of vehicle i (100%).

$SoC_{i,min}$ Minimum SOC of battery of vehicle i (20%).

Ψ_{i}^{deg} Battery degradation costs for vehicle i during the day.

Ψ_{i}^{rev} Total revenue of vehicle i during the day.

$\Psi_{i,t}^{DOD}$ DOD related battery degradation for vehicle i at time t.

$\Psi_{i,t}^{SOC}$ SOC related battery degradation for vehicle i at time t.

η_{ch} Battery charging efficiency (0.92).

η_{dch} Battery discharging efficiency (0.90).

λ^{t} Electricity rate at time instant t.

υ_{i}^{t} Binary optimization variable.

ε Positive constant of AUGMECON $\in \left[10^{-6} 10^{-3}\right]$

bat_{life} Battery lifetime in years = 10 years or 5000 cycles.

d Linear battery degradation cost-intercept = 6.41×10^{-6}

$d_{i,arr}$ Arrival day of vehicle i

$d_{i,dep}$ Day of departure of vehicle i

$d_{i,park}$ Number of parking days for vehicle i

e_{j} Equality constraint parameter.

f_j	Objective function j.
$grid_j$	Number of gridpoints of objective.
$iter_j$	Iteration parameter.
m	Linear battery degradation cost-slope parameter = 1.59×10^{-5}.
$range_j$	Range of objective function.
s_j	Positive slack variable.
t	Time instant.,
t_{delay}	Delay in providing service to a vehicle
$t_{i,avail}$	Time available before vehicle departure i.
$t_{i,avail}$	Time available for charging vehicle i.
$t_{i,req}$	Time required for full charge for i.
t_{park}	Total parking hours for a vehicle
ub_j	Upper bound of objective.
x	Optimization variable.
$x^t_{i,ch}$	Charging power of vehicle i at time t.
$x^t_{i,dch}$	Discharging power of vehicle i at time t.

1. INTRODUCTION

The increasing penetration of electric vehicles in the automotive market has led to the development of public and private charging infrastructures, especially on the east and west coast of the USA. Research efforts in the field of drive-trains, batteries and power electronics will make them more affordable in the future. Plug-in electric vehicles (PEVs) may be used not only for travel, but also for providing energy to the power grid. The concept of discharging the electric vehicle energy into the grid is called vehicle-to-grid or V2G. It has been proposed that the aggregated PEV fleets may be used for generating profits by transacting energy in the electricity markets. Their capability to charge/discharge may be used in the ancillary services market for improving power grid operations, especially with widespread distributed, intermittent renewable energy generation. One of the primary drawbacks in using PEV fleets is that the period in which the vehicles are parked does not correspond to periods in which it is advantageous to provide ancillary services through V2G. However, airport long term parking structures have numerous characteristics which make them highly suitable for V2G services. Unlike residential parking in which the vehicle is only available during the night, long term parking lots have the advantage of a large number of vehicles that are available at all hours of the day and night. Furthermore, unlike shopping center parking lots where vehicles are only available for short periods of time (typically 1-4 hours), airport parking lots have the advantage that vehicles are typically available for longer than 24 hours and usually up to several days. Lastly, consumers are able to predict with high probability when they will retrieve their vehicle, so guaranteeing full state of charge upon exit is achievable.

Generally, vehicles remain idle for a continuous period when parked in the airport long-term parking structures. One of the significant costs associated with air travel is the fees associated with personal vehicle parking. Parking fees can be even more significant for close proximity or covered structure parking. However, airport parking structures offer considerable potential for collaboration between electric vehicle owners and structure owner/operators. Aggregated electric vehicle batteries may be used to emulate bulk energy storage systems and can be used for earning profits through energy transactions on the spot market or through energy or ancillary service contracts. There is potential for lucrative models that may increase the PEV utility and value to customers.

We envision a future in which a PEV owner can park at the airport for a significantly reduced fee (or even free) by simply allowing the parking structure owner/operator access to the stored energy in their vehicle battery for short periods of time. We propose an algorithm in which the vehicle owner parks their automobile, plugs it in, enters their expected return date and time, and then returns days later to a fully charged vehicle at little or no parking cost to themselves. We propose to accomplish this through a novel aggregation and control algorithm that buys and sells power on the spot energy market. We believe that both parking structure owner/operators and travelers can benefit through participation.

The parking lot central controller collects individual PEV information such as battery capacity, incoming state-of-charge, and duration of availability. The vehicles are then divided into two groups: a continuous- parking group and a departure-day parking group based on the day the vehicle is scheduled to leave the parking facility. The PEV owner has the option to choose among a standard or a set of variable admission fee options and charger types (Type I, II, III). The PEV owner is also requested to set its minimum energy requirement at the end of its parking period (i.e. how full they want their battery).

Once parked, the battery state-of-charge is controlled by the proposed algorithm. The algorithm maximizes parking lot owner (PLO) profits through continuous charging and discharging of aggregated fleet based on utility price signals, constrained by battery degradation costs. A customer satisfaction index, based on admission fee and revenues earned, is used as a metric for maximizing vehicle utility. The PLO is penalized for any expected energy not served at the time of departure of the EV. The PLO may use a net metering approach to sell electricity at the market price or may add a profit margin. The PLO may act as a player in the ancillary services market to sell the energy discharged from the EVs and thus make additional profits.

