A Smart Parking Lot Management System for Scheduling the Recharging of Electric Vehicles

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***Abstract*—In this paper, we propose a centralized electric vehicles (EVs) recharge scheduling system for parking lots using a realistic vehicular mobility/parking pattern focusing on individual parking lots. We consider two different types of EV based on their mobility/parking patterns: 1) regular EVs; and 2) irregular EVs. An extensive trace-based vehicular mobility model collected from the Canton of Zurich is used for the regular EVs, and a probabilistic pattern built on top of this trace is used for modeling the behavior of irregular EVs. To the extent of our knowledge, this is the first EV charging scheduling study in the literature that takes into account a realistic vehicular mobility pattern focusing on individual parking lots. We compare the performance of our proposed system with two well-known basic scheduling mechanisms, first come first serve and earliest deadline first, with regard to two objective functions: 1) maximizing the total parking lot revenue; and 2) maximizing the total number of EVs fulfilling their requirements. Comparison results show that our proposed system outperforms well-known basic scheduling mechanisms with regards to both objectives. Parking lots managing the recharging of a high number of EVs will greatly benefit from using such recharge scheduling systems in the context of smart cities.**

***Index Terms*—Electric vehicles (EVs), recharging, scheduling, smart grids.**

I. Introduction

ELECTRIC vehicles (EVs) require significant amount of time to be recharged. Fully recharging a contemporary EV even with a modest sized battery (e.g., 16–24 kWh) takes several hours. This recharging time limitation severely hinders the usability of EVs even for short distance urban transportation purposes. To alleviate this drawback, it has been hypothesized that parking lots can be utilized as recharging locations. In a typical day, cars are not actively-driven for long periods of time during which they mostly reside in parking lots. Therefore, these long parking periods can be considered as recharging opportunities if the parking lots are to be converted into smart parking lots capable of recharging EVs.

Considering the mobility/parking pattern of each single EV, vehicles will have several options for recharging throughout the day. Hadley and Tsvetkova [1] have shown that unregulated, uncoordinated mass EV recharging can lead to disruptions in the grid (e.g., brownouts and blackouts) or unwanted demand peaks. Hence, recharging strategies determining "where" to charge, "when" to charge, and "how much" to charge should be developed and parking lot recharge scheduling (PLRS) systems that should implement and maintain these strategies are required.

This EV recharging coordination problem and design of an efficient PLRS system have been addressed in the literature in the recent years. These studies look at the problem from different points of views with various objectives (e.g., maximizing the parking lot revenue, minimizing the total cost of recharging to the EV owners). Based on the decision location of the scheduling, these studies can be broadly categorized into two groups as centralized solutions [2]–[8] and distributed solutions [9]–[16]. However, these systems generally use fixed or randomly distributed mobility/parking patterns for EVs, which does not reflect the realistic EV use cases. Several studies use traffic surveys [e.g., National Household Travel Survey (NTHS)] to build a statistical mobility/parking pattern [7], [17]–[21]. Albeit, being much more realistic than randomly distributed ones, these patterns are build upon statistically analysing tens of thousands vehicles (e.g., more than 40 000 users all around U.S. for NTHS), where the destination parking lots are different from vehicle-to-vehicle. A realistic mobility/parking pattern focusing on individual parking lots is crucial to evaluate the applicability of these systems. Also, most of these works utilize either a day-ahead or real-time approach for the scheduling time horizon of the system. In contrast, our PLRS system utilizes both a day-ahead and real-time scheduling component. Further details on the above-mentioned works and mobility/parking patterns used can be found in Section II.

In this paper, we propose a PLRS system that takes into account the arrival and departure times, EV battery information, and travel distances of EVs and tries to generate a

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TABLE I
CENTRALIZED APPROACHES TO EV RECHARGING

Authors	Point of View	Objective	Method	Time horizon	V2G	Local gen.	Hardware issues
Galus et al. [17]	EV owners	Max. user utilization	Game Theoretic	Real-time	No	No	No
Huang et al. [2]	EV owners	Min. missed requirements	Scheduling algorithms	Real-time	No	No	No
Nguyen et al. [3]	EV owners	Min. total cost of energy for users	Optimization	Day-ahead	Yes	No	No
Sundstrom et al. [22]	EV owners	Min. total cost of energy for users	Optimization	Day-ahead	No	Yes	Battery lifetime
Hutson et al. [23]	EV owners, AU	Max. AU profit	Heuristics	Real-time	Yes	No	No
Sortomme et al. [4]	EV owners, AU	Max. AU profit	Optimization	Real-time	Yes	Yes	No
Han et al. [5]	EV owners, AU	Max. AU profit	Optimization	Day-ahead (corrected in Real-time)	Yes	No	No
Tushar et al. [6]	EV owners, AU	Min. total cost of energy for users	Optimization	Day-ahead	Yes	Yes	No
Wu et al. [7]	EV owners, AU	Min. total cost of energy for users	Optimization	Day-ahead (corrected in Real-time)	No	No	No
Acha et al. [8]	DSO	Min. energy loss on the distribution system	Optimization	Day-ahead	Yes	No	No
Mets et al. [24]	DSO	Min. peak load, flatten the load	Optimization	Real-time	No	No	No

daily recharging schedule for EVs. We analyze and utilize a 24 h trace-based vehicular mobility model that is conducted in Zurich, Switzerland [25]. In order to evaluate the advantage of such a system, we describe two objective functions: maximizing the total revenue (MaxR) of the parking lot (see Section IV-B) and maximizing the total number of EVs fulfilling their recharging requirements at its time of departure (see Section IV-C). Then, we compare the results of our proposed system with two well-known basic scheduling mechanisms: first come first serve (FCFS) and earliest deadline first (EDF) (see Section VI-A). Unlike similar EV recharging studies in the literature, this paper is the first EV recharging study that considers a realistic mobility/parking pattern focusing on individual parking lots.

The main features and contributions of this paper are as follows.

1) We describe a PLRS system for planning and scheduling the recharging of EVs. Our system is a two-layered system working both in the day-ahead and real-time horizons with its routine and correction layers.
2) We define two objectives and construct mathematical optimization functions to evaluate the performance of our proposed system: a) maximizing parking lot revenues and b) maximizing the number of recharged EVs.
3) We use a realistic trace-based vehicular mobility model for the mobility/parking pattern of EVs focusing on individual parking lots and propose a mobility/parking model to simulate the occupancy of the irregular vehicles.
4) We compare the performance of the proposed system with two basic scheduling mechanisms and show that there is a significant gain in utilizing such PLRS systems when considering realistic vehicular mobility data.

