Static Charging Scheduling of Electric Vehicles at Private Stations

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***Abstract* – In this short paper, considering the significant increase on the number of electric vehicles (EV) and the additional load they bring on the power grid, we propose a static charging scheduling algorithm in order to effectively schedule the charging of EVs during nighttime at private charging stations. Given the vehicles and the volume of their charging demands, we first determine the additional load to the grid assuming all EVs need to charge to the maximum level recommended by the manufacturers within the given time period. Then, the proposed algorithm calculates the energy and the time needed to charge the EV battery to the level requested by the owner. After finding the slack time (the latest start time for charging – the current time), it schedules the charging of EV by giving priority to the one whose slack time is minimum. If it is not possible to charge all vehicles to the requested battery level within the time constraints, the algorithm evenly distributes the available energy to EVs that need more charging.**

Keywords—electric vehicle, resource allocation, latency constrained, scheduling, private EV charging

I. INTRODUCTION

Electric vehicles (EVs) have become very popular and widely used in recent years all over the world due to various advantages compared to their counterparts. These advantages include being environmentally friendly, lower operating cost (including miles per dollar and maintenance), higher energy efficiency, predictable driving cost (mainly due to diversified sources of electricity) and reduced energy dependence. Considering the cost-saving incentives provided by governmental bodies (such as states and municipalities) along with the above-mentioned advantages, it is projected that the use of EVs will continue to increase significantly in upcoming years. This will bring additional challenges for the electrical grid.

Although charging outlets become common at parking spots of workplaces and social places such as movie theatres and supermarkets, people cannot charge EV battery to a sufficient level due to the limited number of outlets and relatively long charging times. Additionally, public charging stations that provide fast/rapid changing options are very limited. Therefore, it is a feasible option to charge EVs at home using private charging stations during night time. This will bring significant additional load on the power grid and requires a well-managed charging of EVs for a heathy operation of the grid.

Despite noteworthy improvements in recent years, the capacity of EV battery is still limited and the batteries require frequent charging. EV battery swapping is well known, but unfortunately, EV manufacturers have different standards for battery access, attachment, and type. EVs face significant battery-related challenges. The time needed to charge an EV battery using a private station is long ranging from 4 hours to 11 hours depending on type of charging outlet and capacity of the battery. Rapid charging systems (e.g., 22kW and up power options) require installation of special circuitry and are expensive to set up, hence, they are currently not reasonable options for home charging. Primarily two reasons, namely the increased number of EVs and the required large amount of time to charge, cause an increase on the number of private charging stations at home. This may eventually create a hazard for the power grid if it is not properly managed.

In this paper, we focus on private charging stations to maintain a restricted grid load by applying scheduling algorithms. The static scheduling approach proposed in this work for EV charging aims at maintaining the power grid load at a safe level; causing no harm to the infrastructure. We first determine the total amount of energy needed to charge all EVs to the maximum level recommended by the manufacturers. Then, the proposed algorithm tries to evenly distribute the total energy over time considering the charging speed of EVs, charging capacity of private stations and the target charging level (i.e., state of charge) requested by the owner. The charging scheduling of EVs are done in such a way that the amount of power drawn from the grid does not exceed a certain threshold. Selection of an EV to schedule is based on the slack time (the latest start time for charging – the current time). The EV with the smallest slack is given priority. If it is not possible to charge all vehicles to the requested battery level within the time constraints, the algorithm evenly charges the remaining EVs to the highest possible level.

The remaining of the paper is organized as follows: Section II briefly introduces the background work including challenges of the increasing number of EVs, load of the power grid, and limitations of the current solutions. Section III discusses the proposed approach with details. Section IV presents preliminary experimental evaluation and Section V concludes the paper with future directions.

[*]This author is supported by the grant, Pathways to STEM Careers, funded by HSI STEM program of DOE.