With the current advancements in information and communication technology and smart grid applications, electric vehicles can participate in demand response as controllable loads and resources for grid support through unidirectional (grid-to-vehicle) or bi-directional (vehicle-to-grid) energy transactions [1]. Aggregated EV fleets can emulate a bulk energy storage system with the capability of earning profits through energy transactions on the spot market or through ancillary service contracts [2]. They can support intermittent renewable energy integration and provide effective solutions to their ramping requirements. The recent adoption of ramp capability services by MISO and CAISO is a significant step in this direction [3]. Active participation in economic or emergency-based demand response programs and spinning reserves market can provide financial incentives to the customers [4]. The aggregated impact of fleet PEVs can make a compelling case as an active entity in market operations.

Some of the challenges associated with EV parking lots include:

- Optimal location of the parking lots for minimizing system-level impacts of aggregated EV charging
- Dependence of parking lot energy requirement on uncertainty in EV mobility pattern
- Management of grid-to-vehicle (G2V), vehicle-to-grid (V2G) and vehicle-to-vehicle (V2V) interactions
- Parking lot aggregaor as an agent or actor in energy markets
- Customer convenience including the impact on battery degradation
- Dynamics in the presence of renewable energy generation at the parking facility

Optimal placement of parking lots in a distribution system with renewable energy penetration was studied in [5]. A two stage problem to minimize system costs was formulated to maximize parking lot owner profits while considering network constraints. The results show that the parking lot owner and the vehicle owner may be benefited simultaneously while maintaining network constraints. The study showed that it would be more beneficial if the parking lot owner participates in the reserve market instead of the energy market. In [6], the authors deal with mobility uncertainty by designing a system that uses a trace-based mobility model to account for regular and irregular vehicle arrivals at the parking lots and seek to maximize revenues while maximizing energy transfer to the vehicles. Energy management in G2V, V2G and V2V modes have been explored in [7]. The proposed direct load control policy uses a mix of residential and commercial charging to ascertain economic service to the vehicles while minimizing battery degradation. [8] uses the V2V idea to develop an 'ad-hoc' mini-grid with vehicles. It suggests a paradigm for optimizing driving experience using a carbon-efficient charging schedule. It is important to note here, that even though EVs are zero-emission vehicles, there are indirect emissions involved based on fuel used for generating electricity [9]. Articles [4] and [10] concentrate on economic operation of a parking lot equipped with renewable energy generation. In [4], a multi-stage optimization was performed based on the offer chosen by the owner, thus providing her with greater control. The proposed scheme made compensations for any battery degradation costs incurred during the demand-response implementation. While [4] uses a neural network based stochastic model to predict EV arrivals, [10] uses a real-time model-predictive control strategy to deal with this uncertainty. The two-stage optimization in [10] predicts the electricity sales price under uncertain solar generation to maximize the revenues.

Because of these challenges, a detailed model for optimal charging at long-term parking facilities has not been developed. We propose to bridge this gap while leveraging the ideas in [5]-[10]. Furthermore, a technical construct has been proposed and built around the control and charging paradigm proposed in [11]-[12].

Smart parking facilities could promote the carbon neutrality of airports [13]. Airport parking structures offer considerable potential for collaboration between EV owners and parking lot operators. In this study, an optimal energy transaction policy to coordinate EV charging and discharging for the mutual benefit of the customer and the parking lot operator has been proposed. Customer satisfaction indices and a profit model based on different pricing structures are developed. A novel aggregation and control algorithm that buys and sells at spot energy market has been proposed. It has been shown that both the parking lot owner and the customers can benefit through active engagement. The key contributions of this work include:

- A novel aggregation scheme for long-term EV parking structures,
- A control architecture for optimal energy transactions for the EV fleet,
- A transactive business model for airport parking,
- High customer satisfaction guarantees and mutually beneficial profit models for the principal entities, and
- Understanding the internal charge/discharge dynamics of a fleet in a centralized control architecture.

2. BUSINESS MODEL

The dynamics among the principal entities depends on the plans, options, and transactions specifications. Together with subsidiary entities, they complete the model for the parking facility as shown in Fig. 1. The cost and revenue components for the principal entities are summarized in Table 1.

2.1. Principal Entity Portfolios (PEP). The principal entity portfolio (PEP) defines the major players in the model. The principal entities include electric vehicle owners (EVO), the parking lot operator (PLO), and the energy provider (EPO). The EVO has the authority to choose from and approve the set of operating options for their individual vehicles. These operating options are designed by the PLO in accordance with their market transactions with the EPO. This information regulates the monetary transactions and profits made by each entity and thus determines the energy transaction portfolio for each principal entity.

2.2. Plans, Options and Transactions (POT). Plans, options, and transactions (POT) determine the major costs incurred and revenues earned by the principal entities. They will be inherently affected by the services the PLO offers to the grid through contractual agreements with the EPO. Certain schemes could be designed to encourage specific behavioral patterns. Table 1 provides a list of cost/revenue components, a subset of which has been used in this study. It is assumed that all contractual agreements between PLO and EPO are enforced.

2.3. Subsidiary Entities (SE). External businesses can network with the PLO for providing value-added services to the customers. This can improve the value proposition of the smart parking facility. These benefits may take the form of retail coupons, rebates, special services at the airport, etc. Such subsidiary entities (SE) support the infrastructure and may offer mutual benefits by attracting more customers. Additionally, entities specializing in business analytics may be engaged in the study of prosumer data, travel habits, etc. (with due authorization) for value enhancement. The analysis may include market effectiveness, user compliance, asset management, adoption behavior, load balancing, grid utilization, etc.