II. RELATED WORK

The problem of EV recharging coordination has been studied in the literature with different points of views, objectives, and methodologies. These studies generally consider a grid architecture, in which a high number of EVs connect to a central control device, called the aggregator unit (AU). These AUs manage the recharging of EVs and they are in turn connected to a higher layer control device, called the distribution system operator (DSO). DSOs are situated between the transmission and distribution networks and manage the overall energy demand of the connected AUs [26]. Based on this architecture, the EV recharging coordination studies can be divided in two major groups according to the location of the recharging decision: 1) centralized methods; and 2) distributed methods. Tables I and II summarize the features of various studies on centralized and distributed methods in the literature, respectively.

Each study has a decision time horizon which is usually selected as one day ahead of time (i.e., day-ahead) or one time step ahead of time (i.e., real-time).[1] Some of these studies offer a hybrid solution for the decision time horizon by building up a rough schedule one day-ahead, and correct it in real-time. Three additional features are considered in the studies: vehicle-to-grid (V2G) capability, local generation capability, and hardware issues. The inclusion of the V2G paradigm enables bi-directional electricity transfer between the grid and each EV. This capability allows the parking lot to participate in the electricity market not only as a consumer but also as a generator. Local generation capabilities, if considered, is used as an alternative energy source for EV recharging. The parking lot can utilize this energy to recharge the EVs at a cheaper price than the grid's price or when combined with a V2G capability, parking lots can use EV batteries as a buffer for shaping the probabilistic behavior of the local energy generation sources. Lastly, hardware issues considered in these works range from physical constraints in the local feeders to degradation of EV batteries.

In centralized methods, EVs send their parking, recharging-related information to the corresponding AU. Then, the AU decides on when and how much to charge each EV in a centralized fashion. In distributed methods on the other hand, EVs build up a charging strategy on their own using some information from the AU (e.g., pricing schemes). Then, they inform these individually decided schedules to the AU. In most of these methods, this information exchange continues for several iterations until the AU and EVs all agree on a schedule. The main advantage of the centralized methods is

[1] In the literature, approaches deciding on the recharging schedule one time step ahead of time is referred to as real-time schedulers.

TABLE II
DISTRIBUTED APPROACHES TO EV RECHARGING

Authors	Point of View	Objective	Method	Time horizon	V2G	Local gen.	Hardware issues
Ardakanian et al. [9]	EV owners	Max. user utilization	Optimization	Real-time	No	No	Local feeders
Wen et al. [10]	EV owners	Max. user utilization	Optimization	Real-time	No	No	No
Gerding et al. [27]	EV owners	Min. missed requirements	Game Theoretic	Real-time	No	No	No
He et al. [11]	EV owners	Min. total cost of energy for users	Optimization	Day-ahead (corrected in Real-time)	Yes	No	Battery lifetime
Jiang et al. [12]	EV owners	Min. total cost of energy for users	Optimization	Day-ahead	No	Yes	No
Yang et al. [13]	EV owners	Min. total cost of energy for users	Optimization	Day-ahead (corrected in Real-time)	No	No	No
Rezaei et al. [14]	EV owners	Min. total cost of energy for users	Medium access	Real-time	No	No	No
Qi et al. [15]	EV owners, AU	Max. AU profit	Optimization	Real-time	No	No	Local feeders
Hu et al. [16]	EV owners, DSO	Min. total cost of energy for users	Optimization	Day-ahead (corrected in Real-time)	No	No	Local feeders
Tan et al. [28]	Home owners, DSO	Min. total cost of energy for users	Optimization	Real-time	Yes	Yes	No
Gan et al. [29]	AU	Min. peak load, flatten the load	Optimization	Day-ahead	No	No	No
Ma et al. [30]	DSO	Min. peak load, flatten the load	Game Theoretic	Day-ahead	No	No	No

the possibility of finding a globally optimal solution at a cost of higher computational complexity (since the AU has all the information). As for the methodology, most of these centralized studies utilize mathematical optimization (e.g., linear programming, quadratic programming) while others use game theoretic approaches, heuristics, scheduling algorithms, and medium access methods inspired from telecommunication literature. The distributed methods reduce this computational complexity by distributing the decision among EVs. However, they are more likely to get stuck in local optimal results rather than finding the global optimum.

Among the studies having EV owners as the point of view, Galus and Andersson [17] defined a centralized game that maximizes the user utilization, while Huang *et al.* [2] used various well-known scheduling algorithms (i.e., FCFS, EDF, shortest job first, and longest job first) to calculate the charging schedules. They compare these algorithms in terms of missed requirement amount and conclude that among the aforementioned scheduling algorithms, EDF performs the best. Nguyen and Le [3] and Sundstrom and Binding [22] defined optimization problems that aim to minimize the total cost of energy of each EV user. Both of these works consider time-varying electricity prices that decide the schedule at the beginning of every day. Sundstrom and Binding [22] also consider the effect of battery lifetime degradation in the evaluation process. Other works look at the problem from a joint EV owner and AU point of view and offer optimization mechanisms for either maximizing the AU profit (considering selling energy to the grid via V2G mechanisms) or minimizing the total energy cost [4]–[7], [23]. Acha *et al.* [8] looked from the DSO point of view and propose an optimization framework for minimizing the energy loss on the distribution system. Mets *et al.* [24] looked from the DSOs perspective and aim to minimize the peak load caused by coordinated EV recharging.

Most of the distributed solutions look solely from the EV owner perspective. Ardakanian *et al.* [9] and Wen *et al.* [10] defined a user utility and consider maximizing them. Gerding *et al.* [27] proposed a game among EVs for minimizing the missed EV requirements. He *et al.* [11], Jiang and Fei [12], and Yang *et al.* [13] each propose a different mathematical optimization problem with time varying electricity prices for minimizing the total cost of energy for the EV owners. He *et al.* [11] also consider a two-sided electricity transfer via a V2G system and includes the battery lifetime degradation related costs in their evaluation. Rezaei *et al.* [14] considered a system that is inspired by the shared medium access techniques from the telecommunication. This paper is different from the rest of the distributed solutions since it does not include any central coordination between EVs. Qi *et al.* [15] looked from a joint EV owner and AU point of view and aim to maximize the AU profit. Hu *et al.* [16] and Tan *et al.* [28] offered similar studies for minimizing the total cost of energy for the users, with an optimization framework. Gan *et al.* [29] and Ma *et al.* [30] aimed to minimize the peak load by optimization and game theoretic methods, respectively.

