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Electric vehicle smart charging and vehicle-to-grid operation

Siddhartha Mal, Arunabh Chattopadhyay, Albert Yang, Rajit Gadh

Abstract—**Electric vehicle (EV) charging must be optimized for grid load while guaranteeing that drivers' schedules and range requirements are met. A system encompassing EV owner input via a mobile application, an aggregation middleware, a charge scheduling and vehicle-to-grid (V2G) operation algorithm, and a radio-frequency identification (RFID) reader, is proposed. The algorithm's parameters and effectiveness are presented and discussed using simulation results. Simulation results show the algorithm to effectively optimize charging and V2G operation for a given electricity price curve. The proposed system is shown to alleviate grid load during peak hours, take advantage of off-peak charging benefits, and generate revenue for the parking garage operator.**

***Index Terms*— Charge Scheduling, EV, Smart Grid, V2G**

I. Introduction

One million electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) are expected to be in use by individuals and fleets by 2015 [1]. Unmanaged EV charging will add to peak grid load and would require additional generation capacity [2], [3]. Charging must be scheduled intelligently in order to avoid overloading the grid at peak hours and to take advantage of off-peak charging benefits. EVs can also serve as an energy resource through vehicle-to-grid (V2G) operation by sending electricity back into the grid thereby preventing or postponing load shedding [4],[5]. Charging and V2G services must be optimized for grid load while guaranteeing owner schedule and range requirements are met.

A system leveraging mobile devices and application to facilitate "smart" charging has been proposed [6], however integration of the mobile component with a charge scheduling component is not specified. In addition, the described system does not account for discrepancies between specified user charge profiles and actual distance traveled and times of arrival and departure. A conceptual framework for V2G implementation has been developed [5], however EV owner input into the system has not been considered. The market penetration of smart technologies and Advanced Metering Infrastructure (AMI) has resulted in smarter EV charging techniques which minimize charging cost to the consumer and grid load at peak hours. Shao et al. [7] proposed a quick charging method where a higher load (240V, 30A) is drawn to enable quicker charging during evening (after 6 p.m.) and off-peak hours. Home-based and off-peak charging (9pm to 11 am) is also considered by Yu [8].

In this paper we present a system that performs electricity price optimized scheduled charging and V2G operation of EVs in a parking garage using owner charge profiles - charge scheduling optimized for electricity price is implicitly optimized for electricity demand. A literature review of RFID, V2G, and charge scheduling is conducted in Section II. In Section III the system architecture and its individual components are described. The charge scheduling algorithm is detailed in Section IV and results are presented in Section V. Concluding remarks are in Section VI.

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II. Literature review

A. Radio-Frequency Identification (RFID)

RFID has been playing an important role in various kinds of supply chain based industrial applications such as warehousing, pharmaceutical tracking and retailing since the past decade. An RFID system consists of one to many readers which communicate with multiple tags by inquiring their identification (ID) [9]. This technology has been widely adopted in supply chain systems to streamline the flow of information regarding identification, arrival/departure and status of objects in the system. Tags are periodically queried by their respective readers, which in turn notify a software service/middleware of their presence or absence, which can be further processed to deliver useful service. RFID tags are separated into three categories based on their energy usage: Passive, Active, and Semi-Passive depending upon their power consumptions [10]. RFID tags are also categorized based on the frequency at which they operate such as Low Frequency (LF), High Frequency (HF), Ultra High Frequency (UHF) and Microwave depending on the application [11].

RFID technology has been used for some time in parking lots in the form of Near Field Communication (NFC). The typical role of NFC in parking lots is to grant entry to authorized users. Our system would employ an RFID reader at every access gate to read an entering vehicle's tag. Once the tag's ID has been read, it is transmitted to the system middleware which performs a database lookup. The middleware will either grant the vehicle access and assign it to a parking spot or deny access.

Porter *et al.* discuss the implementation of RFID based vehicle mileage logger at gas stations [12]. They discussed rates of getting successful reads by the RFID mileage loggers from devices placed in vehicles and the issues that affect the read rates of the RFID readers. They also discussed an architecture where a middleware bills the drivers of the vehicles with the toll based on the distance they drove on toll highways after collecting the data through the RFID readers. They also implemented GPS based technologies to supplement the mileage collection process. Theo *et al.* discuss the concept of an Energy Name Service (ENS) for the smart grid energy infrastructure [13]. The concept they have explained is inspired by the principle of Domain Name System (DNS) and Object Name System (ONS) which is very closely related with the concept of internet of things using RFID tagged objects. The philosophy of their work is that how every entity in the energy domain (like charging stations, vehicles etc) would be given an ID, which would be helpful in identification and hence execution of seamless transactions for charge consumption between multiple geographical entities. This would be similar to the mobile phone service where a user would be billed for their usage regardless of the location of usage of the mobile phone service. They also introduced the concept of Internet of Energy similar to the internet of things where every object related to the energy food chain is interconnected to each other through the internet. Their paper discussed the architecture of such an energy network and methodology for the energy naming service where an object is given an energy ID based on certain parameters such as geographical location, type of object etc. Song discusses the implementation of a home electricity management box installed at every household which acts as an intelligent node to optimize the consumption of electric energy [14]. They propose using the RFID enabled car keys as instruments to authenticate EVs for charging.