Table 1. Cost and revenue components for the principal entities

Vehicle Owner	Parking Lot Operator	Energy Provider
Parking lot Admission Fee	Revenues earned through energy transactions	Energy transaction costs/revenues
Battery Charging Cost	Parking fee	Penalties on contractual violations with PLO
V2G Revenues	Penalties on service violation to customer	
Battery degradation costs	Penalties on contractual violations with the energy provider	
Plan violation penalties		

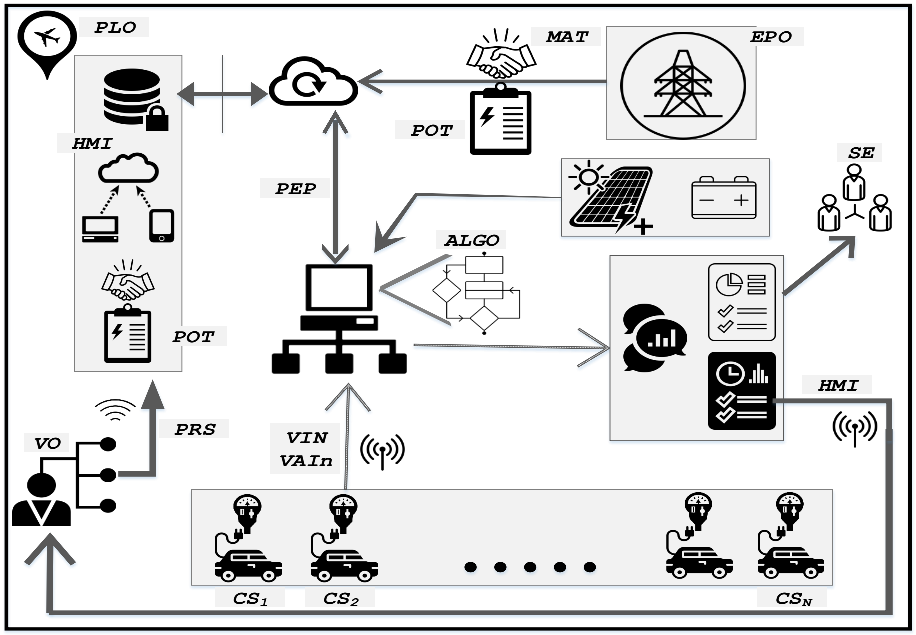

Figure 1. Airport parking lot model.

3. PARKING LOT MODEL

The business model gives the structural and functional framework for the proposed transactive energy paradigm. Successful implementation of the business model requires an understanding of the parking facility characteristics. Although actual PEV arrival/departure times are not known in advance, airport arrival and departure times are predominantly determined by the flight schedules which vary within a known window. Therefore the scheme developed in this paper is based on a prior reservation strategy (PRS) with a buffer window for the arrival time.

3.1. EV-Energy Transaction Potential. Customers are considered to be prosumers due to their involvement as both producers (V2G) and consumers (G2V). The aggregated EV fleet energy transactions have been optimized by coupling customer and parking lot operator objectives. The bi-directional energy transfer capability of EVs can be used for grid-support in two modes: as a dispatchable source or a controllable load. Since

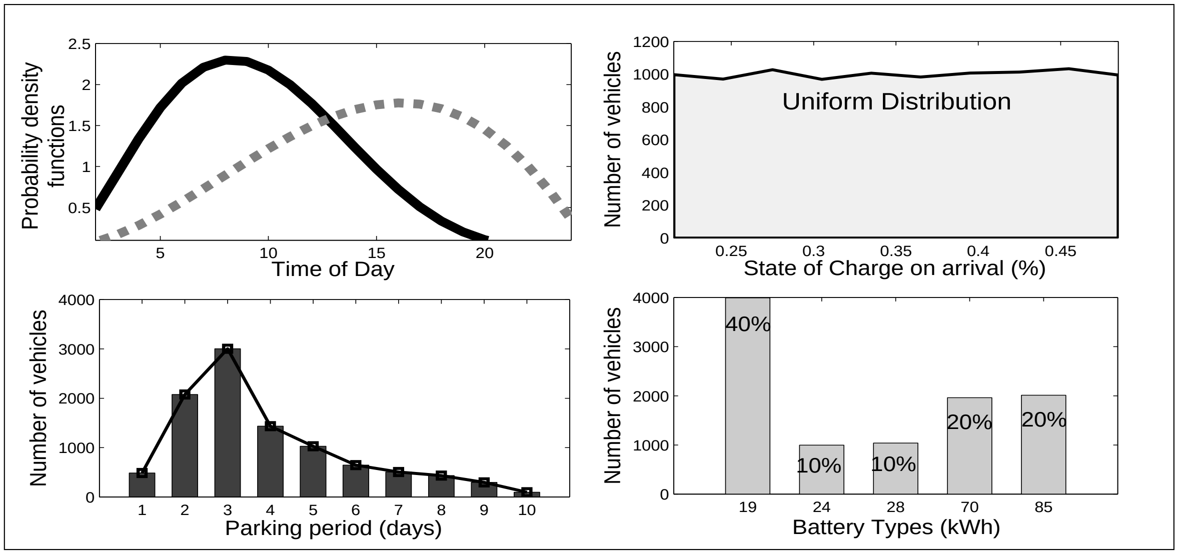

Figure 2. Statistical data generated for a vehicle population of 10000.

the parking period of each vehicle is known, they can be dispatched as a large energy storage system on demand while serving within their individual battery limits. However, even though this problem appears to be conceptually straightforward, the optimal implementation of the proposed strategies requires an integrated solutions.

3.2. Parking Reservation System. Upon arrival, an EVO would select their charger, enter a retrieval time, and select the option plan for their vehicle. These may also be selected in advance via an on-line reservation system. Changes in travel plans may also be made on-line. This portal would serve as the human-machine interface that provides the prosumers with analytics on their vehicles, such as vehicle state of charge, energy use, or real-time parking fee.