TABLE III
MOBILITY/PARKING PATTERN-RELATED PARAMETERS OF EV RECHARGING STUDIES

Authors	Parking pattern	Initial SOC	Target SOC
Acha et al. [8]	Fixed	N/A	100%
Ardakanian et al. [9]	Fixed	N/A	Special[2]
Gan et al. [29]	Fixed	N/A	Special[3]
Han et al. [5]	Fixed	10%	90%
Ma et al. [30]	Fixed	15%	100%
Sortomme et al. [4]	Fixed	Statistical	95%
Yang et al. [13]	Fixed	N/A	Random
Sundstrom et al. [22]	Fixed (only 25 EVs)	N/A	N/A
Jiang et al. [12]	Random	N/A	Random
Huang et al. [2]	Random (Poisson)	0%	Random
Tushar et al. [6]	Random (Poisson)	Random	Random
Hutson et al. [23]	Random (Uniform)	Random	60%
He et al. [11]	Random (Uniform)	Random	90%
Qi et al. [15]	Random (Normal)	Random	100%
Tan et al. [28]	Random (Normal)	N/A	N/A
Wen et al. [10]	Random (Normal)	40%	Special[2]
Galus et al. [17]	Statistical	Random	+10%
Mets et al. [24]	Statistical	N/A	100%
Nguyen et al. [3]	Statistical	Random	Special[4]
Wu et al. [7]	Statistical	N/A	Statistical
Rezaei et al. [14]	Statistical	Statistical	Statistical
Gerding et al. [27]	Realistic (only 25 EVs)	Realistic	Realistic
Hu et al. [16]	Realistic (only 18 EVs)	10%	Special[4]

Aside from these features, all of these studies use vehicular mobility/parking patterns in order to realize their proposed solution. They also define the initial state of charge (SoC) and target SoC for each EV. As summarized in Table III, most of these studies either use a fixed or randomly generated mobility/parking pattern. Galus and Andersson [17] used a normal-like distribution for vehicular arrival times, which is based on a report in Swiss Federal Office of Statistics. Nguyen and Le [3] used a normal distribution for both arrival and departure times of the vehicles to and from the parking lot. They also use a log-normal distributed travel distance in order to calculate the target SoC for each vehicle. Wu *et al*. [7] used a model constructed on top of a survey, called NTHS, conducted by the U.S. Department of Transportation. According to this survey, all vehicular arrivals to the parking lot are around 22:00 in the evening, and all departures are around 06:00 in the morning. The target SoC of each vehicle is also calculated by the travel distance of the vehicle. Mets *et al*. [24] and Rezaei *et al*. [14] used a statistical model in this paper but the details are not explained in their papers. Hu *et al*. [16] and Gerding *et al*. [27] used realistic trace outcomes that are gathered by GPS-enabled vehicle movement in urban areas. Both of these studies are distributed solutions and their objective functions are minimizing missing requirements and minimizing the total cost of energy for EV users, respectively. Gerding *et al*. [27] offer a game theoretic, auctioning-based method while Hu *et al*. [16] considered a linear programming solution which is handled by shadow prices. Although, the traces of these studies offer the most realistic input for a vehicular travel pattern, the small size of the traces (25 vehicles in Gerding *et al*.'s study [27] and 18 vehicles in Hu *et al*.'s study [16]) severely limits their applicability to analyzes conducted for thousands of EVs.

III. PLRS SYSTEM

In this paper, we consider a smart city architecture for EV recharging coordination that is comprised of several micro grids, each having a separate DSO. Each micro grid in turn mainly consists of two type of entities: 1) parking lots capable of charging EVs; and 2) EVs themselves. We categorize EVs into two main groups based on the regularity of their mobility/parking patterns: 1) regular EVs; and 2) irregular EVs. Regular EVs are mostly comprised of commuters who travel daily between their homes and works. They tend to follow a typical pattern every weekday. Some of them start the day in the suburbs while others start in the city center; some come from closer regions while others come from much farther locations. Irregular EVs represent guests from nearby cities, travelers coming to the city from time-to-time, and short non-routine journeys throughout the day (e.g., going to shopping mall, theater, etc.). In contrast to regular EVs, irregular EVs do not follow a typical day-to-day pattern.

Considering these two main EV categories, we divide the PLRS system into two layers: 1) the routine layer (or day-ahead layer); and 2) the correction layer (or real-time layer) (Fig. 1). The routine layer is responsible for handling the recharging scheduling of regular EVs whose patterns can be predicted based on their past mobility/parking information (i.e., arrival and departure times, occupancy at the parking lot, distance to be traveled after leaving the parking lot). Using this mobility/parking pattern and the grid information (i.e., pricing, load), this layer can predict its load and build up a recharging schedule for the regular EVs and allocate the parking lot's resources accordingly one day-ahead of time.

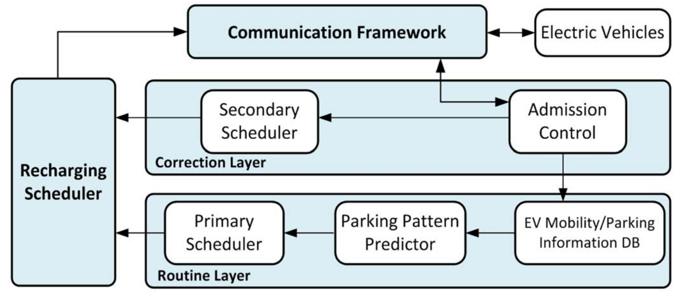

Fig. 1. PLRS system.

From time-to-time EVs will change their patterns. These changes can be either with small deviations (e.g., an EV slowly shifted its arrival time from 9:00 to 9:30), or with huge jumps. While the routine layer can handle the first type of changes in a short period of time, it will make serious rescheduling mistakes if EVs change their patterns too quickly. Additionally, sometimes regular EVs can make some additional daily trips (e.g., going to meetings, hospital, etc.), which constitutes another type of irregular behavior. Also, the system should consider irregular EVs and their recharging requirements. The second layer of our PLRS system, the correction layer, is responsible for handling these nonregular and random behaviors in real-time.

The correction layer is composed of a secondary scheduling mechanism and an admission control mechanism. Regular EVs will inform the correction layer of any mobility/parking pattern deviations they have, so that the system can try to accommodate to these changes. In the case of irregular EVs, these vehicles will transmit their planned mobility/parking patterns to the parking lot when they are in traffic enroute to the parking lot. These information will be transferred to the correction layer via the communication framework. Based on the current load and capacity of the system, the admission control mechanism will make an admission decision whether to allow the new EV to the parking lot or to deny it due to capacity limitations. If allowed, the secondary scheduling mechanism will allocate recharging opportunities to these vehicles. In this paper, we define and thoroughly analyse the two (primary and secondary) schedulers of the two proposed layers. As for the predicted mobility/parking pattern, we used the patterns described in Section V. The communication framework and the admission control mechanism are out of the scope of this paper and will be addressed in our future work.

