Article

Optimal Charging Schedule Planning for Electric Buses Using the Aggregated Day-Ahead Auction Bids

Izabela Zoltowska [1,*] and Jeremy Lin [2]

1 Warsaw University of Technology, Poland; i.zoltowska@elka.pw.edu.pl
2 Transmission Analytics, USA; Jeremy.Lin@transsmisionannalytics.com
* Correspondence: i.zoltowska@elka.pw.edu.pl; Tel.: +48-22-234-7125

Abstract: This paper answers the need to plan a cost-minimizing charging schedule for electric buses and proposes a three-stage procedure, which is oriented around the participation of electric buses aggregator in a day-ahead energy auction. First, optimization models are provided to determine charging availability expressed as minimum and maximum hourly energy requirements taking into account detailed, minutely characteristics and constraints of the charging equipment and the buses. Next, the auction model is formulated by considering aggregated bids submitted by the electric buses aggregator once the charging availability is determined. Hence, the day-ahead prices reflect the optimal schedules of auction participants, and the bus aggregator is safe against peak-hour charging. Finally, hourly auction-based schedules are disaggregated into optimal minutely charging schedules. Mixed-integer linear programming models are formulated for aggregation-disaggregation stages investigated in this paper, while the variables and constraints introduced into the auction model are linear. The proposed methodology has been verified on a recently published case study of a real-world bus service operated on The Ohio State University campus. We show that the auction-based charging of all 22 buses outperforms as-soon-as-possible schedules by 7% to even 28% of daily cost savings. Using the aggregated bids, buses can flexibly shift charges between high- and low-price periods while preserving constraints of the charging equipment and timetables.

Keywords: aggregator; coordinated charging; double auction; mixed-integer linear programming

---

check for updates

Citation: Zoltowska, I.; Lin, J. Optimal Charging Schedule Planning for Electric Buses Using the Aggregated Day-Ahead Auction Bids. *Preprints* **2021**, *1*, 0. https://doi.org/

Received:
Accepted:
Published:

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

1. Introduction

According to the plans for electrification of public transport around the world, we are facing a profound change toward electric bus adoption [1]. One of the foremost anticipated challenges related to this growth is in the design and planning of the electric buses charging system [2]. It is crucial to identify possibilities for cost savings as the incremental charging loads will inevitably impact the power system [3]. Among others, active demand-side participation enabled by bus aggregators can create an opportunity for mutual benefits, both for transport entities and the power system [4]. However, it is a challenging issue, as, on the one hand, the constraints of bus timetables and charging infrastructure must be handled, and on the other hand charging flexibility must be transformed into bids that can be traded in the electricity auction [5]. This paper answers the need to plan a cost-minimizing charging schedule for electric buses using aggregated bids submitted to a day-ahead energy auction.

In order to achieve full effectiveness and competitiveness of the market system, it is necessary to ensure the possibility of expressing many requirements and expectations, which leads to the introduction of a rich parameterization of the market and the definition of bidding parameters adopted for new participation models. That is the reason for including in our paper a critical assumption for the bus aggregator to participate in the auction. This assumption involves the inclusion of market bidding parameters reflecting aggregated bus batteries' physical and operational characteristics. Such a view is in line with recent worldwide trends toward resolving participation barriers for energy storage-based demands, check, for example, FERC Order No. 841 [6], and discussion in [7].

Related works. There is some research work done in the areas of optimal charging schedule for electric buses. The premise behind this research problem is that the current charging schedule for EB fleet is based on the assumption that there is an ample charging capacity available for EB fleet and the changing values of electric charging (electricity). This type of traditional charging can lead to expensive costs and misses the opportunity for cost savings.

In place of this traditional but costly charging scheme, the optimal charging scheme based on the electricity cost or market prices can create opportunities for saving for the fleet dispatcher. The electricity cost considered in those research can be electricity rates determined by the local electric utility or the electricity market operators' electricity prices.

One of the earlier works [8] developed a simulation model to examine how electric bus charging strategies are affected by the type and number of chargers installed. A strict idle charging time was not assumed; instead, the study investigated queuing times to determine the fleet requirements. Thus, the study finds out that all 22 of the buses on the campus lines can be made electric and that one 500 kW or two 250 kW chargers are sufficient to maintain reasonable service frequencies. The simulation is very well documented, so we used their parameters in our case study.

In [9] work, a mixed-integer linear programming problem was formulated to find the optimal charging schedule for EB fleet of Stanford University's Marguerite Shuttle, based on the electricity rates set by the local utility (PG&E) and given the preset physical infrastructure and time-tables for EB fleet. The authors also assume a free on-site solar energy that the fleet dispatcher uses to charge/recharge the EB and is the first choice when solar energy is available. If solar energy is not available, the fleet dispatcher will purchase electricity from the grid as the second choice. While the new charging schedule, which optimizes the EB fleet schedule, can save money for the fleet dispatch, given the electricity rates from the local utility, it is not logical to assume that the on-site solar energy is free. This assumption misses the solar energy opportunity cost, which can obtain some revenue if its energy is sold to the grid.

[10] attempted to solve the problem of optimal charging strategies based on the formulation of mixed-integer linear programming for a plug-in electric bus (PEB) to reduce the charging costs and peak load of electric bus fast-charging station (EBFCS) when responding to the time-of-use electricity prices in a real-time. The authors claimed that the suboptimal charging strategy improves computation efficiency significantly with a slight increase in charging cost. The suboptimal charging strategy is solved as a two-stage model where an ideal charging load profile is optimized without considering the continuous charging at the first stage while the continuous charging loads are scheduled to follow the ideal profile using a heuristic method. The case study employed in their work is the bus transit system in Beijing in the backdrop of the time-of-use (TOU) prices for the relevant charging station.

The same set of authors [11] extended their previous work by modeling and pairing an energy storage system (ESS) with the existing plug-in electric bus fleet charging stations (PEBFCS) with the same goals of reducing both peak charging load and electricity purchase cost when providing a real-time control strategy. Two scenarios – coordinated PEB charging and uncoordinated PEB charging are studied while the price and the valuable life of ESS, the capacity charge of PEBFCS, and electricity price arbitrage are taken into account in the model. As done in their previous work, a similar heuristics-based method was used to obtain a suboptimal charging strategy that can enhance computation efficiency while compromising the optimal solution. The case study employed in their work is the bus transit system and TOU prices in the city of Chongqing, China.

