Response Letter for manuscript TSG-01885-2017 "Online EV Scheduling Algorithms for Adaptive Charging Networks with Global Peak Constraints"

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March 16, 2018

We are very grateful to the referees for their thorough reviews of our paper and their constructive comments. Based on their suggestions, we have greatly improved the quality of our paper. This document provides a summary of changes made in the revised manuscript and detailed responses to the comments of the reviewers. The main changes in the revised manuscript are summarized below:

1. Reorganizing the manuscript by moving important contents such as related works, and offline algorithm design for fractional scenario, to the main body of the paper.
2. Justification of the valuation model based on the comments of Reviewers #1 and #2.
3. Highlighting the contributions of the paper in terms of the scenario and technical solutions

In what follows, we mention first the comments (as appeared in the decision letter, highlighted in blue in this letter) followed by a description on how we addressed those comments in the paper.

Editor's Comments:

All three reviewers have expressed concern regarding the necessity of appendix, which makes the paper over the page limit set by this journal. The authors are advised to reduce the length of their paper. In addition, organization of the paper needs to be improved and contribution needs to be clarified.

Response: We thank the Editor for handling the review process of our paper. Based on the important and valuable comments from the reviewers we revised the paper in 10 pages and and we did our best to fully address all the comments. We clarified the contribution of our paper by highlighting (1) the importance and uniqueness of the specific studied problem based on a real-world scenario and (2) differences with the similar existing works in terms of system model, and proposed technical solutions.

1 Reviewer #1

The authors in this paper present two online algorithms to schedule EV charging for two different business models.

▷ **Response:** We appreciate the reviewer's effort for his/her in-depth review. Below is our itemized response to this comment.

While the authors try to present extensive proof on the optimality of their algorithms, the problem of EV scheduling is an old problem and the problem authors discuss are no longer the most essential/important issues.

▷ **Response:** We agree with the reviewer that the EV scheduling problem has been studied extensively in the recent years, which demonstrates its importance in facilitating the deployment of EVs in energy systems. However, based on a real-world hierarchical architecture in the Adaptive Charging Network (ACN) in California Institute of Technology, in this work, we identified that the global peak constraint of the ACN results in a unique, yet challenging EV scheduling scenario that has not been addressed in the existing work. Consequently, we formulated the corresponding EV scheduling problem and proposed solutions in two possible business models.

The writing of the paper is quite confusing and hard to follow. It's more like a technical report that lacks good context. The authors simply cite certain algorithm from other paper without explaining it, making it very difficult for the reader to follow.

▷ **Response:** Agreed, and we believe that this is because of the page limit in the first submission. In the revised manuscript, we complied a 10-pages manuscript by reorganizing the paper and adding several important contents to the main body of the paper. In particular, we added the optimal offline algorithm from our technical report to the revised manuscript, with detailed explanations. The details of this algorithm is in Section ??, Page ?? of the revised manuscript.

The authors state that most of the existing literature only discusses about optimal operation with single CS, which is not true. The field of EV Demand Side Management has long discussed the optimal operations with EV coordinations, renewable energy and battery storage, which is way beyond the simple scope of single CS scheduling. The reviewer recommends the writer to conduct more in-depth literature review. A good starting point may be "Mukherjee, Joy Chandra, and Arobinda Gupta. "A review of charge scheduling of electric vehicles in smart grid." IEEE Systems Journal 9.4 (2015): 1541-1553."

- -Multiple CS is studied but none of them considered a) solving problem under over-provisioning model b)covering both business models. Also, we provide extensive analysis regarding the competitive/approximation ratio of the algorithms.

1.1 Comments

Comment 1.1:
Page1 line 51: "Caltech ACN[4]". The reference is incorrect.

Response: It is correct actually.

Comment 1.2:
Page 1 line 27: What does valuation mean? There is no clear definition for this value. It looks like a "bid" by each customer for their desired power. However, in current business model, the fee is mostly linearly correlated with the energy user uses, so this "valuation" should mostly be the energy demand of the user. However, it is true that the "valuation" could be more nuanced, given different user's profile, need and other background. If this is the case, it should be more clearly explained and the function for "valuation" should be more clearly defined.

Response:
v_i can has different meanings not just electricity price. For example, it can be a combination of electricity unit price, priority of users, valuation of received power from the user's point of view, etc. Therefore, we solve the problem in a general case where regardless of the meaning of input variable v_i.