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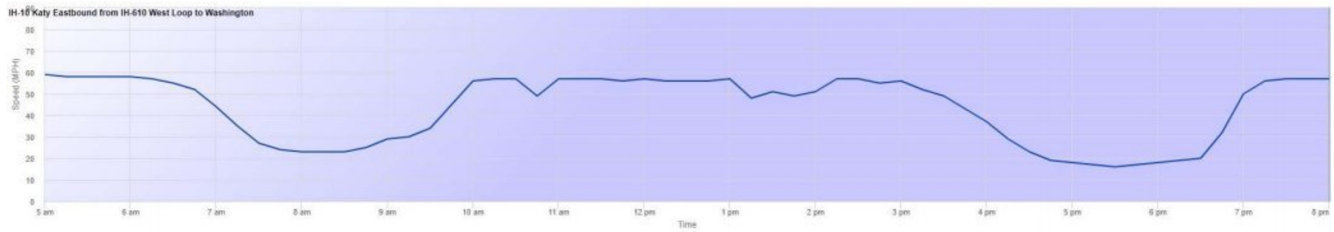

Fig. 1. The traffic speed at IH-10 Katy Eastbound from IH-610 West Loop to Washington Avenue (Houston, TX) between 5am and 8pm [20].

II. Related work

Marcincin and Medvec [1] discuss the practical benefits of active charging stations that are frequently implemented in Micro Grids or Smart Grids and present useful background information about electricity distribution networks and the electric car industry. Yagcitekin et al. [2] present statistics on electric car usage, electric power grid usage, and how often a car is parked. They also discuss what the future grid load in a city might look like in order to sustain a bustling electric car-based economy for use. [3] proposes an on-board charging mechanism that, when connected to a smart grid, optimizes itself to reduce grid load traffic. It allows a car to manage its own charging with its own hardware. [4] focuses on reducing battery support time by increasing the efficient power consumption of the battery. It proposes a system for a charging station that supplements or even fully implements photovoltaic charging to reduce power load on the grid. Talei et al. [5] demonstrate how the hardware architecture works and discuss the inherent value in micro grids.

Ghaman et al. [6] present a useful methodology for analyzing traffic in Houston which can still be used to estimate traffic flow today. [7] proposes a charging system that is to be towed in the storage of the car itself, to wirelessly charge electric vehicles on the go. The proposal intends to reduce the cost of infrastructure building that would be required. Kumar et al. [8] propose in intelligent battery management system to reduce the total charging time. It is a hardware implementation of a power saving mode for electric cars while it is in use. Ajanovic and Haas [9] present an economic prediction model up to the year of 2050 based on energetic assessments of electric, hybrid, and fuel cell vehicles. As with any future economic model surrounding EVs, many assumptions are made about when the cost and efficiency of EVs will decisively surpass combustion engine vehicles. Vestal [10] presents an overview of research surrounding multi-criticality implementations in various private sectors. It covers both multi-criticality as a hardware implementation as well as more abstract implementations such as software development.

Murataliev [11] studies various scheduling algorithms that can be applied to connected electric vehicle systems and proposes a new algorithm based on charge time priority. Hato et al. [12] present quantifiable data on the degradation of a lithium iron phosphate battery to measure parameters that can change a battery lifetime. For instance, authors discuss the ideal State of Charge for a battery to last the longest. The effects of overcharging and undercharging are also presented in [12]. Mies et al. [13] propose that EVs require variable amounts of power when charging, which needs to be accounted for when modeling electric grid infrastructure. They demonstrate the need by showing how models differ when accounting for charge variability. [14] covers four primary ways to measure State of Charge in lithium-ion batteries and compares them quantitatively through experimentation. The four modeling methods are Extended Kalman Filter, Unscented Kalman Filter, Sliding Mode Observer, and Nonlinear Observer. Batteries are graded on prediction accuracy and computational complexity among others. [15] models battery State of Charge at the circuitry level. It proposes that open-circuit voltage can be estimated based on terminal voltage and current variation.

Carrillo et al. [16] propose a three-tier algorithm for smart grid charging of EVs to reduce the grid load requirement for the growing number of electric vehicles. The proposed method considers an ideal state of charge component to maximize efficiency of charging. Topan et al. [17] use the Kalman Filter method on a Thevenin model battery and compare it to a Recursive Least Square method, demonstrating an improvement in state of charge and state of health accuracy in favor of Kalman Filtering. [18] measures variability between batteries of various states of charge. During experimentation, a constant current charging profile is applied to each battery to measure differences in how long each charging and discharging cycle takes. Zhang et al. [19] propose a smart charging station capable of charging many vehicles at once with ideal results in order to reduce the grid load for large populations of EVs. The results are measured against a constant charging profile.