3.3. Vehicle Availability Information (VAIn). Vehicle owners are requested to register with the PLO and provide their vehicle information. Each vehicle is assigned a unique identification number (VIN) and a charging spot in the parking lot. The Vehicle Availability Information (VAIn)-tuple for vehicle i contains a static block including $\langle B_{i,cap}, C_{i,rate}\rangle$ and a dynamic block $\langle d_{i,arr}, t_{i,arr}, d_{i,dep}, t_{i,dep}, d_{park}, SOC_{i,arr}\rangle$. With customer consent, this information may be stored and used for future forecasting, diagnostics, and analysis by the PLO or its subsidiaries. The vehicle information for this study was emulated using statistical distributions based on certain assumptions as illustrated in Fig. 2. These include:

1. The airport arrival and departure times for the vehicles were randomly sampled from beta probability density functions. This data is generated using the assumption that air traffic is more prevalent during the morning and evening hours.
2. The vehicle state of charge (SOC) on arrival varies between 20% and 50%.
3. The parking period of each vehicle was sampled from a multinomial random distribution. The vehicles may be parked for any period between 1-10 days, with a most probable duration of stay of 3 days.
4. The vehicle battery type was selected from a range of available battery sizes according to the probability distribution of that size [14].

3.4. Communication and Infrastructure Design (CID). C_{PL} represents the total number of parking spots in the facility with a total of CS_{PL} charging stations available. The charging stations are divided into Type I, Type II, and Type III chargers ($CS^{I}_{PL}, CS^{II}_{PL}, CS^{III}_{PL}$ respectively). In this study, it is assumed that the parking lot has sufficient charging spots to serve all the vehicles that arrive, thus $CS_{PL} = C_{PL}$ and each vehicle arriving the facility is immediately served. However if $CS_{PL} < C_{PL}$, then vehicles will have wait-times, and a strategic parking token system may be implemented on either first-come-first-serve basis with vehicle-swapping or using priority registration.

The status of each charging spot is encoded as a 3 bit unit. The charger status and vehicle status information is stored as shown in Table 2. This information would have to be updated regularly to maintain PLO control.

Each charging station is connected with the central controller through a two-way communication channel using an automatic energy metering system. The communication infrastructure may be based on ISO 15118 standard or SAE J2847/1 [15]. These standards

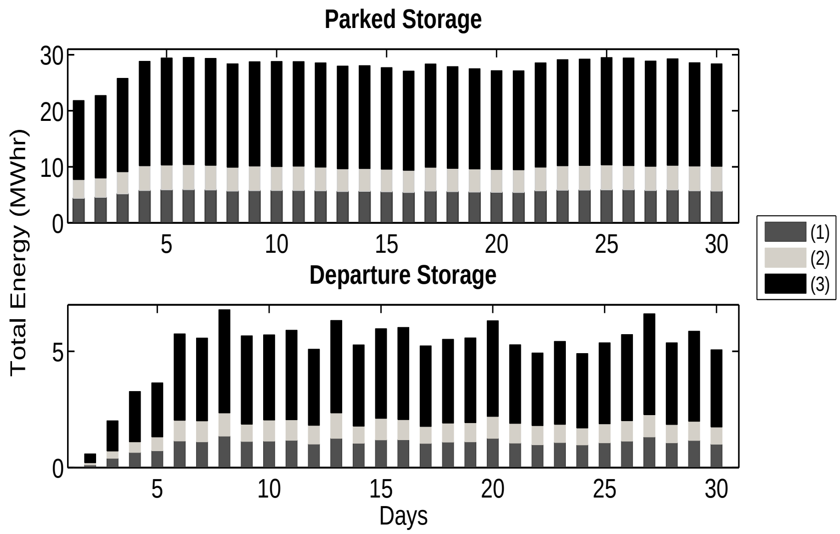

Figure 3. Aggregated Parked and Storage Energy Capacity.

are designed specifically to allow synergistic development of communication, interoperability, and security protocols for EV-utility interface. Grid-networking protocols such as IEEE 802.15.4 (Zigbee), broadband over Powerline and HomePlug, ZWave, etc. may be used for this purpose.

3.5. Parking Lot Controller Design. The parking lot controller collects the vehicle information based on the daily reservations and uses this information to categorize the vehicles into two groups 1) departure storage, and 2) parked storage. If a vehicle is scheduled to depart at the end of the day it is aggregated into the departure group.

Table 2. Charger status and information encoding

Charger Status	**Vehicle Status**	
Charger_ID	Charging	111
Charger_type	Discharging	110
Charger_status [Idle/Engaged]	Charged	101
Vehicle_ID	Idle	000
Vehicle_status		