B. Charge Scheduling

Soares *et al.* have proposed a Particle swarm optimization (PSO) based approach to perform V2G based charge scheduling [15]. Their charging plan also encompasses distributed power generation systems such as fuel cell, solar etc which contribute to the net power generation. Their goal is to minimize the generation cost which includes generation production cost and V2G discharge payment. They compare their optimization approach with General Algebraic Modeling System (GAMS) based optimization software. However, they don't explain the technique employed by the GAMS software to optimize the charge scheduling which makes it challenging to assess the two techniques. In the final result they show that the GAMS based software results in lower total costs but the PSO based approach has a lower execution time. However, this claim is also hard to validate as very little light has been thrown on the technique employed by the GAMS optimization software. Venayagamoorthy *et al.* proposed a real-time digital simulator based vehicle parking lot performing V2G transactions [16]. They have used a binary particle swarm optimization technique to control the power flow to and from a vehicle. The goal of their optimization technique is also to minimize the cost of charging a given EV. In this paper, they analyze the effects of large bidirectional power surges to the batteries and the inverters of individual plug-in vehicles as they are switched from a state of charging to discharging. They concluded that grid faults can be detrimental to vehicles performing V2G transactions unless advanced control and protection is provided. Hutson *et al.* extended the work by Venayagamoorthy on V2G based charge scheduling in parking lots [17]. The charge optimization was again based on the BPSO algorithm previously discussed. They considered two cases. The first case study takes the price curve and finds the best selling price for each vehicle over the desired departure State of Charge (SOC) and the best buying price for each vehicle under the desired departure SoC. Case 2 allows for multiple transactions to occur for each vehicle throughout the day leading to more profit oriented charging. However, the Binary PSO (BPSO) algorithm being stochastic, the same solution is not found each time leading to a standard deviation of 0.045% of the average. Wu *et al.* introduced the concept of intragrid which aggregate the contributing EVs under an umbrella to act as a single unit feeding and taking energy from the grid [18]. They considered different scenarios where either the cost of charging the EVs or the emission from the charging or both can be minimized. The optimization algorithm used is Particle swarm optimization. They achieved their optimum solutions after 1000 iterations. Saber *et al.* propose the concept of an intelligent Unit commitment (UC) by using V2G to reduce operational costs and emissions [19]. BPSO was used to perform scheduling of thermal units while Balanced PSO was used to determine the number of V2G units to be connected to grid to minimize the cost of operation and emission by the thermal units. Different scenarios were simulated by optimizing the cost, emission and combined goals. Schieffer *et al.* have proposed a decentralized charging strategy in their work [20]. First they employ linear programming to optimize charging duration by minimizing charging events during peak load (or high priced) hours. On completion of this step they use probability density functions indicating the distribution of charging slots to determine the exact time choices for charging. They have many similarities with our work such as charge time optimization, division of entire day into smaller charging/discharging time intervals etc which would be highlighted in greater detail during algorithm discussion.

C. Vehicle-to-Grid (V2G)

Guille and Gross [5] present a conceptual framework for implementation of V2G based on bi-directional energy transfer between vehicle and grid and aggregated use of EVs as generation and storage devices. Aggregated EVs can provide grid services such as up and down regulation, load leveling, and peak shaving more economically and with less environmental impact than current systems. EVs must be

aggregated because individually their battery capacity is small and would not make an appreciable difference at the grid level. In contrast with unmanaged EV charging that can add to reserve and regulation requirements, aggregated EVs can be charged during off-peak periods thereby levelizing grid load and reducing these requirements. The proposed framework emphasizes the Aggregator as the enabling entity for V2G. The Aggregator has the following communications relationships: 1) each EV sends status data and receives charging control signals 2) the Energy Service Provider (ESP) receives charging and sends load levelization requirements 3) the independent system operator
or regional transmission organization ISO/RTO sends resource requirements and receives resource availability data. This work presents seminal ideas for future V2G work, however specific components of the proposed framework are neglected including EV owner input into the system and charge scheduling for random arrival and departure times.

Kempton and Tomic [4] present profit calculations for using EV fleets for V2G services including up and down regulation. Assuming an availability of 17 hours per day for 252 RAV4 EVs, an initial state-of-charge of 30-50%, a required range of 36 miles, and circuits able to handle 6.6 kW, profits range from $144,800-912,000 for regulation down/up market prices from 12.9/14.0-39.7/62.5 US$/MW-h. When a 15 kW limit is considered the range is $358,000-2,102,000. The results include equipment costs and battery life degradation.

Han et al. [21] present a method for optimally controlling EV charging to maximize EV regulation service revenue. The model developed accounts for varying electricity and regulation price over time, a variable time the vehicle will be parked, a variable amount of charge needed, and a maximum charge rate. A maximum revenue of $.42 is determined assuming a 20 kWh battery, maximum charge/discharge rate of 2 kW, an arrival time of 00:00, and departure time of 12:00.

III. System Architecture

A. Overview

EV owners will register one or more vehicles with the system. Each registered vehicle will wear an RFID access tag that will allow it to enter enterprise owned and affiliated garages. The tag's unique ID is used by the Parking Garage Aggregation Middleware (PGAM) to lookup the associated owner and act on his/her charging profile and billing information. At the access gate (Fig. 1) the driver will be designated a numbered parking spot based on availability. Once the owner plugs in to the EV Supply Equipment (EVSE), the PGAM checks for an existing charging profile. If none is found he/she will be prompted to enter one via the EV Command Portal (EVCP) application on their mobile device or charge station touchscreen (Fig. 2). Fig. 3 shows the sequence of events when a car arrives at the gate. If the user fails to enter a profile within a given time window, the system uses a default. The EV owner can use the EVCP to monitor the status and control the charging modality of his/her vehicle within system parameters at any time. Based on user charge profile the Aggregated Charge Scheduler (ACS) will schedule charging to meet user charge requirements, minimize cost, and maximize profit from V2G services. Fig. 4 shows the flow of the aforementioned data among system components.