Authors [12] formulated a dispatch cost minimization problem for a virtual power plant while incorporating electric bus fleet as storage resource with their capacity and energy constraints in a market setting. The optimal charging strategies for the electric bus fleet were implemented as the mixed-integer linear programming problem. The optimized dispatched schedules are provided to the forecasted day-ahead and intraday market prices. The electric bus fleet is represented by an EV supplier/aggregator that interacts with the virtual power plant operator interacting with the market operator. The schedule for the electric bus fleet was based on the bus operation in Berlin metropolitan area, where three bus types - standard, articular, and double-decker buses - were considered in that work. The authors claimed that their proposed methodology could fully integrate electric bus fleets in the virtual power plant operation while providing economic benefits to both the EV aggregator and power plant operator.

[13] conducted a research work that identified and investigated the optimal charging strategy of an EB fleet from the StarMetro bus fleet in Tallahassee, Florida, intending to reduce demand charge and minimize the fuel cost (aka electricity cost). The authors employed an energy consumption model which provided flexibility to simulate different EB modules. An exhaustive enumeration method covering the full range of charging threshold (CT) of 0-95% was used to search for the optimal CT. The authors found that the CT of 60-64% provided the most cost-saving while the CT of 0-28% produced the highest demand, hence the highest demand and highest fuel costs. The authors also investigated and found that fleets of 4 and 12 buses achieve the lowest cost per mile driven when one fast charger is installed.

As the authors of [11] note, integrated charging schedule planning of buses with fast charging stations is a valuable research object. To the best of our knowledge, all relevant works consider flat rates or the perfect foresight of TOU prices. It can be a reasonable assumption, as early investigations of [14] suggest. However, there is a considerable improvement area, especially when deciding whether to postpone charging in a specific hour, which can be very sensitive to prices, as shown in our case study. This paper further studies the optimizing charging schedule of buses and proposes the full market participation of electric buses for the first time by using bidding parameters adopted for their aggregated charging characteristics.

The process analyzed in this paper is summarized in Fig. 1: individual bus and charging stations parameters related to their charge states, operational duration, and the other physical characteristics serve as basis in the aggregation phase; resulting aggregated bid parameters are submitted to the market operator a day before the operation; the detailed operating plan is computed in the final, disaggregation phase when aggregated dispatch plan is received from the market operator.

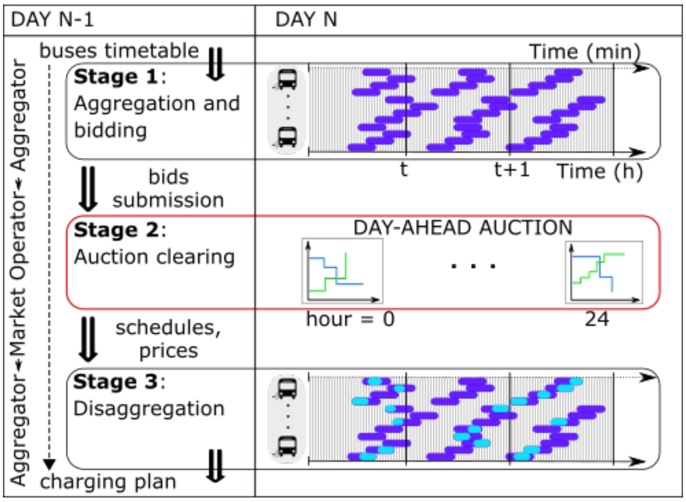

Figure 1. The phases of optimization process proposed in this paper.

Contribution. This paper formulates mixed-integer linear programming (MILP) optimization models for charging planning of bus fleet, taking into account charging stations limits so that it allows it to competitively participate in the day-ahead auction, based on price signals. Such an approach enables the bus fleet aggregator to react to the wholesale price of energy flexibly and obtain higher cost savings without accurate price forecasts. Defining only a few aggregated bids parameters used in linear programming (LP) constraints newly introduced into the day-ahead market is another contributing factor

 doi:10.20944/preprints202107.0063.v1

of this paper, allowing to economically schedule storage-based participants and increase the efficiency of an evolving grid.

2. Materials and Methods

All the nomenclature is provided in the Abbreviations list at the end of the paper.

2.1. Aggregation model

We propose the aggregation of periods (minutes) and buses to let the buses aggregator participate in the day-ahead energy auction and flexibly adjust to uncertain hourly market prices.

Individual parameters regarding demanded trip energy can be summarized:

$$E_h^{\text{Agg,Trip}} = \sum_b E_{bh}^{\text{bus,Trip}} = \sum_b \sum_{t=(h-1)\cdot 60+1}^{h\cdot 60} E_{bt}^{\text{Trip}}, \ \forall h. \tag{1}$$

Further, the total energy E^1 that must be loaded by buses is equal to the total amount of energy needed for trips, minus the initial energy stored in batteries:

$$E^1 = \sum_h E_h^{\text{Agg,Trip}} - \sum_b (\text{SoC}_b^0 - \underline{\text{SoC}}_b). \tag{2}$$

On the other hand, the total battery capacity provides the value of additional energy E^2 that can be loaded by buses:

$$E^2 = \sum_b (\overline{\text{SoC}}_b - \underline{\text{SoC}}_b). \tag{3}$$

In adverse market conditions expressed in high energy prices, the buses would charge only the minimum amount of energy required for driving, and at the end of the day, they would return to the depot with depleted batteries. However, they may as well finish their service with full batteries if the prices are low enough. The threshold price the aggregator decides c, one reasonable level may be the average nightly price. Charging during the night hours is not a problem. First, because the buses are fully available, second, the prices level and volatility are much lower than prices during the day.

Setting other parameters is a challenging problem because there are two dependencies between periods and the buses. One linking constraint valid for each minute and links the buses is the number of charging stations available. Another linking constraint connects each period, so the SoC level of each bus sustains within the admissible limits. The solution strategy for dealing with the charging constraints when we determine aggregated charging demand is to resolve the aggregated minimum and maximum energy requirements separately, but considering the detailed constraints.

In the following two sections, we discuss these aspects and show how we use them to form the aggregated parameters that can be submitted directly to the auction.

