Electric Vehicle Battery Swapping Station: Business Case and Optimization Model

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***Abstract*—In order to increase the adoption rate of electric vehicles, they need to appeal to customers as much as their fossil fuel equivalents. However, major concerns include long battery charging times and range anxiety. These concerns can be mitigated if customers have access to battery swapping stations, where they can meet their motion energy requirements by swapping batteries for charged ones, in as much time as it takes to fill the gasoline reservoir of a conventional vehicle. Besides benefiting the customers, the battery swapping station is beneficial to the power system because it emulates an energy storage station capable of participating in electricity markets. In this station, the batteries can be scheduled to charge in grid-to-battery mode, inject power to the grid in battery-to-grid mode, and transfer energy between batteries in battery-to-battery mode, if there are economic advantages in doing so. This paper discusses how these various modes can be optimized and the results translated into a business case for battery swapping stations.**

***Keywords*—Battery Swapping Station, Electric Vehicles, Energy Storage, Electricity Market.**

I. Introduction

CUSTOMER acceptance of electric vehicles (EVs) is starting to be evident. However, there are still concerns hindering the wide spread adoption of these devices, chiefly related to limited mileage range, long charging times, and large battery replacement costs. Although the number of battery charging locations is increasing, the charging time at these stations is either too long or reduce battery life by forcing them to undergo fast charging processes. An alternative to these charging stations is the deployment of Battery Swapping Stations (BSS), which swap a customer's discharged battery with a fully charged one of the same type. These stations could reduce the customers' concerns about long charging times or having enough stored energy to finish a trip.

By using electrical energy for motion, EVs are expected to increase the overall demand for electrical energy [1]. For this reason, it is crucial to examine the impact of EVs and BSSs on the power system. Since EVs are equipped with batteries, they can act as both a load or a power source [2]. This feature has been the focus of a number of research papers because the stream of services that can be catered by EVs is highly attractive to several power system stakeholders. However, in order to have a noticeable effect on the system, a significant number of vehicles must be aggregated and operated as an ensemble. In this sense, a BSS acts as a battery aggregator and has, on its own, enough capacity to participate in markets for electrical energy and reserve.

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Although the BSS concept is not new, there are few works that analyze the operation and business model for these entities. In [3], the risks associated to both customers and BSS, upfront investment classification, and commodities that could be sold are briefly discussed. A BSS business model of a subscription-based pricing structure and infrastructure costs are discussed in [4]. However, none of these business models include the interactions between the customer, the BSS, and the wholesale electricity markets.

In [5], an economic dispatch model that stabilizes and compensates wind energy intermittency using a BSS is presented. However, this model is simplified, up to the degree where the benefits that could be derived from BSSs are not included. In [6], a basic dynamic programming model is developed to determine the number of batteries to be purchased by the BSS for operation and the optimal battery charging schedule. However, the model does not consider the individual battery characteristics and no market interaction is considered.

Some commercial businesses have developed BSSs to take advantage of the market opportunities. One such company, Better Place, installed numerous stations handling certain types of EVs [7]. Tesla Motors introduced proprietary stations for their lineup of EVs [8]. Though, in these case it is assumed that the BSS does not participate in electricity markets and thus, their profits are solely based on service fees neglecting the stream of revenues that can be collected by operating the BSS as a storage station.

The BSS can maximize its profits by providing services to the system, such as voltage support, regulation reserves, or energy arbitrage. Voltage support and frequency regulation operate at short time scales and are beyond the scope of this paper. This work presents the case where the BSS exploits the difference in wholesale electricity market prices at different periods of time [9]. To take advantage of such differences, a two-stage action is required. First, it must forecast the day-ahead (DA) market prices and the demand for battery charging. Second, it must optimize its bids and offers in the DA energy market. The demand for batteries throughout the day may be estimated based on historical data. DA market prices can be forecasted using techniques similar to those discussed in [10]. The optimal bidding and offering strategy for BSS in the energy markets can be implemented using the techniques described in [11]. For the BSS to operate in an optimal manner, it needs to take advantage of the low electricity prices to charge its battery stock in Grid-to-Battery (G2B) mode and sell energy when the price is high in Battery-to-Grid (B2G) mode. However, batteries should be discharged only if they are not to be swapped in the near future. Similar modes of operation,

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but from an EV perspective, known as Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) are studied in the recent literature, see for example [12] and [13]. Therefore, G2B and B2G are the counterparts of G2V and V2G but for the batteries rather than the vehicles.