In our proposed system, we do not consider any V2G capabilities, local generation, or direct energy transfer between the parked EVs. The EVs are uniform in their technical aspects, so we consider two types of EVs: 1) regular and short distance traveling irregular vehicles; and 2) long distance traveling irregular vehicles.

IV. Optimization Problems

As explained in Section III, in an EV recharging coordination system, we can look at the system from different point of views. For example, we can look at the system from the parking lot owner (or AU), who is trying to maximize the total revenue of his/her parking lot; or an EV owner who wants his/her car to receive the required charge as cheap and fast as possible; or the DSO who wants to shape and flatten the energy demand of the parking lot according to the grid's requirements. So, based on the chosen point of view, the performance of the system can be evaluated using different metrics.

Each of these objectives can be modeled as separate problems. In this paper, we look at the parking lot owner and EV owner point of views, whose objectives are MaxR and maximizing the number of EVs fulfilling their recharging requirements (MaxNRQ), respectively.

A. Problem Formulation

In both MaxR and MaxNRQ problems, each parameter and variable is defined over one or two of the two sets: 1) **I**, the set of EVs in the system; and 2) **T**, the set of time slots. We consider a day to be divided into equally sized time slots (τ) and select τ as half an hour. Three parameters are defined over the set **T**: unit buying price of energy from the grid (bp_t), unit selling price of energy to each individual EV (sp_t), and the total capacity of the parking lot (pc_t). Total capacity of the parking lot is divided into two parts, pc_t^R as the capacity of the parking lot reserved for the routine layer, and pc_t^C as the capacity, which can be used by the correction layer. If the pc_t^R is not fully allocated by the routine layer, its remaining capacity can also be used by the correction layer. The rate of the overall capacity allocated to each part depends on the expected load of both layers. Usually, it is expected that the system will allocate a high capacity to the correction layer in the beginning, but as time passes and the system stabilizes the routine layer will be having more capacity than the correction layer. This rate will be set dynamically by the parking lot.

Each EV visits the parking lot in question once during a given day (from 00:00 to 23:59) and stays there for at least τ amount of time. The arrival time of EV_i ($\forall i \in \mathbf{I}$) to the parking lot is denoted by ar_i, whereas the departure time of EV_i is denoted by dp_i. If $\mathrm{dp}_i > \mathrm{ar}_i$, it means that EV_i visits the parking lot during the day. If $\mathrm{dp}_i < \mathrm{ar}_i$, it means that EV_i stays at the parking lot during the night. Based on these two parameters, av_{it} is a binary parameter that defines the availability of EV_i for recharging in the parking lot. For a given EV_i, its corresponding availability values are defined as

$$\text{if } \mathrm{dp}_i > \mathrm{ar}_i, av_{it} = \begin{cases} 1, & \mathrm{dp}_i > t \geq \mathrm{ar}_i \\ 0, & \text{otherwise} \end{cases} \quad \forall t \in \mathbf{T} \tag{1}$$

$$\text{if } \mathrm{dp}_i < \mathrm{ar}_i, av_{it} = \begin{cases} 1, & t \geq \mathrm{ar}_i \text{ or } t < \mathrm{dp}_i \\ 0, & \text{otherwise} \end{cases} \quad \forall t \in \mathbf{T}. \tag{2}$$

Finally, there are charging-related parameters and variables: the battery capacity of each EV (cp_i), the required amount of energy for EV_i (rq_i), the amount of energy remaining in the battery of EV_i when it arrives at the parking lot (rm_i). The main variable in the optimization problems is ch_{it}, which defines the amount of energy given to EV_i in the time interval t. Lastly, cr_i defines the maximum charging rate of EV_i. Table IV summarizes all sets, variables, and parameters that are used in the two optimization problems.

TABLE IV
NOMENCLATURE

I	Set of EVs
T	Set of time slots
bp_t	Buying price of 1 kWh of electricity at time t
sp_t	Selling price of 1 kWh of electricity at time t
pc_t^R	Base Routine Layer capacity of the parking lot at time t
pc_t^C	Base Correction Layer capacity of the parking lot at time t
pc_t	Total capacity of the parking lot at time t
ar_i	Arrival time of EV_i to the parking lot
dp_i	Departure time of EV_i from the parking lot
av_{it}	Availability of EV_i at the parking lot at time t
cp_i	Battery capacity of EV_i
rq_i	Required charge amount of EV_i
rm_i	Remaining charge amount of EV_i upon arrival
ch_{it}	Amount of charge EV_i gets from the parking lot at time t
cr_i	Maximum charging rate for EV_i
mr_i	Binary indicator showing whether EV_i has the required energy at time dp_i, or not

B. Maximizing the Revenue (MaxR) Problem

The first problem looks at the system from the parking lot owner's point of view and aims to maximize the revenue of the whole parking lot and can be formalized as

$$\underset{\mathrm{ch}_{it}}{\text{maximize}} \sum_{t \in \mathbf{T}} (sp_t - bp_t) \sum_{i \in \mathbf{I}} \mathrm{ch}_{it} \tag{3}$$

subject to

$$\mathrm{rm}_i + \sum_{t \in \mathbf{T}} \mathrm{ch}_{it} \cdot av_{it} \geq \mathrm{rq}_i \quad \forall i \in \mathbf{I} \tag{4}$$

$$\mathrm{rm}_i + \sum_{t \in \mathbf{T}} \mathrm{ch}_{it} \cdot av_{it} \leq \mathrm{cp}_i \quad \forall i \in \mathbf{I} \tag{5}$$

$$\sum_{i \in \mathbf{I}} \mathrm{ch}_{it} \leq pc_t^R \quad \forall t \in \mathbf{T} \tag{6}$$

$$cr_i \geq \mathrm{ch}_{it} \geq 0 \qquad \forall i \in \mathbf{I}, \forall t \in \mathbf{T}. \tag{7}$$

Here, the goal can be achieved by giving each EV as much energy as possible while adhering the requirement, battery capacity, parking lot capacity, and charging rate constraints. The requirement constraint (4) states that at its time of departure, each EV should have at least enough energy in his battery for its return trip (regardless of where the EV stays during the night). The battery capacity constraint (5), defines the upper bound of how much total charge an EV can get from the parking lot in total, due to its battery size. Based on the available energy amount in the grid and the physical features of the parking lot (e.g., local transformers, cables), (6) defines the total available energy during the given time slot (the parking lot capacity constraint). Lastly, the charging rate constraint (7) defines the maximum energy amount that can be given to EV_i in the time slot t due to EVs and parking lot's charger features.

The system will first give enough energy to each EV in order to satisfy their requirement constraints. Then, if possible, it will give as much charge as possible. In both cases, the system will start from the time slot in which the buying price is cheapest, the EV in question is available, the EV battery and parking lot itself has ample capacities, and the charging rates are not exceeded. In the realization of this problem, pc_t^R is selected as sufficient for fulfilling all EV requirements.