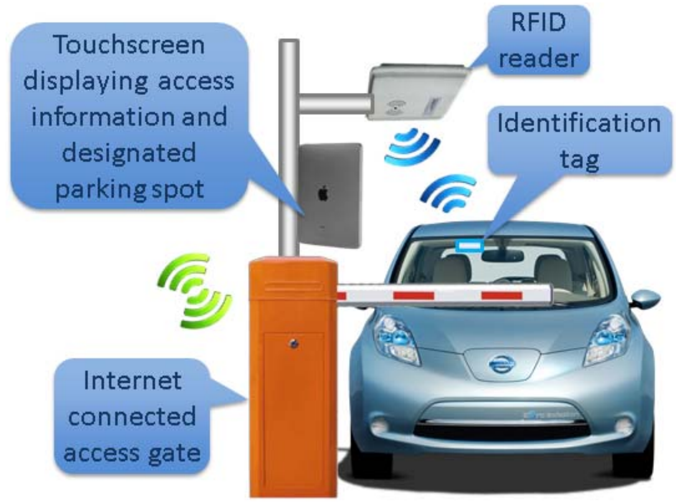


Fig. 1. Parking garage access gate.

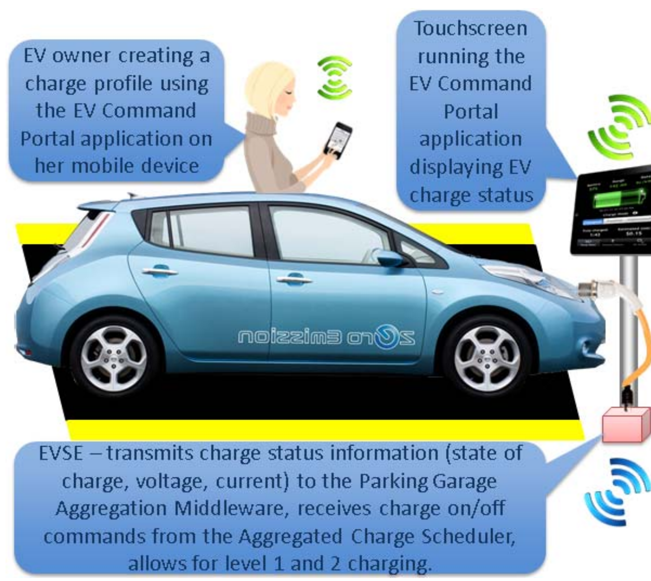


Fig. 2. Charging station equipment and activities.

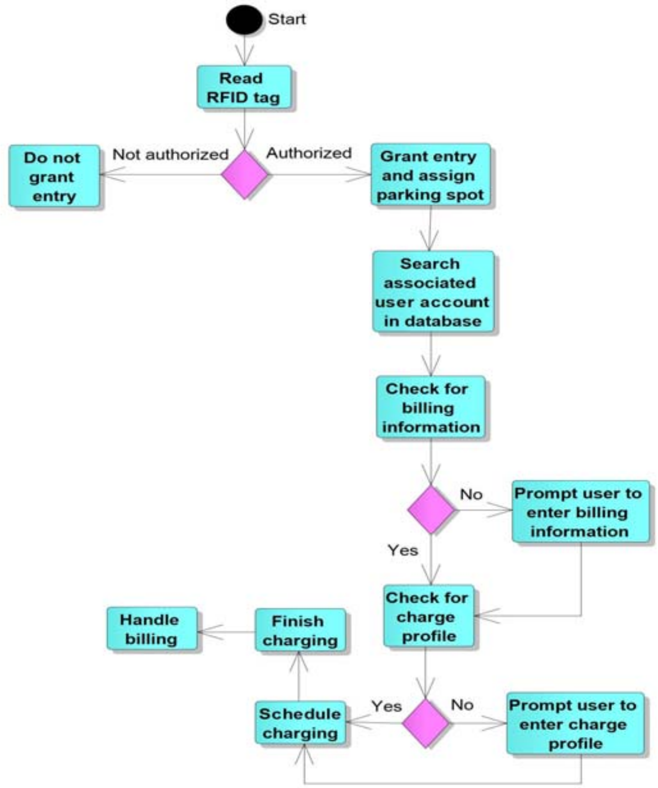


Fig. 3. Event sequence for EV arrival at parking garage.

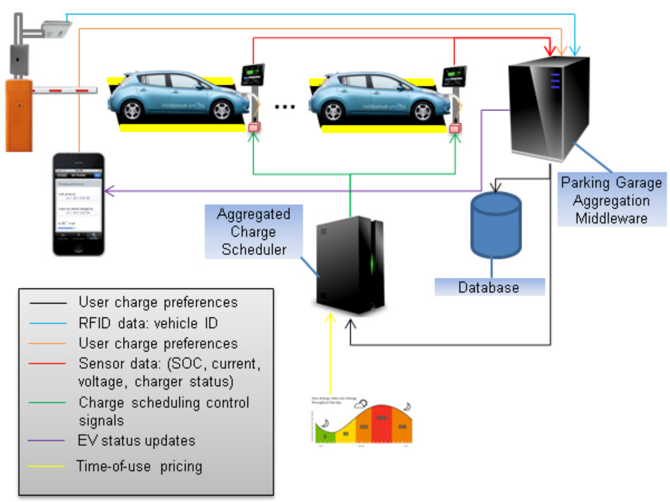


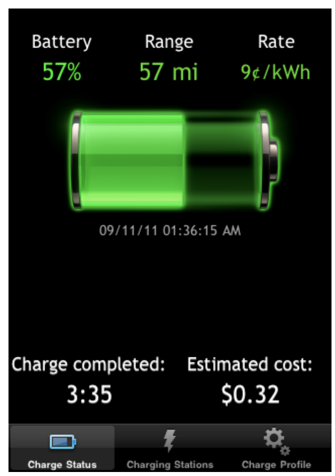
Fig. 4. Data flow among system components.