The BSS business model presented in this paper models explicitly the interactions between the customer and the BSS. This model also accounts for the benefits to the customer as well as the benefits to the power system. The optimization model operates on a day-ahead basis and determines the BSS's optimal charging schedules for the battery stock and its optimal bidding strategy in the electricity markets. The BSS model considers the wholesale market prices, EV characteristics, customer behavior, and related battery swapping fees. In addition to the G2B and B2G operating modes, Battery-to-Battery (B2B) mode is allowed to take place within the BSS. B2B mode enables the BSS to transfer energy between batteries, thus minimizing electricity purchases during high-price periods.

The remainder of this paper is organized as follows. Section II describes the BSS business model. Section III explains the BSS optimization model. Section IV discusses the results. Finally, Section V concludes the paper.

II. Business Model

A. Customer benefits

Owning an EV will allow the customer to use electricity for motion rather than fossil fuels. However, potential EV owners are concerned about the long charging times, inability to install chargers, limited range, and limited number of public charging stations. These concerns can be alleviated but require infrastructure investments. For example, at the household level high-power chargers can minimize wait-time for charging but at a considerable monetary expense to the customer. These high-power chargers might also not be allowed in rental housing or in places where the current electrical supply cannot accommodate an increased power demand. Another major concern is the limited range of the average EV, i.e. the infamous "range anxiety". In order to relieve this concern, customers require access to public charging stations that provide a service equivalent to gasoline stations. The BSS could eliminate these concerns.

Typical EVs are equipped with a standard 1.6 kW Level I chargers that connect directly to household outlets [14]. At maximum power (i.e. 1.6 kW), the wait-time until a 24 kWh battery is fully charged is approximately 15 hours. A Level II charging installation (charging at 3.3 kW) reduces the charging time to approximately 7 hours, but this would come at an extra cost to the customers (approximately $2150 with itemization of the costs given in [15]). Moreover, chargers are available only to customers that reside in detached single-unit housing. Customers residing in attached multi-unit housing, e.g. apartments, may have difficulties charging their EV due to the inability to install chargers. These reasons provide a business opportunity for BSSs, because the customers do not need to make an upfront investment in a high-power charger and will get the expected service in a short-time.

B. Power system benefits

From the power system's perspective, the BSS could operate as a storage facility and help avoid or defer investments in the distribution network. A BSS emulates an energy storage station that has the ability to reshape its demand so that peaks are shaved rather than increased if the BSS injects electricity back to the power system. This storage capability enables the BSS to perform arbitrage in the electricity market and hence increase its profit. Additionally, as the EV penetration increases, more customers will install chargers with large power requirements. This trend may require upgrades in the distribution network. On the other hand, if enough customers utilize battery swapping as an alternative to residential charging, less investment in the distribution network will be required. However, upgrades to the system may be required at the location of the BSS which should be reflected in the business model. Lastly, the energy storage capabilities of the BSS can provide services to a microgrid by supporting the transmission system in cases of a contingency [16].

C. BSS operations

Figure 1 illustrates the main features of the operation of a BSS. It shows that the BSS communicates bidirectionally with the power system to participate in market activities [17]. The BSS optimally schedules batteries to discharge energy to the grid (B2G), charge energy from the grid (G2B), or discharge/charge energy to and from other batteries (B2B). These features will pose the BSS as an ideal candidate to participate in electricity markets by submitting bids/offers and thus exploiting the time-dependency of wholesale electricity prices, while satisfying the energy needs of its battery stock. The BSS also incorporates several replacement platforms for different groups of batteries.