The variable v_i defined in the paper is valuation of EV i when it receives its demand D_i. The valuation v_i in simple and default case is the price imposed by charging station that the owner of EV i should pay to receive its demand, D_i (as it is in the paper). In this case, the charging station is allowed to use any pricing policy as it does not affect our algorithms. With this interpretation, our algorithms solve revenue maximization problem for utility provider. v_i can also represent the valuation of demand from the user's point of view indicating that how much the user will be happy if it receives its submitted demand. With this interpretation, our algorithms try to maximize users' satisfaction or users' social welfare. Therefore, our proposed algorithms are general and work for any valuation setting that is proposed by either EVs or charging stations.

Comment 1.3:
The integral model is not quite a practical and meaningful one. It is rarely the case that if a service provider fails to provide full service, they will not charge for service at all. Again, as in 2, most of the income of current (and near future) existing service providers are linearly correlated to the energy, so this problem will never come across. However, although it doesn't exist yet, it is also true that there can be a "guaranteed" service to charge "all-or-nothing" to users. This can be an interesting business model but there are many questions that need to be answered, such as: what if the customer proposes a demand that can be never reached (such as ask for 40kWh with a 30kWh to be filled battery) and a high valuation? In this case, the system will charge him with high priority but will never charge him for fee. Also, what happens to the users who get rejected due to request not being feasible? It would appear that they will occupy a charging station without getting charged, which is a waste of physical resources and a bad service to customer.

Response:
In integral model, the charging algorithms need to be designed in a way that they give a user all its demand or nothing as it is done by our algorithms. Therefore, it cannot happen that a user receive partial demand and pay nothing.

In the paper we assumed that the submitted demands are feasible with respect to arrival time, deadline, battery capacity and maximum charging rate. In practice the state of charge a battery is known and therefore, non feasible demands can be easily detected by the charging system.

Regarding rejected users, they need to leave the charging station when they are rejected as it can happen in conventional fuel stations. However, an important point is that users should be informed at their arrival time about the decision not at the deadline otherwise they might wait for a long time in the charging station and finally leave the station with empty hands. To solve this issue, charging solutions with "on-arrival commitment" should be proposed. This problem is quite challenging and we addressed it in a separate paper.

Comment 1.4:
It seems that the ranking of both models is largely dependent on different "unit valuation" of different users (page 3 line 46-49, page 4 line 25-27). However, in most of the cases, most users only want to pay for standard rate and very few are fine with high premium (let alone government regulation). Its also a very impractical assumption that every user will propose their desired valuation every time they charge their car, and everyone proposes a different one so that the ranking is meaningful. Given this, is there any value of the algorithm if everyone's unit bid is the same? In most of scheduling algorithms, the ranking is done with requested kWh or remaining time, which the authors did not take into account in their presented ranking.

Response:
First, this is the same question about valuation and explanations there apply here as well.
Second, the same model is used in [**?**].

Comment 1.5:

Constraint (1d) is wrong: y_i^t should always be less than k_i no matter how much energy is charged overall, because the max power rate is governed by the physical charging station hardware.

Response: Note that we always have $\sum_t y_i^t \leq D_i$ as it is guaranteed by constraint (1a). Therefore, in constraint (1d), $\frac{k_i}{D_i} \sum_t y_i^{t'} \leq k_i$ holds.

Comment 1.6:
Eq (2) the min function seems unnecessary because (1a) already guaranteed the second term will never be larger than the first term.

Response: We used the min function to make sure that over-charging of an EV (i.e., when $\sum_t y_i^t > D_i$) cannot bring any benefit for the charging station. However, we agree that under a proper algorithm design where over-charging is guaranteed to not happen, as in our algorithm, the min function is unnecessary. However, in terms of readability, we think that current form of the equation is more clear.

Comment 1.7:
Page 2 line 21: the authors claim they use a ”valley filling” algorithm. What algorithm is used and how do they affect the scheduling? The effect should be quite significant to the results as many paper solely discusses the optimal operation of those but the author did not mention at all. Also is the entire fCS algorithm copied from [12]?

Response: The valley-filling strategy is explained in Section IV-A-1. Also, its effect is shown by simulation in Section V, subsection “Comparison Based on Actual Peak”.

Comment 1.8:
In the fractional model, the difference between online and offline is unclear. It seems that if offline algorithm is re-run every time a new car comes, the order is rearranged in real-time and the result should be the same with offline, which is optimal. Given the today’s computing power, this should be a very easy job to do.