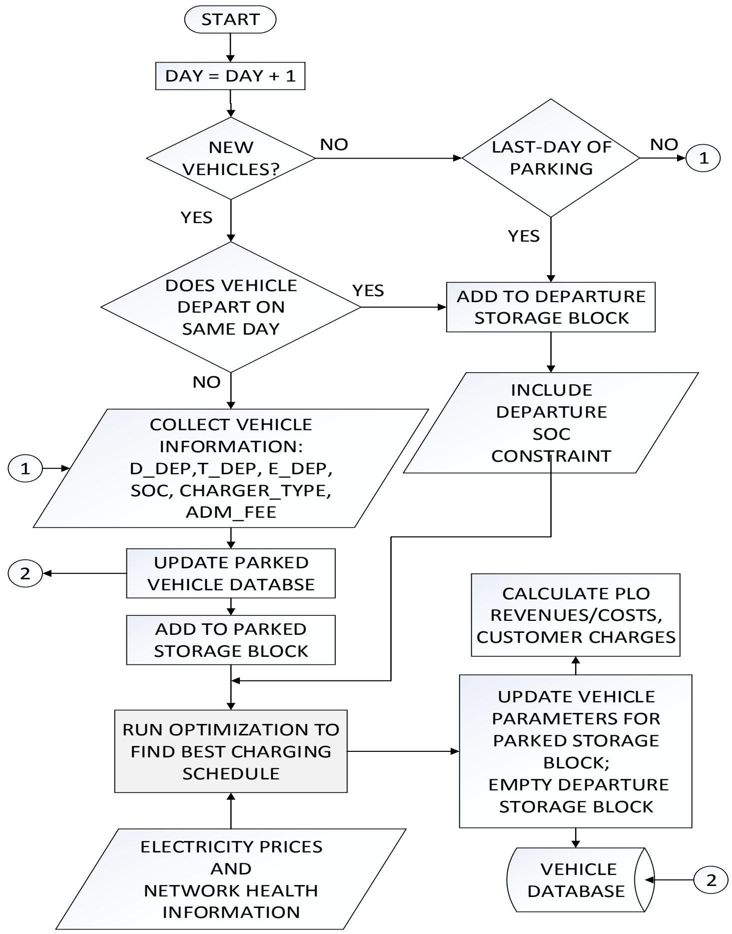

Figure 4. Flowchart for parking lot control algorithm.

The departure battery group has limited V2G capability since these vehicles must be charged to the customer desired SOC (typically at, or near, full SOC) by the end of their specified parking periods. Vehicles scheduled to remain in the structure beyond that day are assigned to parked storage group and have greater resource flexibility because they have no daily hard target SOC. Fig. 3 shows the aggregated battery capacity for the two storage groups. Note that there is a start up period for these results that would not exist in a real-time system.

Once the participating vehicles have been categorized into one of the two groups, the parking lot controller optimizes the energy transactions for the aggregated fleet as shown in Fig. 4. Depending on the business strategy adopted, a wide range of objectives might be applicable to the optimization process; they may be classified into 1) PLO-driven, 2) customer-driven, 3) system-driven, or any combination of these three categories. Vehicle charging constraints have been adopted from [16]. These business strategies are described in the following sections.

3.5.1. Maximize PLO Profits. This objective seeks to maximize the parking lot owner's profits. This strategy generates revenues by selling maximum energy to the power grid (during high price periods) and buying energy from the grid to charge the vehicle fleet during the low-cost periods of the day. It also seeks to avoid any penalties based on contractual violations with the ESO or the customer. The PLO may buy/sell at the wholesale rate by transacting energy between the vehicles and the EPO. This profit may be shared between the PLO and the EVO. The total costs incurred/revenues earned by the customer are given by Ψ_i^{rev} in:

$$\Psi_i^{rev}(x) = \sum_{t=1}^{t_{i,avail}} \left(\frac{x_{ch,i}^t}{\eta_{ch}} - x_{dch,i}^t \cdot \eta_{dch} \right) \left(\lambda^t \right) \tag{1}$$

3.5.2. Minimize Battery Degradation. One of the major challenges associated with V2G is battery degradation during cyclic charging/discharging of the battery that may adversely affect the automotive life of the battery. Because numerous charge/discharge cycles can degrade the battery, nn additional objective is to minimize battery damage, thus protecting EVO interests. Simple linear approximations for SOC and DOD related degradation costs have been adopted from [17] and [18]:

$$\Psi_i^{deg}(x) = \sum_{t=1}^{t_{i,avail}} \Psi_i^t = \sum_{t=1}^{t_{i,avail}} \Psi_{i,t}^{SOC} + \sum_{t=1}^{t_{i,avail}} \Psi_{i,t}^{DOD} \tag{2}$$

$$\Psi_{i,t}^{SOC} = C_{bat} \frac{m \cdot SOC_{avg,t} - d}{CF_{max} \cdot bat_{life} \cdot 8760} \tag{3}$$

$$\Psi_{i,t}^{DOD} = \frac{C_{bat} \cdot B_{cap} + C_{labor}}{bat_{life} \cdot B_{cap} \cdot DOD} E_{\Delta t}^{dch} \tag{4}$$

3.5.3. Optimize Vehicle Utility. The major aspects of vehicle utility include:

- Maximize utilization of the battery capacity during the entire parking period, while
- Minimizing battery degradation costs, and
- Maximizing energy transaction profits.

The PLO seeks to maximize its profit by optimizing vehicle utility.

3.5.4. Customer Satisfaction Index (CSI). A customer satisfaction index may be defined based on 1) total costs incurred including any portion of the PLO profit shared with the EVO, 2) total expected energy served by the PLO, and 3) the SOC at time of departure. This index is defined as a weighted sum of three components 1) total costs C_{total}, 2) expected energy served E_{SOC}, and 3) delay in service T_{delay} due to inadequate SOC at time of departure. The weight w_i is a user defined ratio based on external priorities.

$$CSI = w_1 \cdot C_{total} + w_2 \cdot E_{SOC} + w_3 \cdot T_{delay} \tag{5}$$

$$C_{total} = 1 - \frac{(C_{rev} + f_{adm} + C_{batdeg})}{f_{adm}} \tag{6}$$

$$E_{SOC} = \frac{E_{sup}}{E_{reqd}} \tag{7}$$

$$T_{delay} = 1 - \frac{t_{delay}}{t_{park}} \tag{8}$$

4. MODEL DEVELOPMENT

The airport parking lot is modeled as a structure that has predictable (within set variances) arrival and departure of vehicles. A minimum of 500 vehicles are available at any time during the 30 day consideration period. The number of vehicles arriving or departing the parking lot on any day is selected randomly based on the probability distribution shown in Fig. 2. After the vehicle information is obtained through the parking reservation system, the scheduling controller runs the optimization under the constrained scenarios generated using the PLO-defined single or multiple objectives. This optimization for day d is completed using the information available by 23:59 hours on day $d - 1$. The obtained profiles Ω are appended to the VIN and sent over the communication channels to the assigned charging station. Once the vehicle is parked in a designated spot, its energy transaction profile follows the pattern stored at the corresponding charging station. On completion of the parking period, the energy transactions are evaluated and the financial logs are updated.