B. EV Command Portal Application

Range anxiety is one of the main obstacles to consumer adoption of EVs. The problem stems from 1) limited range compared to conventional gasoline vehicles 2) inadequate charging infrastructure [22]. This anxiety can be mitigated if EV owners have better access to and control of the charging of their vehicles. This control can be achieved intuitively via a web or mobile application. Users should be able to monitor their vehicle's state of charge (SOC), range, estimated charge completion time, and estimated cost of charging. They should be able to control the charging of their vehicle using parameters including desired SOC, time of arrival, time of departure, and, if available, V2G opt-in.

The EV Command Portal (EVCP) application will play an integral role in the scheduled charging of EVs by allowing owners to monitor the status of their vehicles as well as control the way they charge. The application will provide the user with real-time updates on the SOC of their battery, real-time charge status alerts e.g. charge completed, and allow users to control the charging modality of their vehicle by creating charging preferences and schedules.

The EVCP interface is comprised of three screens: 1) Charge Status 2) Charging Stations 3) EV Profile. "Charge Status" is the main screen and displays the EV's SOC, range, time remaining until charging is completed, current electricity price, and estimated total charging cost (Fig. 5a). The "Charging Stations" screen displays charging stations on a map along with charger type and real-time availability information. The "Charge Profile" screen displays a calendar and a list of existing profiles where the user may create one or more profiles per day. The profile creation screen allows the user to enter arrival and departure times, initial and final SOC values, and their V2G participation preference (Fig. 5b).



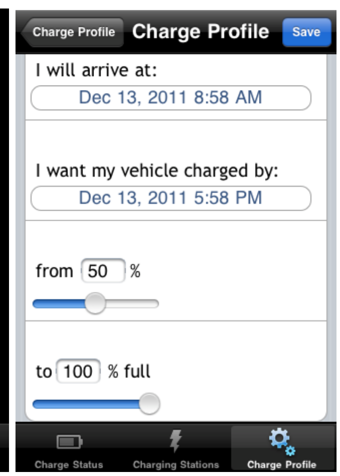


Fig. 5a. Charge status screen. Fig. 5b. Charge profile screen.

C. Parking Garage Aggregation Middleware

The Parking Garage Aggregation Middleware (PGAM) is a lightweight middleware that handles parsing of user charging profiles, aggregation and dissemination of charger and vehicle status, billing, and alert notification delivery.

A vehicle's RFID tag is scanned at the access gate and the ID is sent to the PGAM which looks it up in the system database. If it is authorized the PGAM assigns a parking spot, shown on the gate's display screen, and signals the gate to open. The middleware then checks for billing information and a charge profile. If either is missing, the owner is prompted to enter the required information on his/her mobile device or via the touchscreen at the charging station (Fig. 6).

The EVSE sends charging voltage and current data to the PGAM. The vehicle's SOC is estimated using the ISOC provided by the user, charging power as a function of time, and the vehicle's battery charge profile. Charging cost is calculated using power draw/supply data from the EVSE, electricity price as a function of time, and the vehicle's charging schedule. EV updates are pushed to the EVCP over a long-poll HTTP connection (Fig. 6).

A buffer time, *T_buff*, is provided between when the ACS schedules cars to be charged to the desired SOC and the specified departure time. By default this value is equal to zero. Based on the difference between specified departure time and actual departure time, provided by the RFID reader at the garage exit, the middleware will alter the value of *T_buff* for a given driver. A charge profile is received from the EVCP in XML format, parsed by the middleware, and sent to the ACS. If the profile is verified by the ACS the PGAM adds it to the database. If the ACS determines the charge profile cannot be satisfied it sends an error message to the PGAM, which sends an alert to the user, detailing the parameter(s) and corresponding value(s) to change.

IV. Aggregated Charge Scheduler

A. Overview

The Aggregated Charge Scheduler (ACS) optimizes EV charge scheduling for minimal cost using user charge profiles and electricity price as a function of time. By optimizing charge scheduling for electricity price it is implicitly optimized for electricity demand. The ACS sends a control signal to each EVSE to charge, discharge, or turn off according to the created schedule.

The ACS receives an owner charge profile from the PGAM which includes time of arrival (*t_arr*), time of departure (*t_dep*), buffer time, *T_buff*, initial state of charge (*ISOC*), and final state of charge (*FSOC*) of their EV. Charging must be completed *T_buff* minutes before the owner's scheduled departure. The value of *T_buff* is calculated by the PGAM based on owner adherence to his/her specified departure schedule. Once the ACS receives a charge profile its task is to charge the EV from *ISOC* to *FSOC* within the time span of *t_arr* and *t_dep – T_buff*.

B. Algorithm Description

1) Charge Scheduling

The 24 hour period of a day is quantized into smaller time intervals which are the smallest units of time used by the algorithm to schedule the occurrence of a charge, discharge or no-activity.