2.1.1. Minimum hourly SoC level

To find the minimum SoC level of the buses at the end of each hour, we consider a hypothetical situation where buses charge as frequently as possible to keep the charge level as low as possible. With this goal in mind and unlimited access to chargers, buses would load just enough energy to make the next trip. However, when chargers are limited, we need to solve the following MILP optimization problem.

$$\min \sum_h \text{SoC}_h^{\text{Agg,min}}, \tag{4}$$

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 July 2021 doi:10.20944/preprints202107.0063.v1

$$\begin{aligned}
\mathrm{SoC}_h^{\mathrm{Agg,min}} &= \textstyle\sum_b \mathrm{SoC}_{bh}^{\mathrm{min}} && \forall h, && (5)\\
p_{bt} &\le s_{bt}\cdot r && \forall b,t, && (6)\\
s_{bt} &\le A_{bt} && \forall b,t, && (7)\\
\sum_b s_{bt} &\le C && \forall t, && (8)\\
\mathrm{SoC}_{bt} &= \mathrm{SoC}_{b,t-1} + p_{bt} - E_{bt}^{\mathrm{Trip}} && \forall b,h,t, && (9)\\
\mathrm{SoC}_{bt} &\le \overline{\mathrm{SoC}}^{b} && \forall b,t, && (10)\\
\mathrm{SoC}_{bt} &\ge \underline{\mathrm{SoC}_b} && \forall b,t, && (11)\\
\mathrm{SoC}_{bh}^{\mathrm{min}} &= \mathrm{SoC}_{b,h\cdot 60} && \forall b,h. && (12)
\end{aligned}$$

The goal is to determine minimum hourly SoC levels (4), defined as the summary minimum hourly SoC levels of each bus (5). Detailed SoC level of each bus SoC_{bt} is inspected in typical constraints (6)–(11), while we are particularly interested in SoC level at the end of each hour (12).

2.1.2. Maximum hourly energy requirements

Solution to the problem (4)–(12) provides reference values to further determine maximum amount of energy $\mathrm{P}_h^{\mathrm{Agg,max}}$ that can be possibly loaded in each hour. When considering maximum amounts of energy, we should not restrict to the total maximum demanded energy $E^1 + E^2$. Instead, we need to determine *potential* maximum amounts of energy in particular hours. That is why we must solve each hour's problem separately but consider some multiperiod characteristics, like the requirement on minimum SoC level at the beginning of each hour. Thus, the following model considers the SoC level of each bus separately in each hour but charging energy has multiperiod limits.

$$\max \mathrm{P}_h^{\mathrm{Agg,max}}, \tag{13}$$

$$\begin{aligned}
p_h^{\mathrm{Agg,max}} &= \textstyle\sum_b \sum_{t=(h-1)\cdot 60+1}^{h\cdot 60} s_{bt}\cdot r && \forall h, && (14)\\
s_{bt} &\le A_{bt} && \forall b,t, && (15)\\
\sum_b s_{bt} &\le C && \forall t, && (16)\\
\sum_{k=1}^{i_b} s_{bk} &\le \textstyle\sum_{k=1}^{i_b} E_{bk}^{\mathrm{Trip}} + \overline{\mathrm{SoC}}_b - \mathrm{SoC}_b^0 && \forall b,i_b, && (17)\\
\sum_{k=1}^{i_b} s_{bk} &\ge \textstyle\sum_{k=1}^{i_b-\delta} E_{bk}^{\mathrm{Trip}} + E_b^{\mathrm{cycle}} - \mathrm{SoC}_b^0 + \underline{\mathrm{SoC}_b} && \forall b,i_b, && (18)\\
\mathrm{SoC}_{bt} &= \mathrm{SoC}_{b,t-1} + s_{bt}\cdot r - E_{bt}^{\mathrm{Trip}} && \forall b,h,t=((h-1)\cdot 60+2,\ldots,h\cdot 60), && (19)\\
\mathrm{SoC}_{bt} &\le \overline{\mathrm{SoC}}_b && \forall b,t, && (20)\\
\mathrm{SoC}_{bt} &\ge \underline{\mathrm{SoC}_b} && \forall b,t, && (21)\\
\mathrm{SoC}_{b,h\cdot 60+1} &\ge \mathrm{SoC}_{bh}^{\mathrm{min}} && \forall b,h>1. && (22)
\end{aligned}$$

The goal is to determine aggregated maximum amounts of energy that can be loaded in a particular hour h (13), which is simply equal to all charging statuses of buses in all minutes belonging to a given hour (14). Charging statuses may not violate bus timetables (15), nor summary chargers number (16), just like in (7)–(8). New constraints introduced into this model (17)–(19) are responsible for ensuring that despite the SoC level at the beginning of each hour is independent of the SoC level at the end of the previous hour (

19), still charging is limited by the total amount of energy used so far plus the initial free battery capacity (17). On the other hand, all of the charged energy till the end of the specific idle period must cover all the trip energy used so far plus energy demanded in another cycle minus the initially stored energy (18). Detailed SoC level of each bus must be within acceptable limits (20)–(21). Starting SoC level is independent of ending SoC level in the previous hour but must be at least equal to the minimum hourly SoC level (22).

2.2. Auction model

The energy auction we consider is a single-price and double-sided auction that balances supply and demand in a 24-hour horizon of the next day. The independent market operator collects demand bids and offers from all auction participants, solves the auction clearing problem, and posts day-ahead hourly dispatch and prices.

Bidding parameters allowed in the auction provide clear, quantitative boundaries to the buses' energy storage capabilities and operating limits. Specifically, they state the total energy E^1 requested by buses, plus an additional amount of energy E^2 that can be potentially loaded by buses when the auction price of energy is below the price c of their bid to buy. To enable the control of aggregated states of charge, summary hourly trip energy of buses $E_h^{\mathrm{Agg,Trip}}$ is reported, together with aggregated hourly minimum battery State of Charge $\mathrm{SoC}_h^{\mathrm{Agg,min}}$. Final parameter is the aggregated maximum amount of energy $\mathrm{P}_h^{\mathrm{Agg,max}}$ that can be loaded in each hour.

For clarity, we present the auction model considering a single bus aggregator; however, there may be multiple participants of this type. In such a case, the aggregator-specific index should also be considered when defining the bidding parameters.