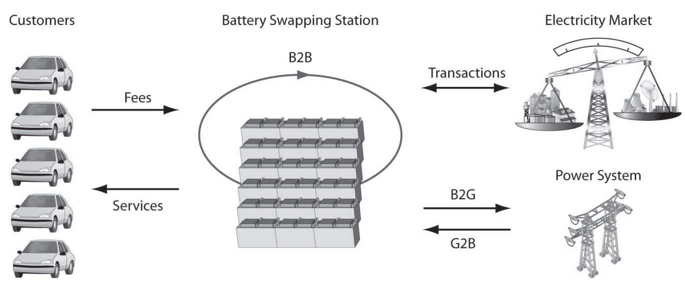

Fig. 1. BSS interactions with customers, market, and power system.

The BSS is assumed to own batteries that it leases to the EV owners [3]. Battery degradation due to charging/discharging, maintenance, and labor costs are thus incurred by the BSS. In return for the swapping service, customers pay a fixed service fee. From the customers' perspective, they would not incur the battery replacements costs which range from $12,000 to $14,400 (500-600 $/kWh) for a 24 kWh battery as of 2012 [18] and are thus the most expensive component of EVs. A lease-based approach would allow customers to purchase an EV without factoring in the cost of battery replacements. The only cost to customers, in terms of the EV battery is the cost of household electricity, in case of residential charging or the service fee for battery replacements when they use the BSS services.

III. Optimization Model

The following nomenclature is utilized for clarity. The set of time-periods is denoted by T with index t. Batteries are part of the set I with index i. The set of battery group is denoted G with index g.

A. Model assumptions

The BSS model relies on several assumptions. First, it relies on the DA electricity market to derive the optimal offering/bidding schedule. Second, the BSS forecasts the number of battery replacements and the DA wholesale market prices for each period of the following day. Additionally, it is designed to manage multiple groups of batteries. Customers expect a 100% charged battery, and if the BSS cannot meet this requirement, the customers receive a discount as compensation.

B. Model formulation

At the DA stage, the BSS derives optimal charging/discharging schedules for batteries, identifies the batteries that should be replaced to match the battery demand, $N_{g,t}$, in each hour, and determines the amounts of electricity that should be purchased or sold in the DA market. The model is formulated as follows:

Maximize

$$BSR \sum_{(t\in T)} \sum_{(i\in I)} x_{i,t} - VoLC \sum_{(t\in T)} \sum_{(g\in G)} bat^{\text{short}}_{g,t} - \sum_{(t\in T)} \lambda^{\text{DA}}_t \left(em^{\text{buy}}_t - em^{\text{sell}}_t\right) - BSR \sum_{(t\in T)} \sum_{(i\in I)} \beta_{i,t} \quad (1)$$

subject to:

$$soc_{i,t} = \left(soc_{i,t-1} + bat^{\text{chg}}_{i,t}\eta^{\text{chg}} - bat^{\text{dsg}}_{i,t}\right)(1 - x_{i,t}) + SoC^{\text{init}}_{i,t} x_{i,t} \quad \forall i \in I, \forall t \in T \quad (2)$$

$$soc_{i,t-1} + soc^{\text{short}}_{i,t} \geq BC_g S_{i,g} x_{i,t} \quad \forall i \in I, \forall g \in G, \forall t \in T \quad (3)$$

$$\sum_{(i\in I)} S_{i,g} x_{i,t} + bat^{\text{short}}_{g,t} = N_{g,t} \quad \forall g \in G, \forall t \in T \quad (4)$$

$$em^{\text{buy}}_t - em^{\text{sell}}_t = \sum_{(i\in I)} \left(bat^{\text{chg}}_{i,t} - bat^{\text{dsg}}_{i,t}\right) \quad \forall t \in T \quad (5)$$