III. Charging Scheduling of Electric Vehicles

In order to identify the time period EV charging may heavily affect the power grid, we first study the traffic flow. Figure 1 shows the average traffic speed at IH-10 Katy Eastbound from IH-610 West Loop to Washington Avenue (Houston, TX) between 5am and 8pm. This graph provides data to accurately estimate the arrival and departure times of vehicles. As seen in the figure, the traffic starts slowing down at around 4pm in the afternoon. Similarly, the traffic speeds down at around 6:30am in the morning. Given this, we identify [5pm-7am] as the time period EV charging may affect the grid. Please note that the EV charging at private stations may be done outside this time period as well but with some small effect, which is not the focus of this work.

Now let us model the static charging scheduling of electric vehicles proposed in this work. V = $\{v_i;\ i = 0, 1, 2, 3, \ldots, n\}$ represents the set of EVs demanding charging where v_i represents each EV and n is the number of EVs. State of Charge (SoC) is the level of charge of EV battery where 0% indicates the battery is empty while 100% means full. For each v_i, the terms below are defined as follows:

$SoC_{initial}$: SoC value when EV is plugged into the system

SoC_{recom}: Highest SoC value recommended by manufacturer

SoC_{target}: SoC value requested by EV owner after charging

$t_{initial}$: The time EV is plugged into the system

t_{start} : The time EV starts charging

$t_{complete}$: The time EV charging is completed

$t_{recharge}$: The time period needed to charge EV

t_{LS}: The latest start time to charge EV to SoC_{target} level

t_{slack}: The time period from current time to t_{LS}

load: The amount of current EV is drawing from the grid

E_i: The amount of energy needed to charge v_i to SoC_{recom}

In addition, the following terms are defined for the entire charging system.

E_{total}: The amount of energy needed to charge all EVs

GL: The amount of current the system draws from the grid

GL_{asap}: The maximum amount of current the system would draw if scheduling is not done

GL_{max}: The maximum amount of current the system is allowed to draw from the grid

Given the parameters above, Algorithm 1 schedules charging of EVs without considering any constraints. This is an ASAP (As Soon As Possible) scheduling algorithm where each EV starts charging once it is plugged into the charging system and it is taken out of the system when its battery level reaches at SoC_{recom}. Basically, this algorithm generates a charging schedule of EVs using the charging start times (i.e., t_{start} for each v_i) and calculates the necessary parameters for Algorithm 2. In lines [1-7], it schedules each EV (v_i) to the time it is plugged into the system. In addition, it calculates charging time ($t_{recharge}$) and the energy needed to charge (E_i) each EV along with the total energy to charge all vehicles (E_{total}). Then, in lines [8-18], the algorithm calculates the maximum amount of current that would be drawn from the grid (GL_{asap}) if no scheduling is done. This provides useful information regarding the behavior of EV owners in respect to charging their vehicles. Please note that our algorithm schedules the charging of EVs from 5pm to 7am and the unit of l is minute (e.g., l=0 means 5:00pm, l=1 means 5:01pm, etc.).

Algorithm 1: ASAP Charging Scheduling of EVs

Input : V = {v_i; i = 0, 1, 2, 3, …, n}
Output : $t_{recharge}$ and E_i for each v_i, E_{total}, GL_{asap}

1: $E_{total} = 0$
2: for each v_i := 1 to n
3: Schedule v_i to t_{start}
4: Calculate E_i
5: Calculate $t_{recharge}$
6: $E_{total} = E_{total} + E_i$
7: end for
8: $l = 0$
9: $GL_{asap} = 0$
10: while ($l < 840$) **{**
11: $GL = 0$
12: **for each** v_i := 1 to n
13: **if** $t_{start} <= l < (t_{start} + t_{recharge})$
14: $GL = GL + load$
15: **end for**
16: **if** $GL > GL_{asap}$ **then** GL_{asap} = GL
17: $l = l + 1$
18: }