Thanks to including the aggregated bus parameters, the auction can economically schedule the hourly charged energy based on the aggregated states of charge of the buses. This leads to the auction model of pool type, where power scheduling is conducted by the operator aiming at social welfare maximization. The model can be formulated as a price-based unit commitment problem, with generators' technical constraints, etc.. Moreover, the network power flow constraints can also be included. Detailed, centralized auction model may be found, for example, in [15]. Here, we concentrate on the newly introduced constraints of demands representing (aggregated) storage-based participants.

$$\max Q = c \cdot \Big(\sum_h p_h - E^1\Big) - \sum_h Cost(NetSupply_h). \tag{23}$$

Subject to:

$$
\begin{aligned}
p_h^{\mathrm{Agg}} &= NetSupply_h && \forall h,\ \perp \pi_h, && (24)\\
\sum_h p_h &\le E^1 + E^2, && && (25)\\
p_h^{\mathrm{Agg}} &\le \mathrm{P}_h^{\mathrm{Agg,max}} + \mathrm{SoC}_h^{\mathrm{Agg,min}} - \mathrm{SoC}_{h-1}^{\mathrm{Agg}} && \forall h > 1, && (26)\\
p_1^{\mathrm{Agg}} &\le \mathrm{P}_1^{\mathrm{Agg,max}} && , && (27)\\
\mathrm{SoC}_h^{\mathrm{Agg}} &= \mathrm{SoC}_{h-1}^{\mathrm{Agg}} + p_h^{\mathrm{Agg}} - E_h^{\mathrm{Agg,Trip}} && \forall h, && (28)\\
\mathrm{SoC}_h^{\mathrm{Agg}} &\ge \mathrm{SoC}_h^{\mathrm{Agg,min}} && \forall h, && (29)\\
& NetSupply \quad constr. && && (30)\\
& Transmission \quad constr. && && (31)
\end{aligned}
$$

The social welfare Q defined as the difference between consumption willingness-to-pay and the generation offered costs is maximized in the auction objective (23). Equilibrium prices, also known as marginal prices derived as the shadow prices to the energy balance constraint (24) are used to settle the trading energy volumes in each hour. In (25), we limit the total energy bought by buses while (26) preserves hourly limit. Recall, that

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 July 2021 doi:10.20944/preprints202107.0063.v1

aggregated maximum amount $\mathrm{P}_h^{\mathrm{Agg,max}}$ is determined considering the minimum SoC level, as explained in Section 2.1.2. This value must be decreased with a higher actual SoC $\mathrm{SoC}_{h-1}^{\mathrm{Agg}}$ at the end of previous hour. In (28), the standard linear SoC update is modeled, using aggregated values. Aggregated SoC must not drop below the acceptable limit, as given by (29). Finally, (30) symbolically represents all the constraints of other market participants (generators, loads, etc.), including representation of costs $Cost(NetSupply_h)$. Similarly, (31) represents network constraints. Notice, that the variables and constraints representing (aggregated) storage-based participants, which are newly introduced with our proposed approach, are linear (LP).

2.3. Disaggregation model

Once the bus fleet aggregator receives from the market operator the planned hourly energy schedules p_h, the final step is to determine detailed, minutely charging plans. The disaggregation model uses the same individual bus and charging station parameters as aggregation models developed in Sections 2.1.1 and 2.1.2. Here, it finds the feasible solution that considers the characteristics and constraints of the charging equipment and the buses and the amount of available energy in each hour. Specifically, the following constraints must be met.

$$
\begin{aligned}
p_h^{\mathrm{Agg}} &= \textstyle\sum_{t=(h-1)\cdot 60+1}^{h\cdot 60} \sum_b p_{bt} && \forall h, && (32)\\
p_{bt} &\leq s_{bt}\cdot r && \forall b,t, && (33)\\
s_{bt} &\leq A_{bt} && \forall b,t, && (34)\\
\sum_b s_{bt} &\leq C && \forall t, && (35)\\
\mathrm{SoC}_{bt} &= \mathrm{SoC}_{b,t-1} + p_{bt} - E_{bt}^{\mathrm{Trip}} && \forall b,t, && (36)\\
\mathrm{SoC}_{bt} &\leq \overline{\mathrm{SoC}_b} && \forall b,t, && (37)\\
\mathrm{SoC}_{bt} &\geq \underline{\mathrm{SoC}_b} && \forall b,t. && (38)
\end{aligned}
$$

In (32), we ensure that all energy bought on the market is charged by buses every hour. Constraints (33)–(38) represent standard characteristics of the charging equipment and the individual buses. Model is of MILP type because of binary charging state variables s_{bt}. It is a simple, standard model; the main novelty is in the fact that any auction-based solution can be safely disaggregated, thanks to the use of proper aggregation models introduced in Sections 2.1.1 and 2.1.2.

2.4. Summary

To summarizing, dependencies between the models introduced in this paper are visualized in Fig. 2. The most challenging phase is developing MILP aggregation models: they consist of a multiperiod model determining minimum aggregated SoC level at the end of each hour, complemented by models setting the maximum amounts of energy that can be loaded solved separately for each hour. For the record, in this phase, total demanded energy is computed, which is simply the sum of the individual trip energy demands. The resulting aggregated parameters constitute bids submitted to the market operator. Hourly charging plan is finally provided to bus fleet aggregator after auction clears, where it is disaggregated into feasible charging instructions using a typical MILP model based on buses states of charge. Aggregation phase may be performed once in a longer horizon, because its results do not depend on changing market environment. Disaggregation, on the other hand, should be executed daily, each time an auction clears.

 doi:10.20944/preprints202107.0063.v1

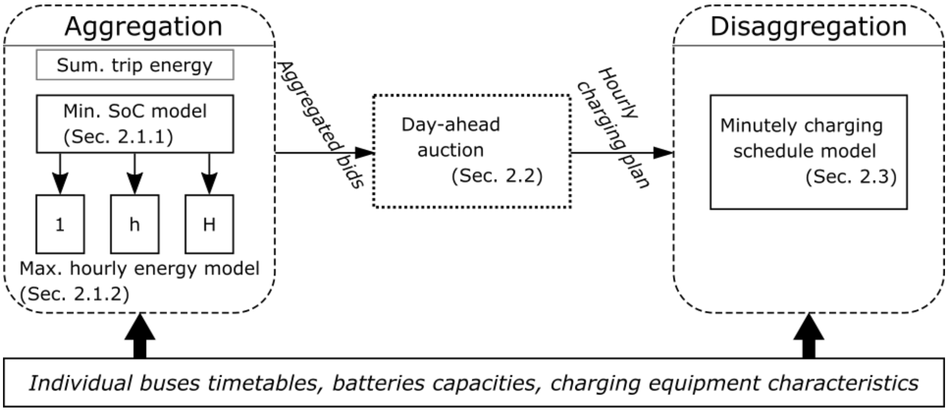

Figure 2. Algorithms.