$$0 \leq bat^{\text{chg}}_{i,t} \leq (1 - x_{i,t}) P^{\max}_i \quad \forall i \in I, \forall t \in T \quad (6)$$

$$0 \leq bat^{\text{dsg}}_{i,t} \leq (1 - x_{i,t}) P^{\max}_i \quad \forall i \in I, \forall t \in T \quad (7)$$

$$0 \leq soc_{i,t} \leq \sum_{(g\in G)} BC_g S_{i,g} \quad \forall i \in I, \forall t \in T \quad (8)$$

$$bat^{\text{dsg}}_{i,t} \leq P^{\max}_i a_{i,t} \quad \forall i \in I, \forall t \in T \quad (9)$$

$$bat^{\text{chg}}_{i,t} \leq P^{\max}_i (1 - a_{i,t}) \quad \forall i \in I, \forall t \in T \quad (10)$$

$$em^{\text{sell}}_t \leq M b_{i,t} \quad \forall i \in I, \forall t \in T \quad (11)$$

$$em^{\text{buy}}_t \leq M (1 - b_{i,t}) \quad \forall i \in I, \forall t \in T \quad (12)$$

Equation (1) shows that the objective is to maximize the BSS profits. The first term in (1) is the revenue collected from service fees priced at the Battery Swap Revenue, *BSR* (\$/battery). The second term accounts for the inability to supply battery demand, $bat^{\text{short}}_{g,t}$, and is priced at the Value-of-Lost-Customer, *VoLC* (\$). This value should be derived from surveys to determine what value customers place on a charged battery. The third term is the cost of purchasing em^{buy}_t (kWh) electricity or profit of selling em^{sell}_t (kWh) electricity in the DA market with wholesale forecasted prices, λ^{DA}_t (\$/kWh). The last term in (1) is the discounts given to customers and is discussed in subsection III.C.

This optimization problem is subject to constraints (2)-(12). The binary variable, $x_{i,t}$, is equal to 1 if battery i is replaced at time period t, and 0 otherwise. Constraints (2) monitor the energy state of charge (eSoC), $soc_{i,t}$ (kWh), of each battery at every time period, accounting for charging power, $bat^{\text{chg}}_{i,t}$ (kW), and discharging power, $bat^{\text{dsg}}_{i,t}$ (kW). Battery charging efficiency, η^{chg}, is accounted for in (2). If $x_{i,t}$ is equal to 1, equations (2) does not update eSoC at this period. Instead, the eSoC of battery i is set to the initial eSoC, $soc^{\text{init}}_{i,t}$ (kWh), of the customer battery that has just been swapped. If a battery is being swapped, the eSoC must be at the nominal battery capacity, BC_g (kWh). Otherwise, a shortage, $soc^{\text{short}}_{i,t}$ (kWh), is captured in equations (3). Each battery belongs to a group, classified by its capacity (kWh), and denoted by binary parameter, $S_{i,g}$. The overall customer battery demand should be met for each group of batteries as in (4). The unmet demand is captured in variable $bat^{\text{short}}_{g,t}$. To meet the demand, BSS submits offers/bids for electricity to the market, which is enforced by equations (5). Additional constraints are needed to ensure batteries are operated within the established limits. Battery charge/discharge power is limited to $P^{\max}_i$ (kW) in (6)-(7), and the eSoC is limited to BC_g by constraint (8). Finally, constraints (9)-(10) ensure that charging/discharging of batteries do not occur simultaneously, and constraints (11)-(12) ensure that purchasing/selling in the market do not occur simultaneously. In (2) and (4), the product of binary variable $x_{i,t}$ and real variables are present. These non-linear constraint are replaced by linear equivalents as explained in [19].