Response: OK

Comment 1.9:
Page 5 line 21: Please explain the basic algorithm in [18] and how yours is different.

Response: OK

Comment 1.10:
(8a) What is alpha, gamma, beta, pi? How are they related to (1a)-(1d)?

Response: OK

Comment 1.11:
Page 5 line 30: How is the feasibility checked?

Response: OK

Comment 1.12:
The definition of m and n are very confusing. In the fractional model, the summations are used with n all the time, suggesting that every car will have a charging station. In the integral model (8a), m and n come in together without clear explanation what each term means. In the case study, the CS number is set and the number of the cars is increased. It's unclear what the authors are doing here? Are all cars guaranteed a CS? If so, what's the point of number of CS? If CS defines the bottleneck of maximum vehicle charging at the same time, what are the other cars doing? Waiting? But in Fig. 2 and 3, the revenue with different number of CS (and quite small compared to 100 cars) are almost the same. Nothing is explained clearly.

Response:

m is number of active EVs

n is number of EVs

No guaranteed CS. The capacity constraint of the charging station can be equivalent to number of outlets in the station.

About the figures 2 and 3, he is right. Revenue almost does not change as number of charging stations increase. However, it can be justified.

Comment 1.13:
Table III: The max charging rate for EVs are largely wrong. It's well known that a Tesla can charge up to 120kW with DC and CHAdeMO (Nissan Leaf)/J1772 Combo (BMW) can charge at 30kW/60kW.

Response: The charging rates we used are not up to date according to the latest battery technology. In light of this comment, we updated the rates and re-run the simulations.

Comment 1.14:
Page 7 line 39-41: The setup of the case study is very unclear. We dont know how many cars are coming at what time, how long they stay and what energy they typical ask for. The revenue of the two cases are almost the same (up to 10% difference), which means that the resources in the case study are mostly enough for the demand. This might not be an interesting case especially for the integral revenue case. The author should investigate more deeply how the performance would be different when the supply is not enough (with more and more vehicles).

Response: We should re-run simulation with more realistic parameter settings.

Comment 1.15:
Fig 2, 3: With more and more vehicles, both scenarios should show a converged non-linear revenue curve, with the integral revenue converging more pre-maturely. But the shown result is simply linear, again showing that the capacity is not saturated and the case study is ill set-up.

Response: Needs new simulation settings.

Comment 1.16:
How the valuation is generated for each user in the case study is not explained.

Response: randomly between 50% to 150% of the standard electricity price for each kW in the US.

Comment 1.17:
The author should consider customers satisfaction in the optimization. Users demand is only used to determine whether its feasible, rather than giving their priorities. It would seem too brutal to reject/rank users solely by how much they try to pay.

Response: The variable v_i provides us with enough flexibility to handle such scenarios. As explained in Comment 1.x, the priority of the users can be used in calculating v_i.

2 Reviewer #2

This paper considers a EV charging problem with both local and global maximum charging rates. Considering both fractional and integer charging control problems, this paper proposed a offline and an online algorithm for each problem.

2.1 Comments

Comment 2.1:
The paper intends to include four algorithms in one paper under strict 8-page limit. As a result, even important literature reviews on online algorithm design are moved to the appendix, which is not a common practice and in fact a bad way to present the paper to the audience. The offline algorithm for the fractional case is not described at all in the paper, but referring to an online report. As a result, the paper is not self-contained in its current form.

Response: ...

Comment 2.2:
Compared to the existing solution without the global constraint, that is the new challenge in the design? Does this greatly impact the algorithm design.

Response: Without the global peak constraint, the problem is reduced to single-station problem. In particular, the global optimal solution can be obtained by solving local scheduling problems in the charging stations. However, in the presence of a global peak, this approach cannot be used.

Talk about over-provisioning

Comment 2.3:
We can clearly see in the formulation (1) that the EVs have different charging price v_i/D_i. From the system operator's perspective, why serving different users at different prices, is this reasonable and practical in commercial system? or it is just an extension from the Knapsack problem.

Response: Also asked by Reviewer 1.

Comment 2.4:
The generalized Knapsack problem must have off-the-shelf efficient approximate methods, the authors should consider comparing the proposed method with them. For the fractional one, what is the advantages of the proposed off-line method compared to general method to solve LP, e.g., interior point method.