3. Results

We show the applicability of our methodology on a bus network serving the Ohio State University's main campus located in Columbus, as first described in [8].

3.1. Data

The system consists of six lines of varying cycle time and energy consumption. Also, the lines are operating with different frequencies so they use different numbers of buses. All the details are listed in Table 1, repeated after [8].

Table 1. Description of bus lines at the Ohio campus [8]

Bus line	Cycle time [min.]	Per-cycle energy use [kWh]	Frequency [min.]	No. of buses
North Express	23	8.41	9	5
Loop North	31	10.91	9	4
Loop South	31	11.08	9	4
Central Connector	32	12.11	12	3
East Residential	33	11.62	9	4
Buckeye Village	30	12.71	15	2

Altogether 22 buses are sharing four fast-charging stations at the same depot. Each bus has a 55 kWh battery with a capacity of 41.25 kWh (acceptable SoC range from 20% to 95%) while the charging rate of each station is 250 kW with a 5% efficiency loss. Available charging time for each bus is assumed 5 minutes, which means that they could charge up to 19.7 kWh during idle time.

The first bus begins service on each line at 7:00 a.m. Subsequent buses run with corresponding line frequencies until 7:00 p.m. Buses operate 446 trips in total and use 4 762.48 MWh during 12 hours (720 minutes). They begin service with a fully charged (i.e., 95% SoC) battery. Fig. 3 visualizes A_{bt} indicating if bus b is available for charging in minute t. Values of the parameters are summarized in Table 2.

 doi:10.20944/preprints202107.0063.v1

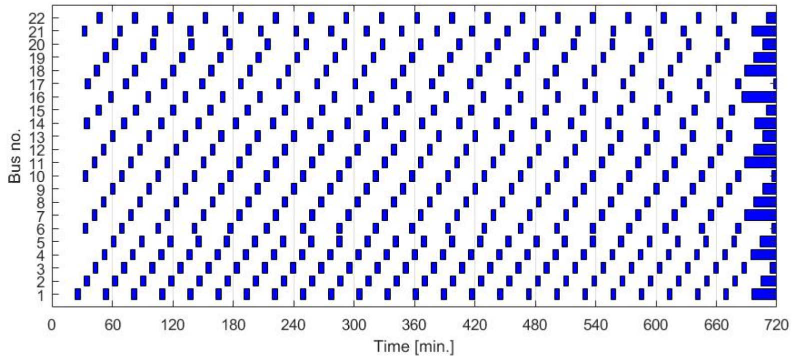

Figure 3. Availability charging periods of buses.

Table 2. Detailed parameters values used in the case study.

δ	C	r	$\underline{\mathrm{SoC}}_b$	$\overline{\mathrm{SoC}}_b$	SoC_b^0	E^1	E^2
5 min.	4	250 kW	11 kW	52.25 kW	52.25 kWh	3 854.98 kWh	907.5 kWh

We compare our results to a typical recharging strategy, that is, charging as-soon-as-possible (Asap rule) and refilling batteries to maximum SoC during each idle time, as illustrated in Fig. 4. Acting like this causes several problems: first, queues may arise because the number of busses would exceed the number of chargers; second, high energy costs may arise because of charging during peak hours. The first problem with Asap charging is shown in Fig. 5.

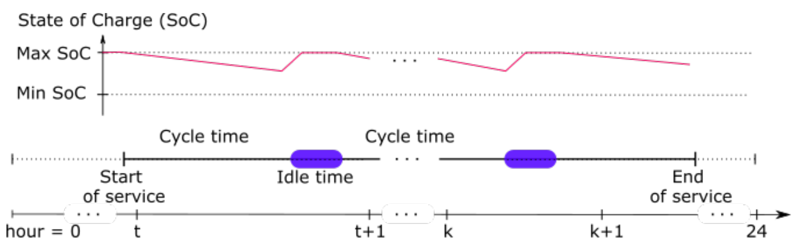

Figure 4. Illustration of the Asap recharging strategy that aims in refilling batteries to maximum SoC during each idle period.

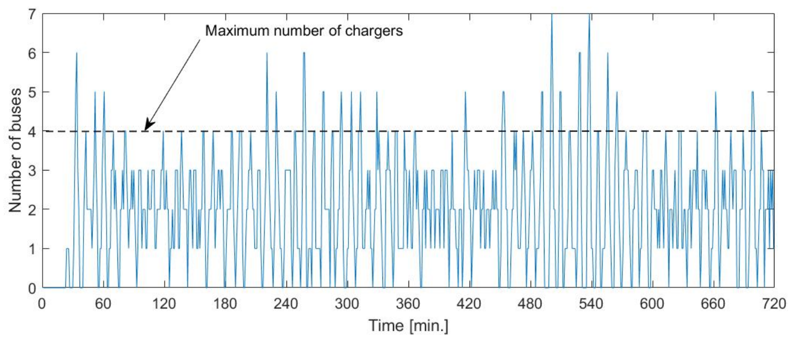

Figure 5. Total number of buses trying to recharge immediately after each cycle under Asap charging strategy.

We computed a feasible Asap charging plan to all constraints and used it as a benchmark to the cost efficacy of our newly proposed approach. The charging energy of the Asap plan aggregated into hourly values is shown in Fig. 6, together with summary hourly trip energy. The charging stations limitations are visible when investigating the first hour – there are about 30 minutes available for charging after buses finish their first cycle tour, then they accumulate, as can be inspected in Fig. 5.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 July 2021 doi:10.20944/preprints202107.0063.v1

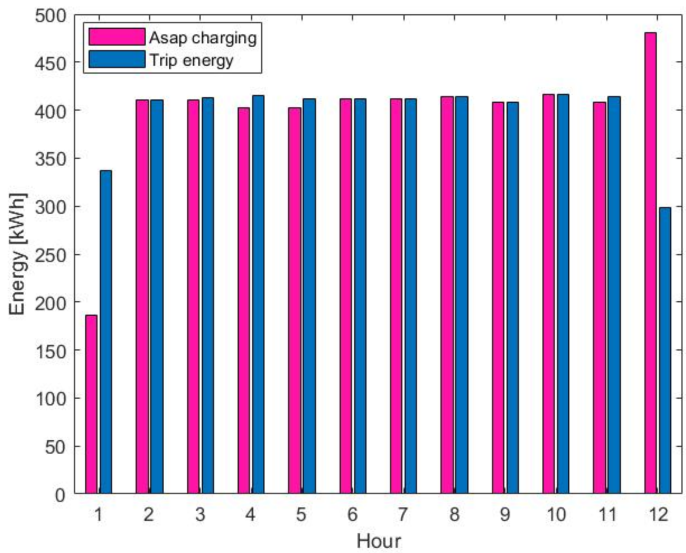

Figure 6. Asap charging plan aggregated into hourly values compared to summary trip energy.