C. MaxNRQ Problem

The second problem looks at the system from the EV owner's point of view and aims to maximize the number of EVs fulfilling their requirements and can be formalized as

$$\underset{\mathrm{mr}_i}{\text{maximize}} \sum_{i\in\mathbf{I}} \mathrm{mr}_i \tag{8}$$

subject to

$$\mathrm{mr}_i \leq \frac{\mathrm{rm}_i + \sum_{t\in\mathbf{T}} \mathrm{ch}_{it} \cdot av_{it}}{\mathrm{rq}_i} \qquad \forall i \in \mathbf{I} \tag{9}$$

$$\mathrm{rm}_i + \sum_{t\in\mathbf{T}} \mathrm{ch}_{it} \cdot av_{it} \leq \mathrm{cp}_i \qquad \forall i \in \mathbf{I} \tag{10}$$

$$\sum_{i\in\mathbf{I}} \mathrm{ch}_{it} \leq pc_t^R \qquad \forall t \in \mathbf{T} \tag{11}$$

$$cr_i \geq \mathrm{ch}_{it} \geq 0 \qquad \forall i \in \mathbf{I}, \forall t \in \mathbf{T}. \tag{12}$$

In this problem, we define another set of variables, mr_i, which is a binary variable and indicates if the charging requirement of EV_i has been met at its departure time (i.e., $\mathrm{mr}_i = 1$) or not. The first constraint (9) forces the system to either fully recharge EVs up to their requirements or not at all. Since the aim is to maximize the number of EVs meeting their requirements, the system should not partially recharge several EVs in favor of recharging an EV up to its requirement. The objective function is defined over the sum of all binary mr_i variables. Therefore, the system aims to assign a value of 1 to as many mr_i variables as possible. Equation (9) states that, setting an mr_i variable as 1 means the right hand of the equation should also be at least equal to 1, which can only be achieved if the amount of energy remaining at the battery plus the amount of charge it receives throughout its parking duration is at least equal to its required amount. Also due to (9), the system has no incentive to recharge an EV more than its requirement. Combined with (10), in order to maximize the objective function, the system will opt to give as little as energy to each EV beyond its required amount.

The rest of the constraints (10)–(12) are as the same with the MaxR problem with the exclusion of the requirements constraint (4), since it is not a hard constraint in this problem anymore. Based on the initial remaining charge amount of EVs, some EVs do not need to be charged at all. Unlike the first optimization problem, this problem focuses on cases where the total daily parking lot capacity is either just enough or not enough for fulfilling all the EV requirements.

V. Mobility/Parking Patterns

We select a realistic vehicular mobility/parking pattern defining the arrival and departure time parameters of each vehicle as well as the distance to be traveled when the EV leaves the parking lot. The last information will be used to derive the required energy parameter (rq_i) of EV_i. The vehicular networking literature offers different types of vehicular mobility models like flow, traffic, behavioral, and trace-based models [31]. Although some of these models are very detailed (incorporating the effects of traffic jams, traffic lights, and vehicle overtakes), they usually do not have any mobility/parking pattern related information. Only trace-based vehicular mobility models, which are built from either real vehicular traces or combining some real trace information with synthetic mechanisms, offer some mobility/parking pattern through the origin/destination (O/D) matrices used in the traces.

A. Mobility/Parking Pattern From the Zurich Trace

There are several vehicular traces that are publicly available in [32]. These traces have different features such as the duration of the trace, the number of vehicles involved, type of the vehicles involved, and what kind of roads are considered in the trace. Among these trace-based models, we select the Zurich trace [25] in this paper since it covers a 24 h of car traffic in a huge physical area (i.e., 65 000 km^2) considering 260 000 distinct vehicles.

The Zurich trace is constructed using three key elements: 1) a national travel survey conducted to Swiss citizens; 2) the road map of Switzerland; and 3) a detailed microscopic-level traffic simulator. The survey defines the O/D matrix of the vehicles in which each vehicle conducts two journeys throughout the day, one outgoing and another incoming from/to the user's home. Considering this O/D matrix and the Switzerland road map, the authors have compiled a trace for each car using the aforementioned traffic simulator. The trace includes vehicles coming into Zurich from outside regions, and vehicles moving between two locations inside the Canton of Zurich. In the trace, there are some number of locations that are visited by a high number of the vehicles. Among these locations, we have analyzed the vehicle arrival and departure patterns of the top five locations with regard to the number of visits during the day. Two different travel patterns can be seen from these locations; while the first four locations follow the same pattern, the fifth location yields a slightly different pattern with a higher vehicle arrivals. We have selected the location with highest number of arrivals among the four as the point of interest (PoI) 1 and name the fifth location as the PoI 2. PoI 1 physically corresponds to the central train station of Zurich (i.e., Zurich Hauptbahnhof) having 3200 distinct vehicle arrivals, while PoI 2 also corresponds to another smaller train station (i.e., Wiedikon railway station) inside the city having 4600 distinct vehicle arrivals.

As seen in Fig. 2, most of the arrivals and departures of vehicles occur during the morning and afternoon hours. There are two groups of vehicles, the first group comes to the PoI in the morning and leave during the afternoon and the second group comes during the afternoon, spends the night at the PoI, and leaves in the morning. Vehicles from the first group stay (i.e., nearly 70% of vehicles) at the parking lot between 6 and 9 h, whereas vehicles belonging to the second group stay for longer periods of time (i.e., 12–16 h). For both

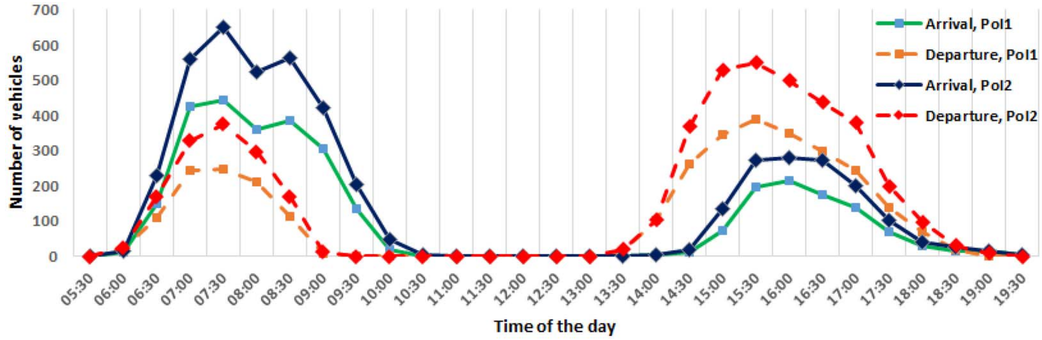

Fig. 2. Arrival and departure histograms of EVs in PoIs 1 and 2.