The parking lot is assumed to be equipped with Type III chargers. These were chosen to maximize energy transaction capability at any time instant, thus maximizing vehicle utility. For the 30 day period, the number of vehicle arrivals/departures, trip duration, arrival SOC, and arrival/departure times were sampled from the data shown in Fig. 2. Locational marginal prices for a node in the Midwest Independent System Operation (MISO) region were selected as the test case data [19]. Figure 5 shows a comparison between the hourly fluctuation of prices during the months of June and January that were selected to account for seasonal variations.

Three cases have been simulated for the months of January and June:

- *Case0:* Traditional parking lot without smart charging
- *Case1:* Parking lot with charging capability (only)
- *Case2:* Smart parking lot for maximizing PLO revenue through active energy transactions

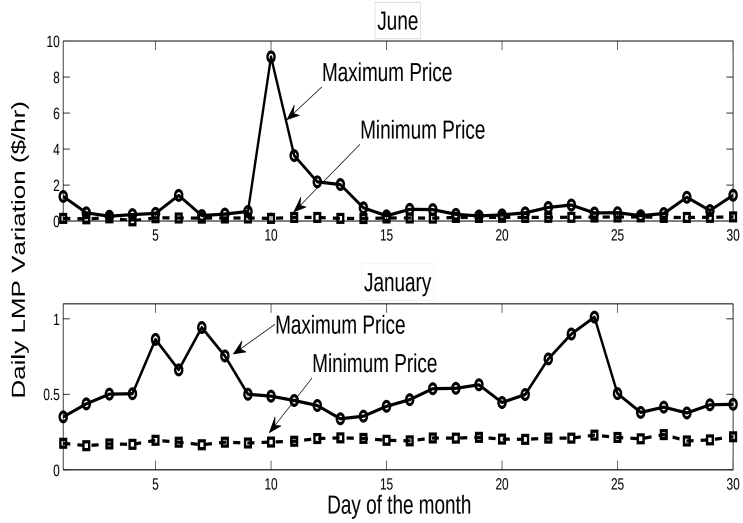

Figure 5. Daily maximum and minimum LMP variation for a node in MISO region (June/Jan).

5. RESULTS AND DISCUSSION

A traditional parking lot operator charges a constant daily admission fee (f_{adm}) to the vehicle owners. This was treated as the base case. Two additional fee structures have been proposed and investigated along-with a flat fee reduction from $20/day to $15/day. These include 1) SOC dependent fee (f_{adm}^{SOC}) and 2) usable capacity dependent fee (f_{adm}^{cap}). A modified admission fee can motivate the customer to participate in the transactive business model.

$$f_{adm} = t_{park}^{days} \times fee_{\$/day} \tag{9}$$

$$f_{adm}^{SOC} = (1 - SOC_{arr}) \times t_{park}^{days} \times fee_{\$/day} \tag{10}$$

$$f_{adm}^{cap} = \frac{(B_{cap} - B_{min})}{B_{cap}} \times t_{park}^{days} \times fee_{\$/day} \tag{11}$$

Remark: Table 3 shows that choosing a modified parking fee incentivizes the customer but results in lower revenues, therefore an alternate revenue stream would be needed to maintain PLO profits.

The total energy demand of the parking lot for $Case1$ is shown in Fig. 6. No activity is observed in the parked storage block. As the vehicle nears its departure time, it gets charged to its full capacity. Highest costs are incurred in this case since the PLO needs to buy energy to charge these vehicles.

The total energy transacted by the PLO during the month (June) in $Case2$ has been shown in Figs. 9 and 10 for choice of fast (Type III) and slow (Type I) chargers respectively.

Remarks: The results show that parked storage undergoes deeper charge/discharge cycles in comparison to the departure storage. During the optimization, it was also observed that these two blocks acted independent of each other. Further, slow charger resulted in lower cumulative energy transactions in comparison to the fast charger. Therefore, for maximizing vehicle utility, fast chargers would be more beneficial than the slow chargers.

Table 3. Monthly revenue from parking fee

f_{adm}	f_{adm}^{SOC}	f_{adm}^{cap}
\$319480.00 (@ \$20/day) \$239610.00 (@ \$15/day)	\$207507	\$255584

Table 4. Monthly revenues for a parking lot with Type III chargers

	Month	**Revenue/ Cost**	**Battery Degra-dation Costs**	**Total Costs**	**Net Profits**	
					\$20/day	\$15/day
Case0: Tradi-tional parking					319480	239610
Case1: Charging only	June	19967.8	198.1196	19967.8	299512.2	219642.2
	Jan	2158.09	198.5275	2158.09	297891.9	218021.9
Case2: Transac-tive	June	-263621	1801.3	-261819.7	581299.7	501429.7
	Jan	-133081	15810	-131500	450980	371110