3.2. *Results of the proposed approach*

3.2.1. Aggregation results

In this section, we describe results obtained by using models from Sec. 2.1. The total energy E^1 that must be loaded by buses, equal to the total amount of energy needed for trips, minus the initial energy stored in batteries, is given in Table 2, where also the value of additional loadable energy E^2 is provided. For the record, we also show summary hourly trip energy $E_h^{\mathrm{Agg,Trip}}$ in Fig 6.

Applying the method described in Sec. 2.1 we first determine the minimum aggregated SoC level at the end of each hour. Results are shown in Fig 7. Notice that aggregated minimum SoC values $\mathrm{SoC}_h^{\mathrm{Agg,min}}$ exceed the simple summary minimum SoC level of batteries ($22 \times 11 = 242$ kWh) in every hour but first and last. In the first hour, batteries are full, so the minimum level will not be reached after all. It is safe to end trips with the minimum SoC level in the last hour as no other trips will be made.

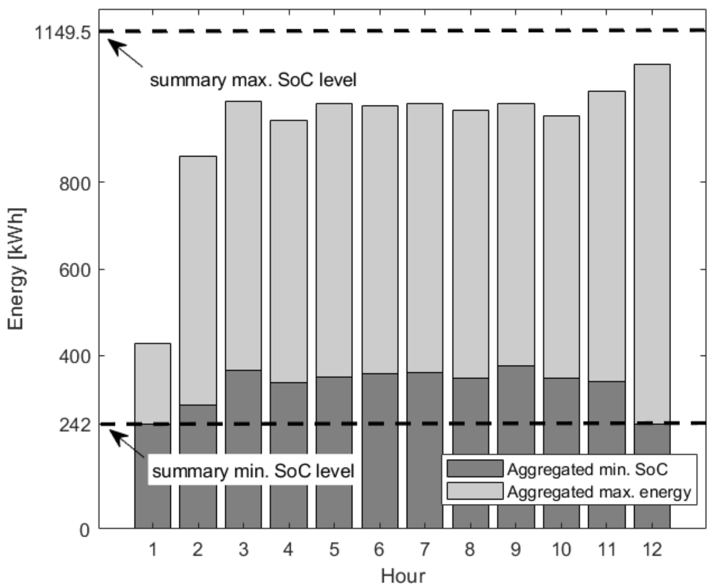

Figure 7. Aggregated minimum battery State of Charge and aggregated maximum amount of energy that can be loaded in each hour

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 July 2021 doi:10.20944/preprints202107.0063.v1

Fig 7 also shows the result of determining maximum aggregated energy to load by solving in each hour the model provided in Sec. 2.1.2. Interestingly, the total capacity of batteries may never be reached when starting from the minimum SoC level within a specific hour.

Detailed values of the computed parameters are summarized in Table 3. These aggregated parameters constitute aggregated bid submitted to the market operator.

Table 3. Detailed bid parameters [kWh] resulting from aggregation stage.

h	$E_h^{Agg,Trip}$	$\mathrm{P}_h^{\mathrm{Agg,max}}$	$\mathrm{SoC}_h^{\mathrm{Agg,min}}$
1	336.8	186.0	242.0
2	410.3	597.7	285.3
3	413.3	740.2	366.4
4	415.0	665.0	336.3
5	412.1	692.7	351.3
6	411.4	700.6	357.9
7	411.4	736.3	360.5
8	414.6	692.7	348.3
9	408.5	649.2	375.5
10	416.1	641.3	347.5
11	414.3	732.3	340.2
12	298.6	843.1	242.0

3.2.2. Auction results

Depending on the market situation, different hourly schedules and prices can be obtained, but buses are guaranteed to receive at least the minimum required energy and be scheduled for charging during hours with the lowest prices. The auction model was solved, assuming netto supply costs reflected in marginal energy price from PJM market [16]. Such an assumption is justified under a price-taking feature of the bus fleet, which is small enough that its charges do not affect the price of electricity.

We examine more closely exemplary scenarios of two consecutive days: in the first scenario (4'th of January 2018), high prices occurred in hours number 4 and 12 (13 a.m. and 17 a.m., translating into daily time), while in the second scenario (5'th January 2018) high prices occurred in hours 1 and 12. Prices, together with the energy schedules determined in the auction, are presented in Fig. 8. Threshold price c was set to 100$ per MWh, so total energy purchased in both scenarios is equal to trip energy used, i.e., 3854.98 kWh. In both scenarios, buses do not charge at all in hours with the highest prices.

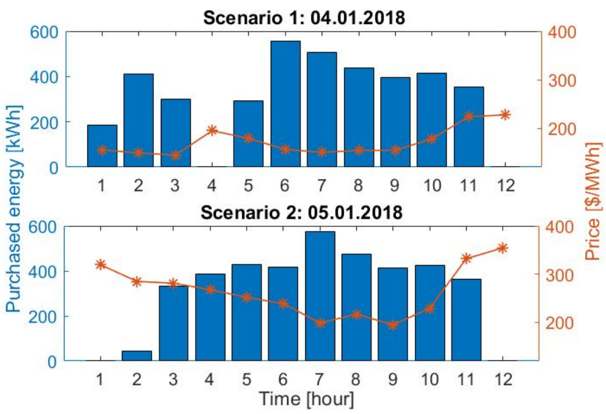

Figure 8. Scenarios of purchased energy.

3.2.3. Disaggregation results

Finally, the disaggregation step is performed applying the algorithm provided in Sec. 2.3. Detailed charging stations occupation obtained in each scenario is shown in Fig. 9. We also show in Fig. 10 specific SoC levels for two exemplary buses (1 and 12) under each scenario. It can be observed that the batteries are correctly managed within the operational limit, i.e., between 11 and 52.25 kWh.