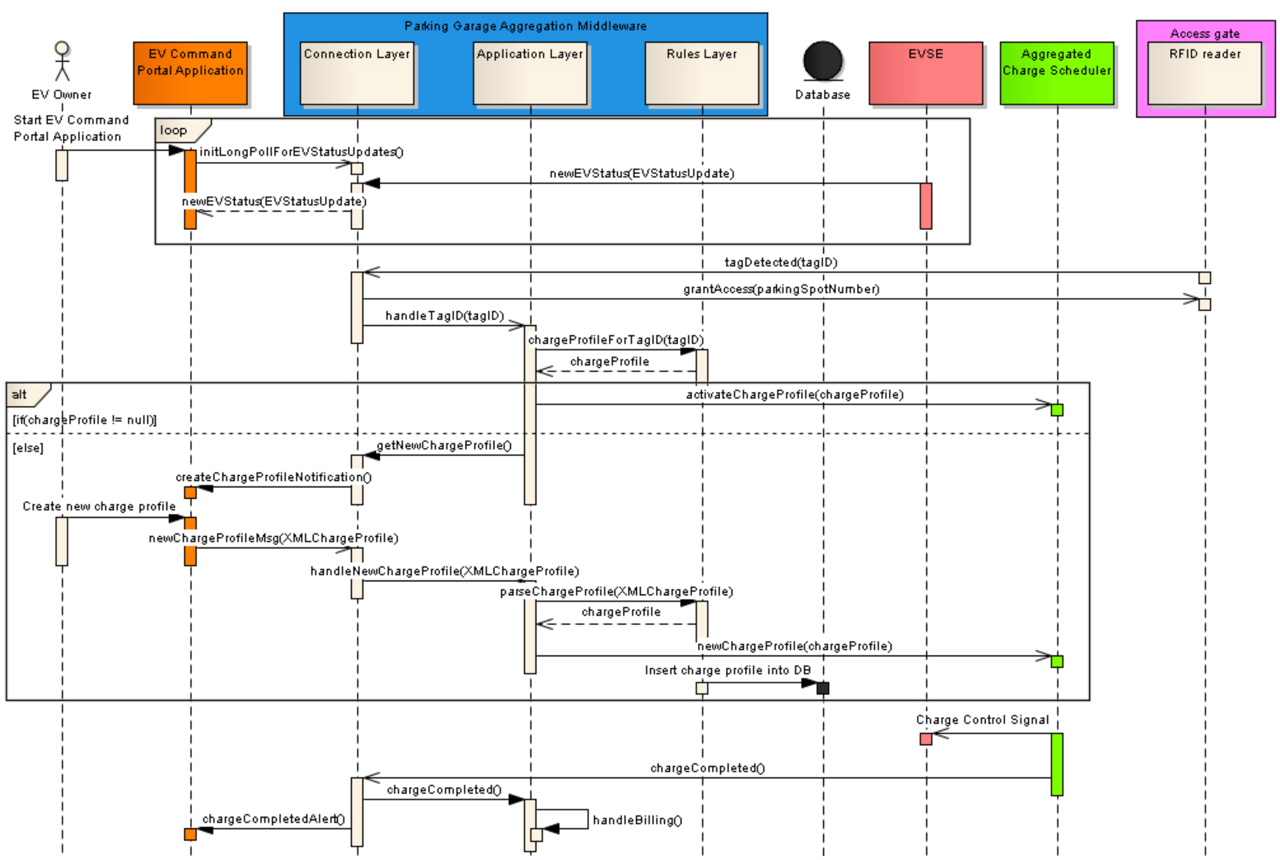


Fig. 6. System sequence diagram.

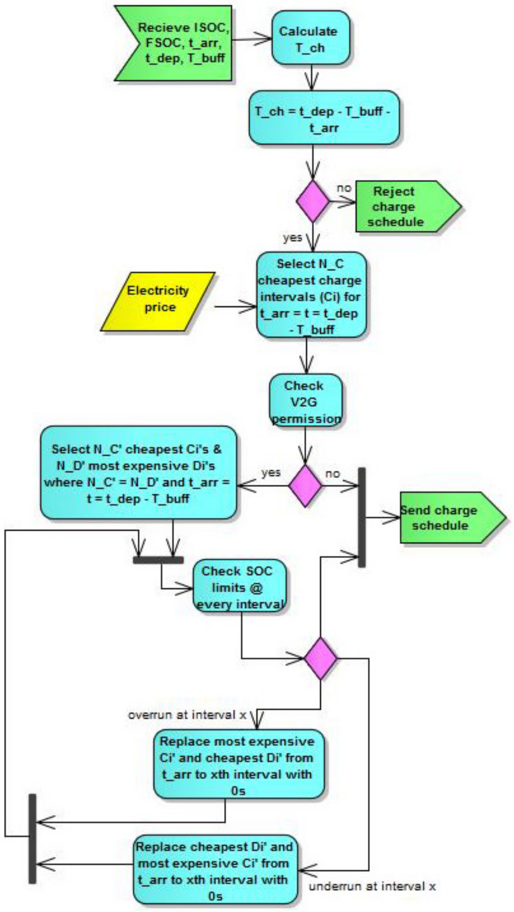


Fig. 7. EV charging algorithm flowchart.