Algorithm 2 schedules charging of EVs without exceeding the allowed level of current the system can draw from the grid (GL_{max}). The algorithm receives the set of EVs (V) and GL_{max} as inputs and generates the charging scheduling of EVs (i.e., t_{start} for each v_i) as output. The algorithm does not let the charging system to draw more current than it is allowed, hence preventing the grid from hazards due to excessive EV charging. In lines [1-4], the algorithm calculates t_{LS} and t_{slack} for each v_i. t_{LS} is the latest start time in order to charge an EV to the SoC level requested by the owner (SoC_{target}). As seen in the algorithm, t_{slack} is calculated by subtracting the current time ($t_{current}$) from t_{LS} and is used to select an EV to schedule for charging. In lines [5-6], l and GL are initialized where l represents the current time. In lines [7-16], the algorithm repeats the following until all EVs are scheduled. It first calculates the total current (GL) the system is drawing. Then, if GL is less than GL_{max}, it selects v_i with the minimum slack time and schedules it for charging. After updating GL with the load of v_i, it removes v_i from set V. This process is repeated until V = ∅.

Algorithm 2: Static Charging Scheduling of EVs

Input : V = {v_i; i = 0, 1, 2, 3, …, n}, GL_{max}
Output : Charging start times of EVs (i.e., t_{start} for each v_i)

1: **for each** v_i := 1 to n
2: $t_{LS} = t_{complete} - t_{recharge}$
3: $t_{slack} = t_{LS} - t_{current}$
4: end for
5: $l = 0$
6: $GL = 0$
7: repeat {
8: Calculate GL
9: **while** ($GL < GL_{max}$) **{**
10: Select $v_i \in$ V such that t_{slack} is minimum
11: Schedule v_i to l *(update t_{start})*
12: $GL = GL + load$
13: V = V - v_i
14: **}**
15: $l = l + 1$
16: **}** until (V = ∅)

IV. Preliminary Experimental Evaluation

In this ongoing work, the preliminary experimental evaluation is conducted assuming that 100 EVs are present in the system requesting charge. The algorithms are implemented in C language. The values of the parameters used in the simulations are randomly generated considering the real-life scenarios. Table 1 shows the values/range of parameters. Note that these values can easily be modified. The algorithm efficiently schedules the charging of EVs without exceeding the maximum level of current the system is allowed to draw from the electrical grid. Table 2 presents the results for charging scheduling of EVs. The first row gives the time period (e.g., 5-6pm covers the time period from 5pm to 5:59pm). The second, the third and the fourth rows report the number of EVs plugged

TABLE 2. CHARGING SCHEDULING OF EVS

Time period	5-6pm	6-7pm	7-8pm	8-9pm	9-10pm	10-11pm	11-12am	12-1am	1-2am	2-3am	3-4am	4-5am	5-6am	6-7am
# of EVs plugged in	15	39	23	9	5	5	3	1	-	-	-	-	-	-
# of EVs started charging	15	10	4	6	6	11	11	13	12	9	3	-	-	-
# of EVs charged to SOC_{target}	-	-	3	8	11	7	10	3	11	10	15	9	8	5

TABLE I. THE PARAMETERS USED IN THE SIMULATIONS FOR 100 EVS

Parameter	Value/Range
$SoC_{initial}$	10% - 50%
SoC_{recom}	80% - 100%
SoC_{target}	50% - 100%
$t_{initial}$	5pm-1am
$t_{complete}$	3am-7pm
load	3.7kW and 7kW

in, the number of EVs started charging and the number of EVs completed charging, respectively, during the corresponding time periods.

V. CONCLUSION

In this paper, we present our model for charging scheduling of electric vehicles and propose two algorithms. The first algorithm is an ASAP algorithm that finds the charging time and the energy needed to charge each EV in addition to the total energy needed to charge all EVs and the total amount of current that would be drawn from the grid if no scheduling is done. The second algorithm generates the charging scheduling of EVs considering the amount of current the charging system is allowed to draw from the grid. The second algorithm aims at preventing the electrical grid from a possible hazard due to excessive EV charging. The planned future work is to investigate the solutions where the power grid is not able to supply the demand to charge all EVs to the requested SoC levels. We also plan to integrate the dynamic behavior into the proposed algorithms where the number of EVs in the system will change during charging time.

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