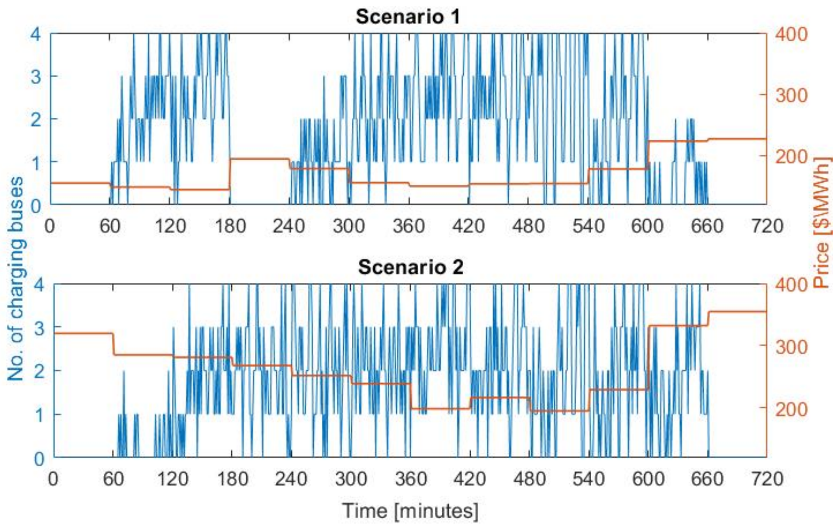

Figure 9. Detailed charging plan in each scenario.

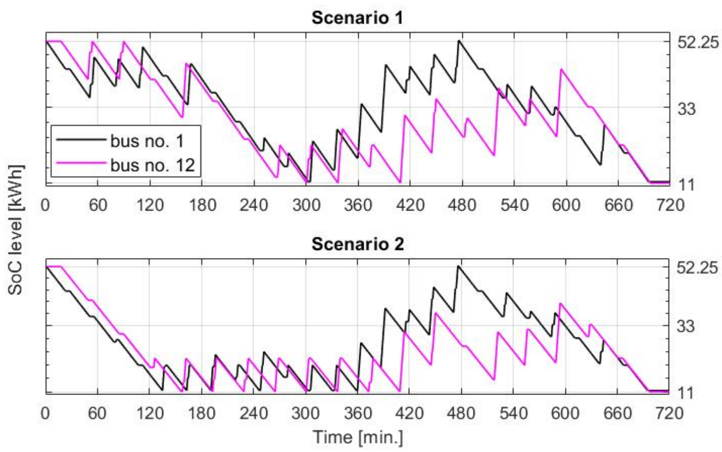

Figure 10. Exemplary SoC levels of buses 1 and 12 in each scenario.

3.3. Cost savings analysis

Comparison of costs incurred under our newly proposed day-ahead auction-based charging and Asap charging in each scenario is shown in Fig. 11. In both cases, the fleet can achieve about 25% savings using day-ahead auction participation models developed in this paper.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 July 2021 doi:10.20944/preprints202107.0063.v1

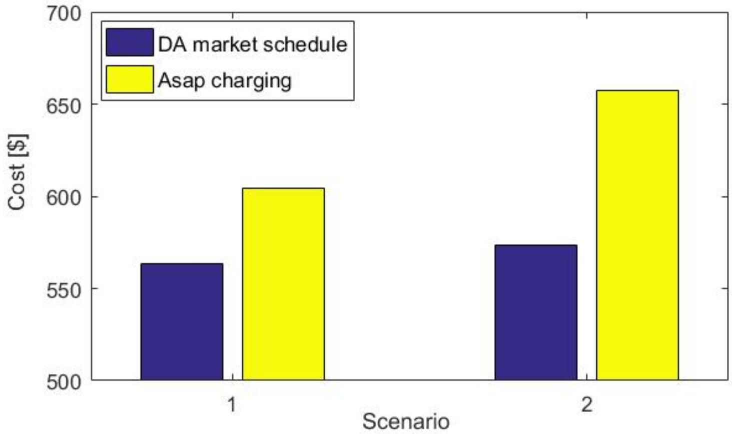

Figure 11. Comparison of costs incurred in each scenario in reference to costs incurred in case of charging buses as-soon-as-possible (asap rule).

Investigating the whole year of historic prices reveals that the savings on average are not as significant as in the test scenarios; instead, they are around 10%. Regardless, there are several days when up to 28% of savings can be achieved, and they are never less than 7%. Histograms of daily savings day in years 2018-2019 are shown in Fig. 12.

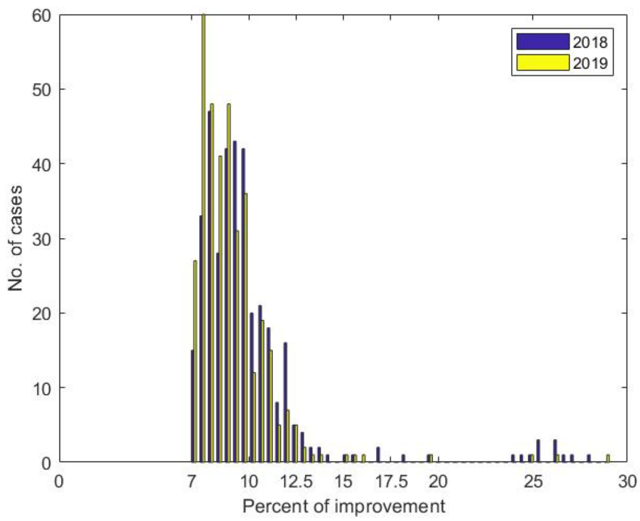

Figure 12. Histograms of costs savings achieved in each day of years 2018-2019 when comparing day-ahead auction-based charging to the Asap charging.

4. Discussion

An optimization model for coordinated charging of bus fleet and fast-charging stations is developed using the market participation concept in this study. By contrast, the conventional methods assume charging as soon as the buses arrive at the charging location or optimization based on forecasted (or fixed) prices. Our results show that it is possible and reasonable to define aggregated energy demands of the bus fleet in such a manner that allows it to fully participate in the markets and take advantage of its charging flexibility. It is worth noting that only five bidding parameters related to bus fleet charge states are required for inclusion in the day-ahead auction. All complicated, individual characteristics are taken into account in the aggregation phase and then in the disaggregation phase, which is formulated as mixed-integer linear problems. The proposition provides flexibility to the market operator, as well as to the bus fleet aggregator.