The electricity price curve (Fig. 8) is also quantized into time intervals where each interval has a fixed price, P_i. Using the charge profile for the given EV and the *ISOC* and *FSOC*, the charge duration, *T_ch*, is calculated. In order to calculate *T_ch*, the charge profile data of lithium-ion batteries of the Nissan Altra from Madrid *et al.* [23] is used. If *T_ch* is greater than the duration of the stay of the car (1), the algorithm rejects the plan and notifies the PGAM to inform the user of the impossibility of charge completion within the supplied parameters.

$$T\_ch \leq t\_dep - T\_buff - t\_arr \tag{1}$$

Otherwise the algorithm calculates the number of charge intervals required for charging, *N_C*, from *T_ch*. The algorithm chooses *N_C* charge intervals (C_i) with the lowest P_j in the interval *(t_arr, t_dep – T_buff)* to charge the EV.

2) V2G Operation

If the owner has opted to participate in V2G, the algorithm chooses *N_C'* C_i' intervals with the lowest P_j to charge the EV and *N_D'* D_i' intervals with the highest P_j to send energy from the EV back into the grid (i.e. sell excess charge at the highest possible price) for maximum profit.

$$\sum_{1}^{N\_C'} C_i' - \sum_{1}^{N\_D'} D_i' = 0 \tag{2}$$

$$N\_C' = N\_D' \tag{3}$$

Purchasing additional charge at cheap time intervals and selling them at higher priced time intervals would generate net profit. It must be noted that the V2G based additional charge and discharge intervals (C_i' and D_i') are equal such that when the EV owner departs, the SOC of his battery is *FSOC* (2), (3). In scheduling charging and discharging for V2G operation the algorithm must ensure the vehicle's SOC never exceeds 100% or goes below 0% (4).

$$\begin{gathered} t\_arr \leq t < t\_dep - T\_buff \\ 0 \leq SOC(t) \leq 100 \end{gathered}, \tag{4}$$

V. RESULTS

A. Overview

The goals of scheduled charging optimized for electricity price are exploiting off-peak charging benefits and avoiding charging during peak load hours. In addition, while vehicles are parked and idle their energy storage capacity is utilized to alleviate grid load during peak demand.

B. Simulation Setup

In order to validate our algorithm, simulations were run using actual day-ahead electricity prices (Fig. 8), assuming all chargers deliver 6.6 kW, assuming all cars are Nissan Altras and have the charge profile given by Madrid et al.[23], and using two EV driver scenarios: 1) variable schedule and charging requirements 2) enterprise commuter schedule and charging requirements.

Charge scheduling without V2G was simulated using a hypothetical parking garage with 10 chargers and 30 vehicles using the variable scenario. Cost and power usage results are compared with unmanaged charging for the same scenario.

The optimal charge interval duration for maximum V2G profit is determined. Maximum V2G profit is simulated for both types of EV owners.

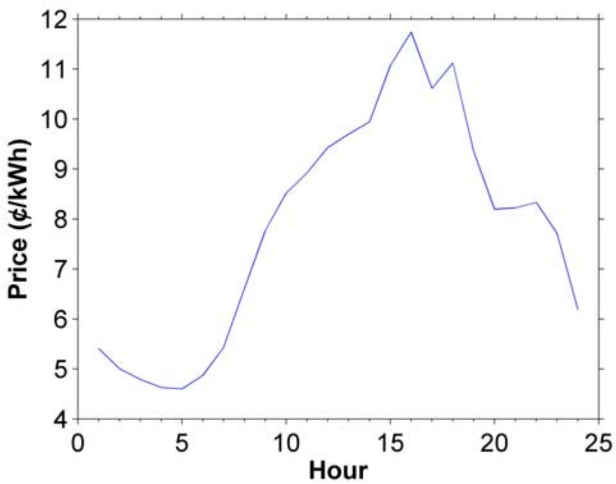


Fig. 8. Electricity price [24].

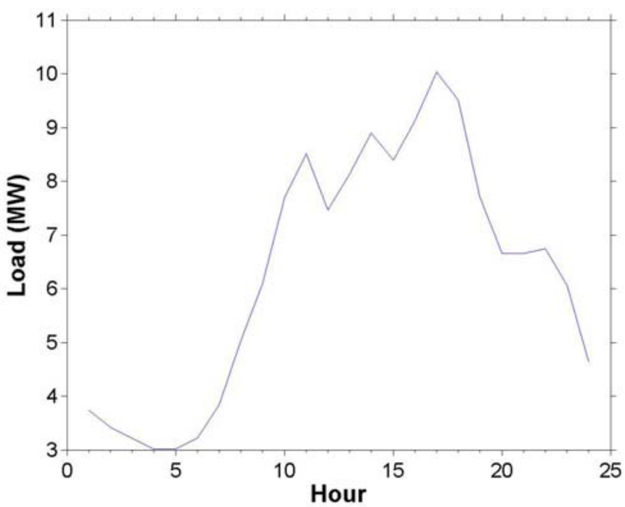


Fig. 9. Actual Load [24].

C. Charge Scheduling

Charging is scheduled during the cheapest intervals an EV is parked. Comparing the price curve (Fig. 8) with the charging schedule for 30 variable scenario cars (Fig. 10) it is obvious that between intervals 10 and 20, when the price is greater than its median value of 8.2 ¢/kWh, charging is minimal. Those cars that are being charged during that interval have time constraints that limit them from being charged at any other time. The V2G schedule for the same 30 cars (Fig. 11) shows a similar dearth of charging from approximately interval 10 to 20. Most of the discharging happens during this interval when electricity price and demand is highest.