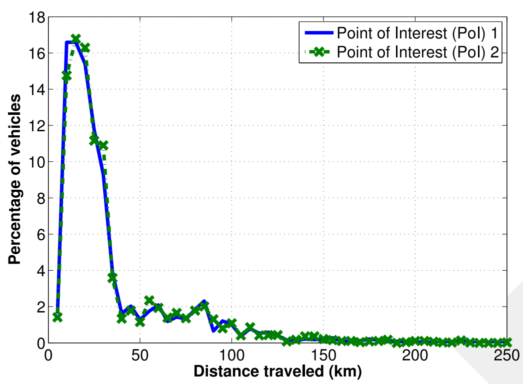

Fig. 3. Travel distance of vehicles.

locations, there are more vehicles in the first group than in the second group. The arrivals and departures of the first group are slightly different (around 07:00 and 15:00) between the two PoIs. Also, since the Zurich trace is based on the national traveling survey, which focuses on commuting, there are no arrivals and departures between 11:00–13:00 and 19:00–05:00.

Fig. 3 depicts the histograms of travel distances of vehicles between the corresponding PoI and the vehicle's destination. For both PoIs, the histogram shows a behavior with a long tail component. While most of the vehicles travel for short distances (inside the Canton of Zurich), some vehicles travel a couple of hundreds of kilometers coming from distant locations in Switzerland. In both PoIs, 95% of all vehicles travel less than 100 km. Based on this observation, one can reasonably assume that these vehicles (named type R) depict an everyday routine and their charging should be handled via the routine layer of our architecture. On the other hand, the vehicles traveling more than 100 km (named type A) can be said to show a nonroutine behavior and make this journey from time to time. We consider these long distance traveling vehicles as atypical, irregular vehicles whose behavior cannot be known beforehand; so, their charging should be handled by the correction layer.

B. Probabilistic Mobility/Parking Model

At an urban parking lot, in addition to the routine commuting vehicles (type R) and irregular vehicles with long occupancy durations (type A), one can expect some vehicles who stay at the parking lot for a short amount of time (e.g., vehicles coming for shopping, theater). Due to its construction method, the Zurich trace does not incorporate any vehicle with a short occupancy duration at any location. For the sake of completeness, we have proposed a probabilistic mobility/parking model for these kind of short occupancy irregular vehicles (named type B).

These type B vehicles are defined by three distributions: 1) occupancy distribution; 2) arrival time distribution; and 3) traveling distance distribution. We use a uniform distribution between 0.5 and 3 h for the occupancy distribution with a step size of 0.5 [$\text{occ}_i \sim U(0.5, 3)$]. For the arrival time distribution, we construct a probability density function based on the arrival time histogram of vehicles from the Zurich trace (Fig. 2). We add some arrival probability in the interval 10:00 and 13:00 to reflect some day time arrivals, and the interval 19:30 and 05:30 to reflect some midnight arrivals. Similarly, for the traveling distance distribution of the type B vehicles, we use the traveling distance histogram of the Zurich trace vehicles (Fig. 3) as baseline.

Since these type B vehicles will not stay at the parking lot for long periods of time, we limit their traveling distance based on their occupancy durations to avoid having vehicles that cannot get the necessary amount of energy even though they are charged during their whole occupancy period. Thus, all type B vehicles have a traveling distance based on their occupancy durations.

VI. Performance Evaluation

We have analyzed the performance of the PLRS system which is described in Section III with respect to total revenue and total number of EVs fulfilling their recharging requirement metrics. We use the Advanced Interactive Multidimensional Modeling System (AIMMS) software to solve the optimization problems. The software uses several solvers like C Parallel Language EXtensions (CPLEX), and our solutions are globally optimal. We compare the results of the proposed two-layered PLRS system with the results of two well-known basic scheduling mechanisms: FCFS and EDF. It has been shown in [2] that among various well-known scheduling algorithms, EDF performs the best in terms of missed requirement amount. The performances of these mechanisms are evaluated via simulations and these results are used as baseline values. For the vehicular mobility/parking pattern defining the behavior of the regular vehicles (type R), we use the trace information from the Zurich trace's two PoIs as explained in Section V-A. We divide the irregular vehicles into two categories: 1) type A—vehicles with long parking lot occupancies; and 2) type B—vehicles with short parking lot occupancies. We use the vehicles with long traveling distances in the Zurich trace as type A vehicles, whereas for type B vehicles, we use generated data from the probabilistic mobility/parking model that is described in Section V-B.

A. Description of the Basic Scheduling Mechanisms

FCFS and EDF are well-known scheduling mechanisms that are being used in a variety of fields. The time horizon of both of these mechanisms is real-time. Being real-time systems, they work at the start of each time slot and decide on which EVs should be recharged in this time slot, and how much energy should be given to them. They manage an EV list which starts with vehicles that have stayed at the parking lot during the midnight, and is updated at the beginning of each time slot by the arrival and departure parameters of the vehicles. While the FCFS mechanism does not sort the EVs added to the list by any parameter, EDF mechanism sorts this EV list at the start of each time slot based on the difference between the current time and the departure time of each EV. Vehicles with earliest deadlines are given priority since they have less recharging opportunity compared to the other vehicles.

The amount of charge given to each EV depends on vehicle's and parking lot's recharging related parameters. First, the energy need of the vehicle is calculated by taking the difference between rq_i and the rm_i. Then, this need is checked by the pc_t and the cr_i. Then, the minimum of these three values [i.e., MIN (MAX ($\mathrm{rq}_i - \mathrm{rm}_i$, 0, pc_t, cr_i))] is chosen as the charge amount of this EV for the current time slot.

In the MaxR problem, in each time slot EVs are first given the necessary amount of energy to fulfill their requirements. Then, if the parking lot has spare capacity, EVs will be given energy up to their battery capacities. In the MaxNRQ problem, like the optimization formulation, each EV can only get charge to up to its required amount. If the rm_i is already more than rq_i, the vehicle will not be given any charge in the second problem.

The routine layer only considers type R vehicles. For types A and B vehicles, the PLRS system incorporates a secondary real-time scheduling mechanism in the correction layer. In both problems, we consider the FCFS and EDF mechanisms as the secondary scheduling mechanism. Therefore, we denote the method of our proposed system as optimization + FCFS and optimization + EDF based on the secondary scheduling system used in the correction layer.