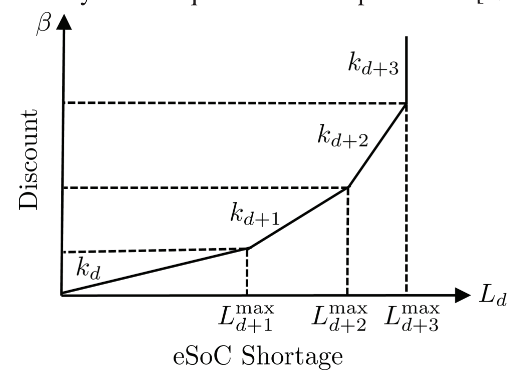

Fig. 2. Piecewise linear discount function.

C. Discounts

The last term in the objective function, (1), represents the discounts given to customers for accepting less than 100% charged batteries. The BSS has a tradeoff of swapping batteries at less than nominal charge, e.g. 80% eSoC, at a discounted price versus not selling the battery and thus, incurring the *VoLC*. The discount given to customers progressively increases as the battery eSoC shortage increases following a piecewise linear curve shown in Fig. 2. The piecewise curve is modeled using constraints (13)-(16), where *D* is the set of discount blocks with index *d*. In (13), the eSoC shortage is limited to the battery capacity. Equations (14) forces the sum of eSoC shortage block variable, L_d, to be equal to the normalized eSoC shortage of a specific battery. In (15), $\beta_{i,t}$ is the discount percentage for each battery that could not be replaced at 100% eSoC. This percentage is calculated with multiplication of the discount slope parameter, k_d, and the respective eSoC shortage block as shown in (15). Lastly, equations (16) limits the eSoC shortage block to the parameter $L^{\max}_d$. The BSS can preset parameters k_d and $L^{\max}_d$ dependent upon its business model.

$$0 \leq soc_{i,t}^{\text{short}} \leq \sum_{(g \in G)} S_{i,g} BC_g \qquad \forall i \in I, \forall t \in T \qquad (13)$$

$$\frac{soc_{i,t}^{\text{short}}}{\sum_{(g \in G)} S_{i,g} BC_g} = \sum_{(d \in D)} L_d \qquad \forall i \in I, \forall t \in T \qquad (14)$$

$$\beta_{i,t} = \sum_{(d \in D)} k_d L_d \qquad \forall i \in I, \forall t \in T \qquad (15)$$

$$L_d \leq L_d^{\max} \qquad \forall d \in D \qquad (16)$$

IV. RESULTS

The proposed model is applied to a small and a large case study. The small case study illustrates the features of the proposed BSS model, while the large case simulates a large-scale BSS system. From the market perspective, the BSS is a price-taker. Parameters for both case studies are as follows. The *BSR* is assumed to be \$70 as used by [8], while the *VoLC* is set to \$200. The discount curve (Fig. 2) is designed with four piecewise approximations: 1) $k_1 = 1.1$ and $L_1^{\max} = 10\%$, 2) $k_2 = 3.0$ and $L_2^{\max} = 30\%$, 3) $k_3 = 5.0$ and $L_3^{\max} = 50\%$, and 4) $k_4 = 10$ and $L_4^{\max} = 100\%$. The charge/discharge maximum power of batteries is 3.3 kW. The model was implemented in GAMS 24.0 [20] and solved using CPLEX 12.1 [21].

A. Small case study

In this study, for illustration purposes, the EV batteries have nominal eSoC of 12 kWh with a single battery group, zero kWh of initial eSoC, and efficiencies of 100%. As for the BSS, it is equipped with a stock of two batteries. For the stock of batteries, the demand in hours 5 and 11 are one battery and hour 19 of two batteries. Fig. 3 displays the results of the study. Fig. 3a shows DA market purchasing/selling actions against the forecasted market prices. Figs. 3b and 3c show the eSoC of battery 1 and 2 and their corresponding charging/discharging profiles where positive power indicates charging and negative power indicates discharging. The demand profile shown in Fig. 3d is itemized by which battery performs the swapping.