Scheduled charging is more cost-effective than unmanaged charging. The average total cost over 1000 trials of scheduled charging of 30 variable scenario vehicles entering a parking lot of 10 chargers over a 24 hour period was $2.77. Unmanaged charging, which is defined as charging the vehicle as soon as it parks, of the same vehicles cost $3.07. The savings for the variable scenario was 10%. The same simulation was run for the enterprise commuter scenario with 30 vehicles using 30 parking spots instead of 10, to accommodate all the overlapping vehicles. Total average cost was $8.45 when their charging was unmanaged versus $7.87, a savings of 7%.

Scheduled charging also reduces load during peak demand. For the load curve (Fig. 9), we define peak load as the interval from 11 AM until 7 PM, when the load is higher is higher than its median from 7 AM until 9 PM. Over 1000 trials for the enterprise commuter scenario, unmanaged charging uses an average of 46.5 kW during the peak load interval versus 24.9 kW for scheduled charging – a reduction of 46%. For the variable scenario, unmanaged charging uses an average of 18 kW during peak load versus 7.89 kW for scheduled charging – a reduction of 56%.

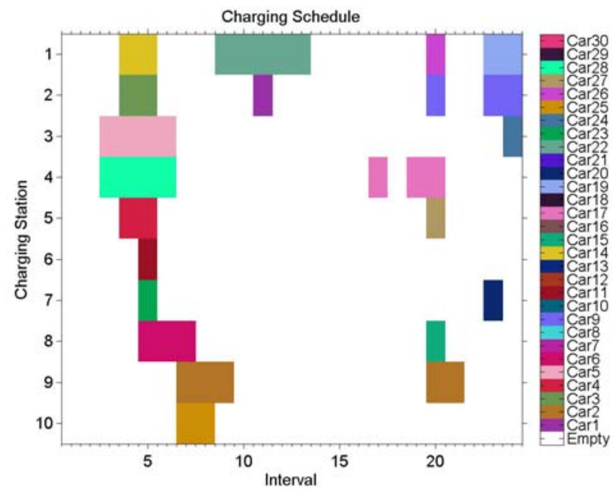


Fig. 10. Charging schedule for 30 cars, 10 chargers

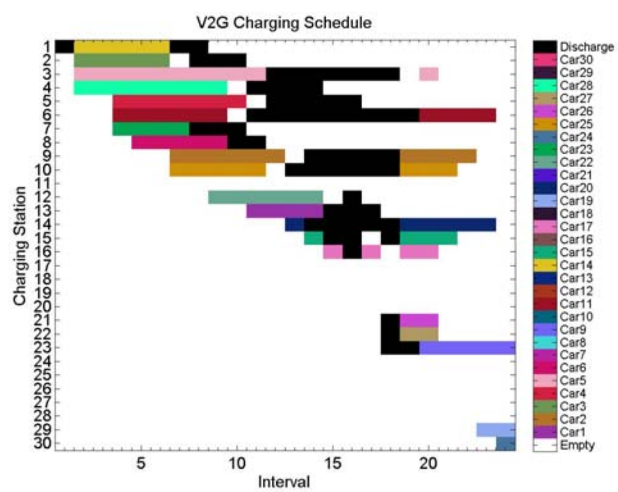


Fig. 11. V2G schedule for 30 cars, 10 chargers

D. V2G Profit

V2G services exploit vehicles' idle time to provide an energy resource during times of peak load. The parking garage operator can incentivize EV owners to participate in V2G using the profits earned by providing V2G services. Profits are earned when vehicles are charged during off-peak times then send their stored energy back to the grid when demand is high. The effectiveness of V2G services is measured by profit per car, not including the cost of charging to fulfill owner charge profile requirements.

V2G profit per car based on the number of incoming cars and charging stations is shown for incoming cars under the variable (Fig. 13) and enterprise commuter scenarios (Fig. 14). It depends on the number and variability of incoming cars, number of charging stations in the parking structure, and the electricity price curve. Each car in the variable car scenario has a random initial arrival time, *ISOC* and random *FSOC* and departure time that are greater than their respective initial counterparts. In the enterprise commuter scenario, arrival times are evenly distributed from 7 AM to noon, departures are evenly distributed from 4 to 9 PM, *ISOC* is log-normally distributed with a mean of 22.3 and a standard deviation of 12.2 [25], and *FSOC* is fixed at 100%.

One hour was determined to be the charge interval duration that maximized V2G profit per car (Fig. 12). Cars used in determining this value were given a random *ISOC*, *FSOC*, arrival time, and departure time. The test was run with 10 chargers, 100 cars, and averaged over 1000 trials.

The difference between the *FSOC* and *ISOC* variables determines how much time is required to charge the client car – the charging time is not included in V2G profit calculations. However, longer charging times reduce V2G profits by reducing the time available for V2G. Also since cars are used as energy storage, arrival and departure times limit when V2G can occur for each car. V2G profits increase as the ratio of parking duration to required charging time increases. In order to determine the maximum V2G profit per car, contour plots were generated for the variable scenario (Fig. 13) and enterprise commuter scenario (Fig. 14), showing V2G profit per car as a function of number of EVs and number of charging stations. The number of incoming cars and charging stations was varied from 1 to 1001 in increments of 50. Each figure plots 441 different combinations of incoming car and station numbers run over 1000 iterations. A charge interval duration of one hour and buffer time of zero were used. Each contour plot has two regions separated by a saturation limit line. This line represents the car to station ratio where every incoming car undergoes V2G and every station is utilized. The slope of the line demarcating the saturation limit is dependent on the variability of the incoming cars.