B. System Parameters

In this paper, we consider two types of vehicles, the Nissan Leaf model 2013 for types R and B vehicles and Tesla Model S for type A vehicles. Nissan Leaf model 2013 has a battery capacity of 24 kWh and a range of 106 km, which leads to an energy expenditure of 0.225 kWh/km. Tesla Model S on the other hand, has a much bigger battery with a size of 60 kWh. It has a range of 335 km and an energy expenditure rate of 0.18 kWh/km. The cr_i parameter is taken as 1.8 kWh for all the three types of vehicles, which is the default half-hour charging rate of Nissan Leaf. No conversion rate loss is considered between the ac and dc transformation.

TABLE V
SYSTEM PARAMETERS

Buying price	bp_t	6.7 ¢/kWh, $t < 07{:}00$
		12.4 ¢/kWh, $11{:}00 > t \geq 07{:}00$
		10.4 ¢/kWh, $17{:}00 > t \geq 11{:}00$
		12.4 ¢/kWh, $19{:}00 > t \geq 17{:}00$
		6.7 ¢/kWh, $t \geq 19{:}00$
Selling price	sp_t	15.0 ¢/kWh
EV battery capacity	cp_i	24 kWh for Type R and B EVs
		60 kWh for Type A EVs
Charging rate	cr_i	1.8 kWh

Two scenarios have been considered for the rm_i parameter: full battery (FB) and just enough battery (JEB). In the first scenario, all EVs start their journey to the parking lot with a FB. Considering EVs travel the same distance between their destination and the parking lot in both directions, they spend rq_i amount of charge in order to reach the parking lot. Thus, the rm_i parameter is set as

$$\mathrm{rm}_i = \mathrm{cp}_i - \mathrm{rq}_i, \forall i \in \mathbf{I} \tag{13}$$

in the FB scenario.

The JEB scenario considers every EV starts its journey to the parking lot with JEB (i.e., rq_i) to reach the parking lot. Therefore, all EVs reach the parking lot with no charge left in their batteries ($\mathrm{rm}_i = 0, \forall i \in \mathbf{I}$).

A three time-of-use electricity pricing is used for the bp_t values following the Ontario Energy Board's winter prices. Hours through 19:00 and 07:00 is called off-peak and has a tariff of 6.7 ¢/kWh. Two peak periods are considered as between 07:00 and 11:00, and between 17:00 and 19:00. During the peak periods, the electricity price is given as 12.4 ¢/kWh. The daytime period between the two peaks are called the mid-peak period during which the electricity price is selected as 10.4 ¢/kWh. For the sp_t values, we choose an arbitrary value of 15.0 ¢/kWh regardless of the time of the day. These parameters are also given in Table V.

As the number of type B EVs, we use 10% of the number of type R vehicles, depending on the selected PoI. The pc_t^C is selected as 20% of pc_t^R not to limit the available energy amount to the irregular vehicles.

C. Results for MaxR Problem

Fig. 4 shows the results of the MaxR problem for PoI 1, using FB and JEB scenarios, respectively. In both scenarios, a clear difference is evident between the PLRS system's results compared to both FCFS and EDF mechanisms. In the FB scenario, the EDF shows some advantage over FCFS when the pc_t value is low. As the pc_t value grows, this advantage begins to wane and disappears completely in high pc_t values. The difference between the EDF and the FCFS results is very marginal in the JEB scenario. Similarly, the selection of the secondary scheduling system for the correction layer has little impact over the results in both scenarios. Fig. 5 depicts the results for PoI 2 in both scenarios. Although the increased EV

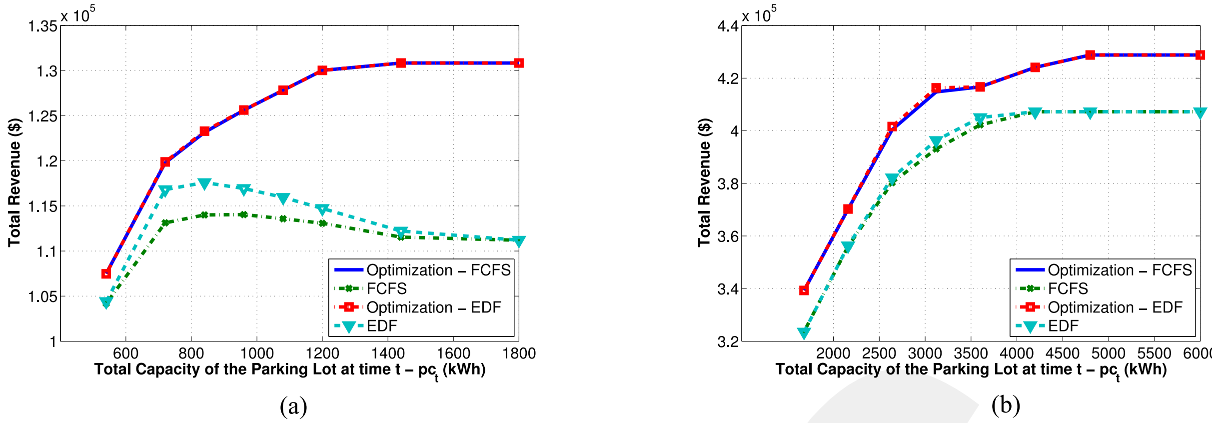

Fig. 4. Total revenue with varying pc_t values—PoI1. (a) FB scenario. (b) JEB scenario.

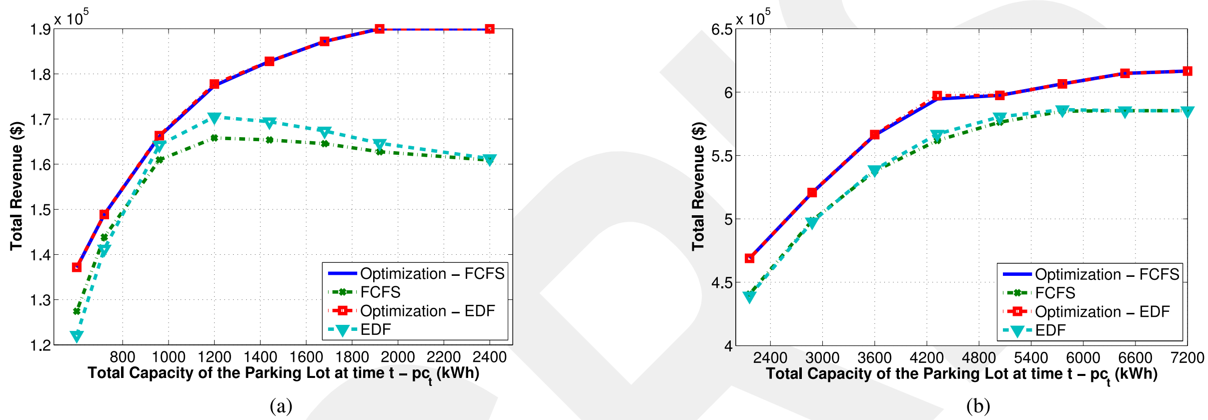

Fig. 5. Total revenue with varying pc_t values—PoI2. (a) FB scenario. (b) JEB scenario.