Several future research areas are further recognized. First of all, we take a price-taking perspective in this paper. Analyzes investigating the effects of large-scale bus fleets on

 doi:10.20944/preprints202107.0063.v1

the price of energy and the overall economics of the energy markets, including network congestion, etc. would be of great interest. An enhancement to integrated decision support including intra-day, and real-time operation, is another good topic. On the other hand, the applicability of the proposed models to estimate the profitability of strategic decisions regarding, i.e., battery capacity or charging infrastructure, seems a natural enhancement of this approach.

Author Contributions: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, writing—original draft preparation, visualization, supervision, project administration, funding acquisition, I.Z.; data curation, I.Z. and J. L.; writing—review and editing, J. L.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 July 2021 doi:10.20944/preprints202107.0063.v1

Abbreviations

The following abbreviations are used in this manuscript:

Indices	
b	Index of electric buses
h	Index of time periods (hours)
t	Index of time periods (minutes)
i_b	Index of minutes when bus b ends the idle period
Parameters	
δ	idle time (in minutes)
A_{bt}	0/1 indicator if bus b is available for charging in minute t
C	Number of chargers
c	Maximum unit price for the excess amount of energy set by bus aggregator
E_b^{cycle}	Per-cycle trip energy demand of bus b
E_{bt}^{Trip}	Per-minute trip energy demand of bus b (per-cycle energy use/cycle time)
$\overline{\mathrm{SoC}}_b$	Maximum battery State of Charge of bus b
$\underline{\mathrm{SoC}}_b$	Minimum battery State of Charge of bus b
SoC_b^0	Initial battery State of Charge of bus b
r	Charging rate of a charger
Variables used specifically in aggregation/disaggregation model	
p_{bt}	Charging energy of bus b scheduled in minute t
s_{bt}	Binary charging status of bus b in minute t
SoC_{bt}	Battery State of Charge of bus b in minute t
$\mathrm{SoC}_{bh}^{\mathrm{min}}$	Minimum battery State of Charge of bus b at the end of hour h
Variables in Aggregation model used as Parameters in Auction model	
E^1	Total energy that must be loaded by buses
E^2	Additional energy that can be loaded by buses
$E_h^{\mathrm{Agg,Trip}}$	Summary hourly trip energy of buses
$\mathrm{P}_h^{\mathrm{Agg,max}}$	Aggregated maximum amount of energy that can be loaded in hour h
$\mathrm{SoC}_h^{\mathrm{Agg,min}}$	Aggregated minimum battery State of Charge in hour h
Variables used specifically in auction model	
$Cost(NetSupply_h)$	Netto supply cost in hour h
$NetSupply_h$	Netto supply in hour h
$\mathrm{SoC}_h^{\mathrm{Agg}}$	Aggregated battery State of Charge in hour h
π_h	Auction energy price in hour h derived as the shadow prices to balance constraint ()
Variables in Auction model used as Parameters in Disaggregation model	
p_h^{Agg}	Charging energy scheduled in hour h

References

1. Pietrzak, O.; Pietrzak, K. The Economic Effects of Electromobility in Sustainable Urban Public Transport. *Energies* **2021**, *14*, 878.
2. Lin, Y.; Zhang, K.; Shen, Z.J.M.; Ye, B.; Miao, L. Multistage large-scale charging station planning for electric buses considering transportation network and power grid. *Transportation Research Part C: Emerging Technologies* **2019**, *107*, 423–443.
3. Clairand, J.M.; Guerra-Terán, P.; Serrano-Guerrero, X.; González-Rodríguez, M.; Escrivá-Escrivá, G. Electric Vehicles for Public Transportation in Power Systems: A Review of Methodologies. *Energies* **2019**, *12*. doi:10.3390/en12163114.
4. Zoltowska, I. Demand shifting bids in energy auction with non-convexities and transmission constraints. *Energy Economics* **2016**, *53*, 17–27.
5. Zoltowska, I.; Lin, J. Availability Bids Enabling Participation of Electric Vehicles in the Wholesale Markets. 2019 Electric Vehicles International Conference (EV). IEEE, 2019, pp. 1–6.
6. Federal Energy Regulatory Commission. Electric Storage Participation in Markets Operated by Regional Transmission Organizations and Independent Systems Operators. https://elibrary.ferc.gov/eLibrary/docinfo?document_id=14643624, 2018. [Online] Accessed: 22.06.2021.
7. Mays, J. Missing incentives for flexibility in wholesale electricity markets. *Energy Policy* **2021**, *149*, 112010.
8. De Filippo, G.; Marano, V.; Sioshansi, R. Simulation of an electric transportation system at The Ohio State University. *Applied Energy* **2014**, *113*, 1686–1691.

 doi:10.20944/preprints202107.0063.v1

9. Moradipari, A.; Tucker, N.; Zhang, T.; Cezar, G.; Alizadeh, M. Mobility-Aware Smart Charging of Electric Bus Fleets. 2020 IEEE Power & Energy Society General Meeting (PESGM). IEEE, 2020, pp. 1–5.
10. Chen, H.; Hu, Z.; Xu, Z.; Li, J.; Zhang, H.; Xia, X.; Ning, K.; Peng, M. Coordinated charging strategies for electric bus fast charging stations. 2016 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC). IEEE, 2016, pp. 1174–1179.
11. Chen, H.; Hu, Z.; Zhang, H.; Luo, H. Coordinated charging and discharging strategies for plug-in electric bus fast charging station with energy storage system. *IET Generation, Transmission & Distribution* **2018**, *12*, 2019–2028.
12. Raab, A.F.; Lauth, E.; Strunz, K.; Göhlich, D. Implementation schemes for electric bus fleets at depots with optimized energy procurements in virtual power plant operations. *World Electric Vehicle Journal* **2019**, *10*, 5.
13. Qin, N.; Gusrialdi, A.; Brooker, R.P.; Ali, T.; others. Numerical analysis of electric bus fast charging strategies for demand charge reduction. *Transportation Research Part A: Policy and Practice* **2016**, *94*, 386–396.
14. Sioshansi, R.; Denholm, P.; Jenkin, T.; Weiss, J. Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects. *Energy Economics* **2009**, *31*, 269–277. doi: https://doi.org/10.1016/j.eneco.2008.10.005.
15. Sen, S.; Kothari, D. Optimal thermal generating unit commitment: a review. *International Journal of Electrical Power & Energy Systems* **1998**, *20*, 443–451.
16. PJM Interconnection, LLC (PJM). PJM Data Viewer: Locational Marginal Pricing. https://www.pjm.com/, 2020.