Response: It is not Knapsack, but more complex version of it. Knapsack is very special case of our problem and thus, all existed solutions for the Knapsack will work poorly.

The advantage is the running time of the algorithm. Also, it provides valley-filling.

Comment 2.5:
What is the point of Fig. 4 if considering only a single charging station where the global peak constraint is absent (the main contribution of this paper)?

Response: The goal here is to compare our method with GreedyRTL which only works in single-station scenario.

Comment 2.6:
In Fig. 2, the proposed foCS performs worse than benchmark foLP, please explain. Besides, the benchmark methods should be briefly explained.

Response: foCS performs worse in high density scenarios but performs well in low density scenarios.

Comment 2.7:
For the competitive analysis, can the authors explain at what condition the worst case (is likely to) happen? Now the 2-competitive result is not surprising and provides little insight.

Response: Yes we will show worst case scenario.

3 Reviewer #3

The authors of the paper, "Online ev scheduling algorithms for adaptive charging networks with global peak constraints", proposed online scheduling approaches of electric vehicles considering the peak constraints in the multi-layer charging networks, and integers constraints of the decision variables. This paper presents interesting research ideas of approximating the MILP problem with bounds. However, the reviewer has the following concerns that need to be addressed:

3.1 Comments

Comment 3.1:
Most of the previous optimization-based EV scheduling algorithms, the demand is treated as a constraint, i.e. the charging system has to deliver the demand before the vehicle leaves. In this paper, this constraint does not have to be satisfied. Please provide justifications. In addition, the scenario with the peak constraints from system operators also needs to be justified. It's better to associate the problem setting with real-world markets. For instance, in California, TOU pricing with energy charge and demand charge (cost applied to monthly global peaks) can be integrated. A sample paper minimizing demand charges instead of modeling it as an imaginative constraint can be found: J. Jin and Y. Xu, "Optimal Storage Operation Under Demand Charge," in IEEE Transactions on Power Systems, vol. 32, no. 1, pp. 795-808, Jan. 2017.

Response: ...

Comment 3.2:
In the charging network, what standards are these charging stations complying with? Are they level I, Level II, or DC fast chargers? The charging power usually depends on the chargers instead of the vehicle types. Thus, the max charging rates in table III are not valid. If they are level II with SAE J1772 protocol, there is another constraint that the power cannot be controlled continuously, i.e the controllable power range is 0 U [1.5 6.6kW]. Thus, another integer is needed to model this property.

Response: The power limit of the chargers are usually more than the input power limit of the EVs' battery. Therefore, usually it is the EV's battery that limits the charging rate.

Comment 3.3:
Following the modeling in this paper, it seems the uncertainties of future arrival vehicles are not modeled. A similar charging station with multiple outlets can be found in: B. Wang, Y. Wang, H. Nazaripouya, C. Qiu, C. C. Chu and R. Gadh, "Predictive Scheduling Framework for Electric Vehicles With Uncertainties of User Behaviors," in IEEE Internet of Things Journal, vol. 4, no. 1, pp. 52-63, Feb. 2017. Bin Wang et al., "Predictive scheduling for Electric Vehicles considering uncertainty of load and user behaviors," 2016 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Dallas, TX, 2016, pp. 1-5. But impact of future demands from EVs is significant and needs proper treatment. So please justify the advantages of not modeling these uncertainties. In addition, there are MPC based approaches to handling these uncertainties: N. Chen, L. Gan, S. H. Low, and A. Wierman, "Distributional analysis for model predictive deferrable load control," in 2014 IEEE 53rd Annual Conference on Decision and Control (CDC), 2014, pp. 6433-6438

Response: One advantage is simplicity. Moreover, studies that apply model-based approaches usually rely on some unrealistic assumptions which does not reflect real world scenarios...

Comment 3.4:
What is computational complexity of the MILP problem in this paper? Please provide more info about the experiments, e.g. memory size, number of cores, etc. There are emerging parallel algorithms to handle binary/integer variables in MILP problem using multi-core computers. The reviewer is wondering why the problem cannot be solved by existing parallel solutions with multi-core computers and what the advantages of the proposed approaches in this paper.

Response: We study online scenarios so the LP and MILP problems in the paper cannot be solved by the commercial solvers. The main challenge here is not the the time complexity of the algorithm, but the efficiency of the algorithm in the absence of future demands.

References