TABLE VI
NUMBER OF EVs FAILING TO FULFILL THEIR REQUIREMENTS BY VEHICLE TYPE

PoI	Initial SOC	pc_t^R	Optimization + FCFS			FCFS			Optimization + EDF			EDF		
			Type R	Type A	Type B	Type R	Type A	Type B	Type R	Type A	Type B	Type R	Type A	Type B
PoI1	FB	Profile 1	0	0	0	24	6	0	0	0	0	19	4	0
		Profile 2	7	7	0	56	7	0	8	3	0	54	5	0
	JEB	Profile 1	0	49	112	138	86	186	0	64	6	175	80	2
		Profile 2	11	68	189	187	91	195	32	88	27	225	81	2
	Vehicle Count		**3037**	**163**	**300**	**3037**	**163**	**300**	**3037**	**163**	**300**	**3037**	**163**	**300**
PoI2	FB	Profile 1	0	2	0	40	12	0	0	2	0	39	10	0
		Profile 2	10	12	0	70	14	0	12	13	0	69	13	0
	JEB	Profile 1	0	76	190	216	130	275	0	99	9	265	128	2
		Profile 2	15	98	275	252	133	280	37	128	30	299	128	3
	Vehicle Count		**4368**	**236**	**430**	**4368**	**236**	**430**	**4368**	**236**	**430**	**4368**	**236**	**430**

count in PoI 2 increases the necessary parking lot capacity and the overall revenue, it does not affect the behavior of the mechanisms and they follow the same patterns as in PoI 1.

The revenue reduction for both basic scheduling mechanisms in the FB scenario is due to the increased charge allocation in the 07:00–11:00 peak period. The more capacity the system has, the more recharging will be allocated during the morning peak period since both mechanisms try to use the current capacity as much as possible regardless of its bp_t values. In the JEB scenario this reduction is not apparent since the total given charge to the EVs are much more than in the PB case and this pricing issue is overshadowed by the increased total charge amount.

D. Results for MaxNRQ Problem

Table VI summarizes the results of the MaxNRQ problem considering both PoIs, the two initial SoC scenarios, and two capacity profiles for the pc_t^R parameter. Unlike the MaxR problem, we consider a time-varying pc_t^R parameter reflecting the three time-of-use periods described in Section VI-B. The total capacity is at its daily lowest value during the on-peak periods and the daily highest value during the off-peak hours. The mid-peak capacity is selected as a value between the on-peak and off-peak values. Two capacity profiles are considered. In profile 1, the pc_t^R is selected as bigger than the total required charge amount of all type R EVs combined, whereas in profile 2, pc_t^R is not enough for all EV requirements.

TABLE VII
PARKING LOT CAPACITIES

PoI	Initial SOC	pc_t^R	pc_t Off-peak	Mid-peak	On-peak
PoI1	FB	Profile 1	450	210	90
		Profile 2	420	180	60
	JEB	Profile 1	1080	780	600
		Profile 2	1020	720	540
PoI2	FB	Profile 1	510	270	150
		Profile 2	480	240	120
	JEB	Profile 1	1470	1128	870
		Profile 2	1410	1080	810

So, unless the secondary scheduling mechanism allocates some charging opportunities to type R EVs, the requirements of some of these vehicles will not be fulfilled. The capacity values used are described in Table VII.

In all cases, the proposed PLRS system is able to fulfill all the requirements of type R EVs while the basic scheduling systems miss between 0.5% and 7.5% of total type R requirements based on the specific case. As for the types A and B vehicles, except few cases, our two-layered system also outperforms both basic scheduling systems. In these exceptional cases, while the basic scheduling mechanisms miss less irregular EV requirements, they miss some regular EV requirements. Considering all three vehicle types, the proposed PLRS system yields a reduced total missed EV requirements compared to the basic scheduling mechanisms while fulfilling all the requirements of type R EVs.

The FCFS and EDF mechanisms does not offer any clear benefit over one another regarding type R vehicles. However, there is a clear difference between the results of FCFS and EDF for irregular EVs. EDF favors type B EVs over type A EVs since type A vehicles have short (i.e., 0.5–3 h) occupancy values and, by definition, EDF prioritizes vehicles with earliest deadlines over other vehicles.

The rate between the allocated capacities to both layers affect the performance of the system. Since, the current rate is suitable for accommodating both regular and irregular vehicles, the schedule is not hindered by this rate. In case the rate is selected to be higher, more irregular vehicles will suffer from not having enough recharging toward their requirements. On the other hand, if the rate is selected to be lower, this time there will be some regular vehicles with their requirements are not met.

VII. CONCLUSION

In this paper, we propose a two-layered PLRS system for recharging EVs considering the mobility/parking patterns of these vehicles. We use a realistic trace-based vehicular mobility model focusing on individual parking lots for vehicular mobility/parking patterns. In order to evaluate the performance of the system, two objective functions have been defined: MaxR, and maximizing the total number of EVs fulfilling their requirements. The proposed system has been compared with two well-known basic scheduling mechanisms, FCFS and EDF, with regard to these two objective functions.

Results show that for both objectives, using such a vehicular mobility aware PLRS system considerably increases the performance of the recharging of EVs. In the first problem, the proposed system better allocate recharging opportunities resulting in an increased overall revenue. Similarly, in the second problem, our proposed method reduces the total number of EVs missing their requirements. Different from the FCFS and EDF schemes, our approach requires tracking of EVs mobility/parking patterns which introduces some storage and computation overhead. However, it is our belief that such additional burden is compensated by the gain amount in system's performance.

As the future work, we plan to extend this paper by incorporating the effects of the admission control and communication framework to the system to develop a complete smart PLRS system for recharging EVs (see Fig. 1). These mechanisms will also manage uncertainty issues both for regular and irregular EVs, where vehicles do not adhere to their proposed schedule (i.e., departing earlier or later than expected). Also, there can be a multitude of ways for scheduling the recharging of many vehicles inside each half-hour time periods. After selecting how much each EV should be recharged at every time period, a third scheduling should be conducted to handle the minute-by-minute fine scheduling of the recharging. This fine tuning is of utmost importance to reduce the instantaneous power build ups which is harmful not only to the parking lot but also to the grid itself. Another issue worth to be explored is the economic aspects of the system, e.g., electricity bids and users dynamically accepting/refusing offered prices, so to cover more aspects of the whole recharging problem in general.

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