The variable incoming car scenario has a saturation limit slope that is greater than one, where the car to station ratio increases with the number of incoming cars. Since there are no constraints on the entry and departure times of incoming cars it is possible for a charging station to accommodate more than one car. Also, as the pool of incoming cars increases, there is an increased likelihood of a car with a later arrival time to fit (park) into a previously occupied charging station after the previous car has left. Below and to the right of this saturation limit line is the charging station overcapacity region where every incoming car is able to park, charge, and go through V2G optimization. Increasing the number of charging stations or decreasing the number of cars in this area will have no affect on the average V2G profit per car, which is 6.9 cents. This particular profit value is a function of the electricity price curve and would vary as the curve varies. In this region, every incoming car is accommodated by an available charging station and thus the V2G profit per car is representative of the entire car population. For example 1 car at 1 parking station over many iterations will have the same mean V2G profit per car as 200 cars at 1000 stations for a given electricity price curve; as they will have similar optimized charge-discharge schedules, giving similar profits. Above the saturation limit line is car oversaturation region where there are insufficient charging stations to accommodate every incoming car. Unlike the overcapacity region, increasing the number of cars or decreasing the number of charging stations in the car oversaturation region significantly affects the V2G profit per car calculation as discussed previously. Maximum profit per car over the entire contour area is 11.7 cents.

For enterprise commuter cars, the latest possible arrival time is noon and the earliest an occupied station is free is 4 PM. Because of these restrictions, it is impossible to have more than one car per station for a large duration (between noon and 4:00 pm) and thus the saturation limit line has a slope of approximately one. Average V2G profit per car is 5.6 cents – this is lower than the variable scenario because of the fixed *FSOC* requirement of 100%, versus a random *FSOC* greater than *ISOC*. Thus on an average, each enterprise commuter scenario car has a longer charging duration and charging stations have less time available for V2G, leading to lower profit.

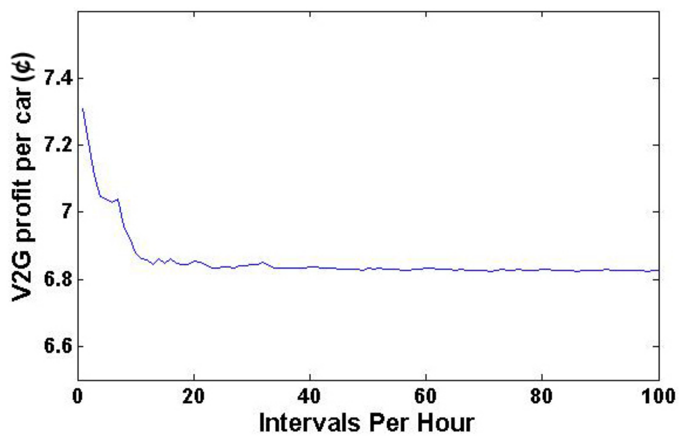


Fig. 12. V2G profit per car as a function of the number of intervals per hour.

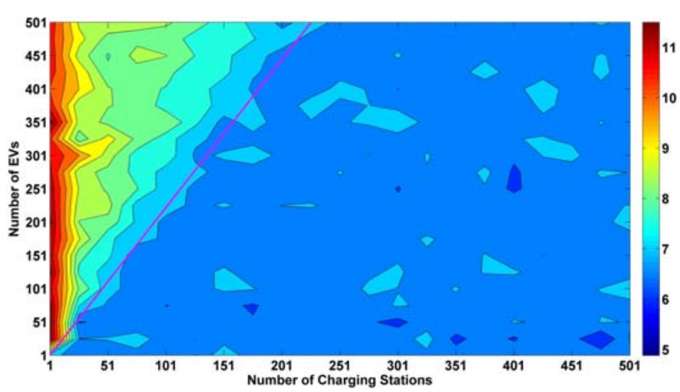


Fig. 13. V2G profit (¢) contour plot for variable scenario.

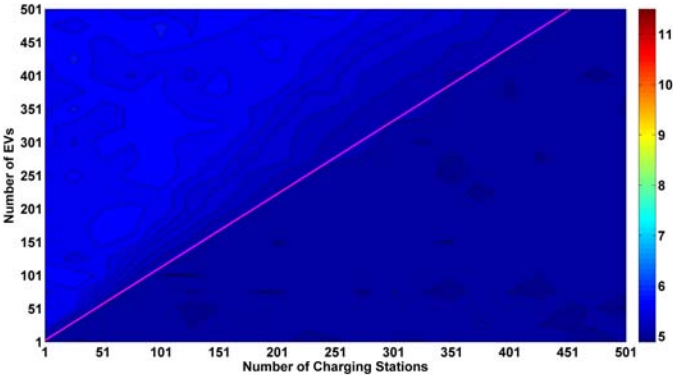


Fig. 14. V2G profit (¢) contour plot for enterprise commuter scenario cars.

VI. Conclusion

A comprehensive system leveraging mobile and RFID technologies, aggregation middleware, and an aggregated charge scheduling algorithm, that effectively schedules charging and V2G operations for cost savings and peak load reduction, has been presented.

Intelligently scheduled charging yields a cost savings of 7% for enterprise commuters and 10% for drivers with variable schedule and charging requirements. Peak load can be reduced by 46% for enterprise commuters and 56% for drivers with variable schedules and charging requirements. V2G services that utilize vehicles' idle time, when they are parked but not charging, can generate a net profit for the parking garage operator. A maximum profit of 11.7 cents per vehicle was determined to be achievable for vehicles under the variable scenario and 5.6 cents per vehicle for enterprise commuters.

The proposed system would be well suited for implementation in an enterprise environment where a large number of EVs could be aggregated to substantially impact peak load alleviation and act as a significant energy resource.

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