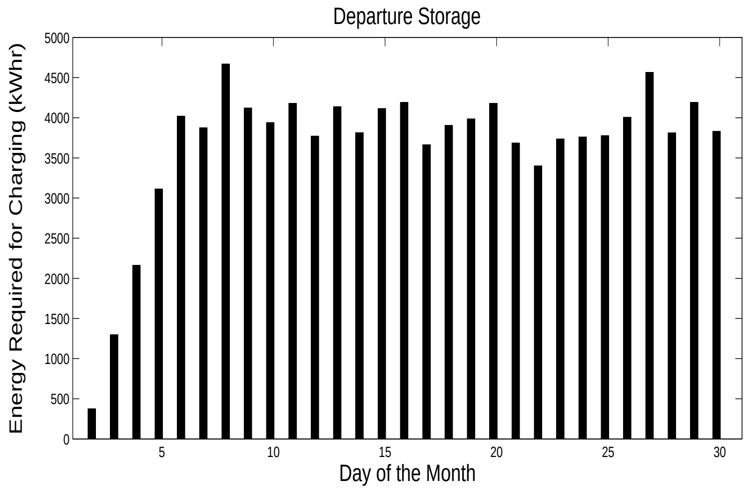

Figure 6. Energy required for charging (Type III chargers) during the month (Case1).

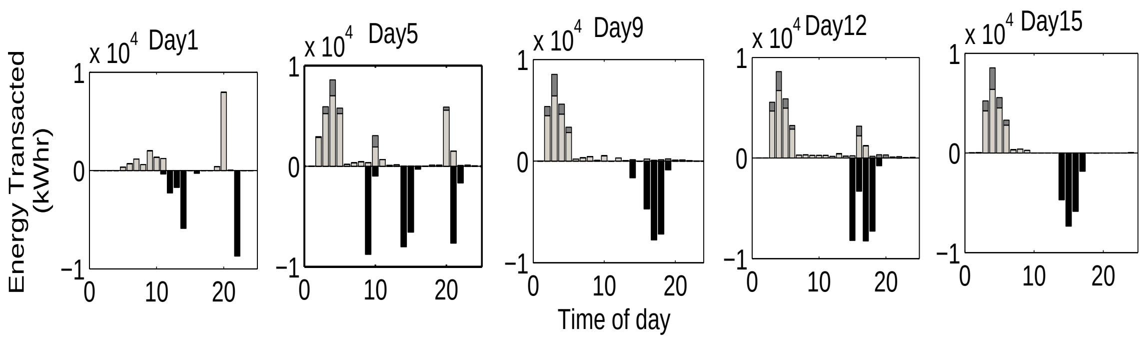

Figure 7. Hourly energy transactions (Type III chargers) for a 5-day sample.

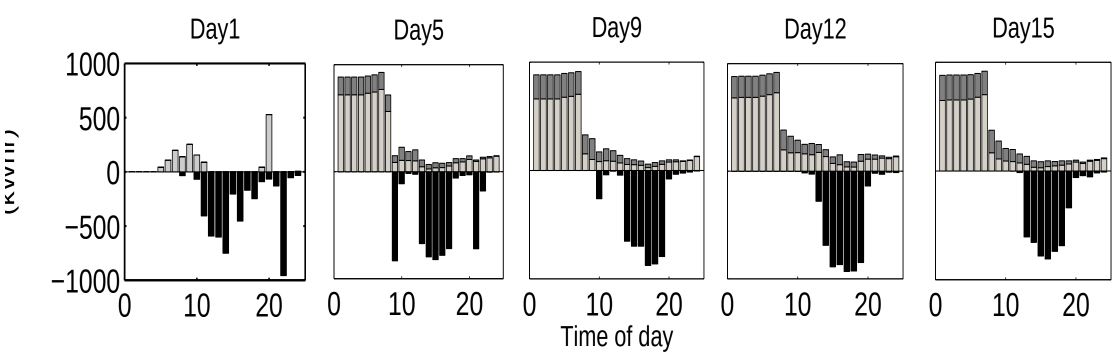

Figure 8. Hourly energy transactions (Type I chargers) for a 5-day sample.

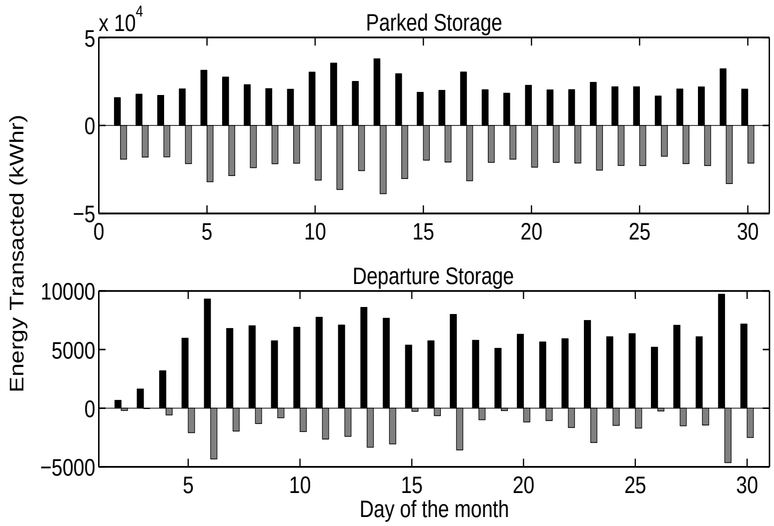

Figure 9. Energy transacted by parked and energy storage blocks (Type III chargers) during the month (Case2).

Figures 7 and 8 show a sample 5-day hourly variation of energy bought and sold by the parking lot fitted with Type III and Type I chargers respectively. Type I chargers result in lower, contiguous energy transactions while Type III chargers lead to non-contiguous, higher transactions. This result can help in understanding the regulation capability of a smart parking lot.

Remark: It is evident from this data that at any time instant some vehicles might be charging while the others are discharging simultaneously. This scheme is decided by the control center after running the optimization.

Table 4 summarizes the cost analysis of the simulations. For comparison, resulting costs with Type I chargers have been presented in table 5.

Table 5. Revenues/Costs of the PLO using Type I chargers

Month	**Case1**	**Case2**
Jan	\$27573.15	-\$1096.04
June	\$28088.87	-\$11286.8

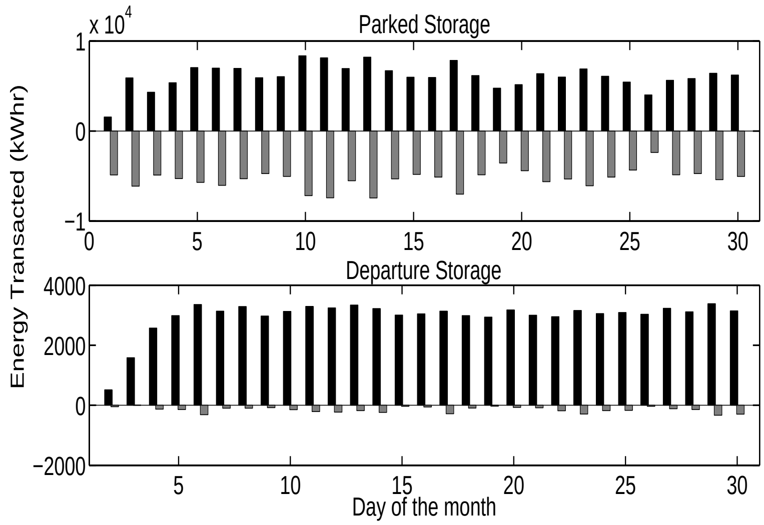

Figure 10. Energy transacted by parked and energy storage blocks (Type I chargers) during the month (Case2).

It can be observed that:

- *O1:* In $Case1$, either PLO profits will decrease or customer expenses will increase to pay for vehicle charging. One solution is to charge the owner with an additional (constant) charging fee. In case \$20/day is charged, this cost would be 17.2¢/kWh while in case the parking fee is reduced to \$15/day, it would be 85.9 ¢/kWh to keep the PLO profits constant. This is is applicable to the modified admission fee also.
- *O2:* In $Case2$, PLO makes profits through energy transactions. Even after accounting for battery degradation costs, this scenario is profitable with fast chargers. Other than decreasing the admission fee, customers may be further incentivized through profit-sharing mechanisms.
- *O3:* Battery degradation costs (calculated based on the degradation model chosen in this paper) can be easily compensated through cost/revenue maximization. Customers with infrequent travel plans may choose to ignore these impacts when choosing probable $POTs$.

- *O4:* Type I chargers did not result in higher revenues due to their limited power rating. Thus, further analysis may be performed on the optimal mix of charger types.

- *O5:* Comparing the results of table 4 and table 5, it can be observed that retrofitting the parking lot with Type III chargers would be more lucrative than Type I chargers. This could be due to greater flexibility, wider range and larger power rating of Type III chargers. Moreover, in order to enter the electricity markets as an ancillary services agent, a higher power output capability would be beneficial.

- *O6:* Higher profits were observed for the month of June in comparison to January. Therefore, larger the variation in hourly pricing, higher the possibility of earning profits from energy transactions.

Such analysis would also enhance customer experience by providing them with an approximate information structure about the impacts of choosing different POT schemes.

6. CONCLUSION

This paper discusses a detailed business model for smart airport parking facilities. The transactive capabilities of a large EV fleet were leveraged to find an optimal charge/discharge paradigm that maximizes vehicle utility, enhances customer experience and provides profits to the parking lot owner. This work provides a framework that may be used to design a business model for any long-term parking facility. Further, the impact of the choice of charger type and hourly price variation has also been discussed. The day-ahead algorithm may be utilized to assess the daily energy transaction capability of the parking lot and provide the customer with impact-assessment of various POT schemes. Uncertainties due to price changes, driver behavior and renewable energy will be explored in future extensions of this work.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the financial support of the National Science Foundation under the project ECCS-1068996.

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SECTION

2. CONCLUSIONS

This dissertation focused on the potential of electric vehicles as controllable loads/resources while keeping customer's convenience, choice and security upfront. The work builds on the foundations of power system concepts and optimization techniques. What started as a day-ahead heuristic aggregation technique is shown to move the current state-of-art into transactive business models through provision of multiple optimal real-time scheduling solutions. The algorithms are scalable, implementable with limited communication needs and provide opportunity for further research. The results presented in the journal papers show that electric vehicle scheduling efficiently manages the load on the system. These results can further translate into solutions to the inevitable problems associated with renewable energy integration, by the potential application of EVs as mobile energy storage systems.

The idea of keeping all the solutions customer-centered underlines the success of any DR scheme and is thus implicitly included. By providing the customers with the flexibility to choose plans, pricing schemes and alternative scheduling schemes can help build their confidence in the utility while reassuring shared responsibility. The customer, utility and vehicle aggregator or market player are, thus, the three principal entities of any related business model.

While technical background is essential to the successful implementation of this scheme, it is crucial to emphasize on the significance of transactive business models in the future energy models pertaining to power systems. While there are inherent complexities associated with this concept, the work presented here proposes a very basic framework for a smart parking facility. It improves vehicle utilization, customer experience and business opportunities.

It is worth noting here that formulating policies are critical to successful EV penetration and usage in the future electric grid. In their absence any of the proposed strategies would fail. Thus, one of the future directions of this work includes policy design and analysis. Inclusion of uncertainty in the solution strategy will make a pronounced addition to the schemes. In future, this work will be extended to implement stochastic, distributed algorithms to demonstrate their performance on power quality and reliability of multiple test systems.

VITA

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