This figure shows that the BSS purchases electricity during low-cost periods to charge batteries (G2B) and sells energy during high-cost periods by discharging batteries (B2G). After a battery from the BSS is replaced with a customer's battery, the received battery can start charging or discharging after identifying its initial eSoC, as shown in Fig. 3c and 3d. Since battery 2 is not scheduled for swapping again until the hour 19, it discharges in hours 12-14 from pre-charged energy in G2B mode performed in prior hours. Specifically, in hours 12 and 14, battery 2 performs in B2B to supply battery 1 due to the high cost of electricity in the market. This mode occurs since both batteries are required to be replaced at hour 19 requiring full eSoC. Altogether, 55.8 kWh is purchased in the market in G2B mode, 7.8 kWh is sold in the market in B2G mode, and 5.4 kWh is transferred from battery to battery in B2B mode. The required electricity for supplying the battery demand is 48 kWh. Therefore, excess G2B charging takes place because there is a perceived benefit in terms of energy arbitrage in future high-cost periods. B2B mode allows for further profit maximization since the energy is transferred between batteries preventing the BSS of having to buy electricity during periods in which the electricity price is high. This case depicts no discounts or VoLC since battery demand is met. The revenue collected from BSR fees is \$280, and within that -\$2.20 is electricity purchase loss in G2B mode, and \$0.374 is electricity selling profit in B2G mode. The overall profit attained by the BSS is \$278.17.

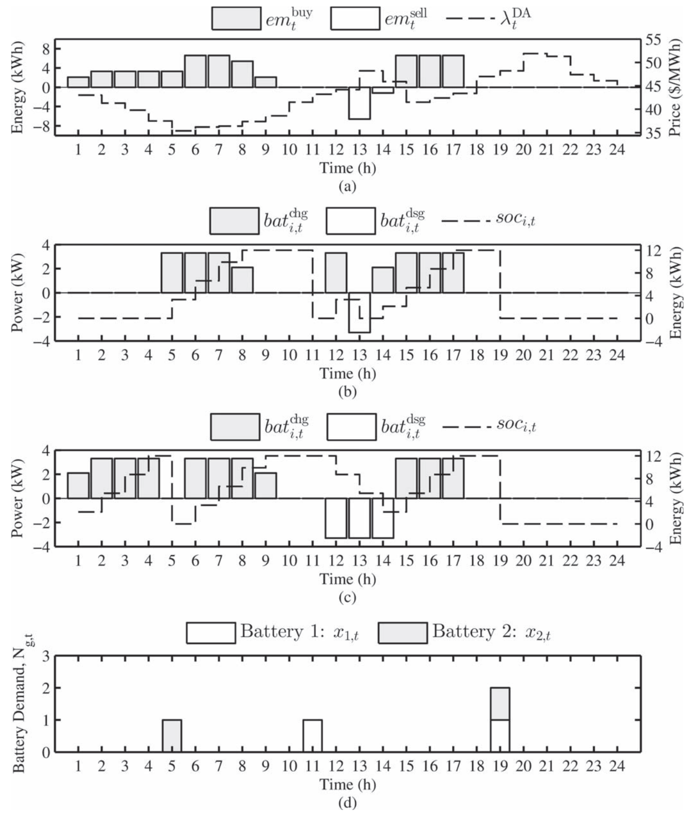

Fig. 3. (a) DA market purchasing/selling actions, (b) battery 1 eSoC and charge/discharge profiles, (c) battery 2 eSoC and charge/discharge profiles, and (d) battery demand profile itemized by each battery's replacement status.

B. Large case study

The large case study assumes a battery stock of 550 batteries for the BSS, of which 150 are 16 kWh and 400 are 24 kWh capacity batteries. The EV and the BSS parameters are the same as in the small case study except the battery charging and discharging efficiencies are 90%, and the initial eSoC for all batteries uniformly randomized between 10% and 50% of the nominal battery eSoC. The vehicular travel data is taken from [22], and it is used to derive a distribution function of the customer arrival times for replacement as shown in Fig. 4a. Furthermore, with the distribution function, battery demand profiles were created for two groups of batteries, 16 and 24 kWh, as shown in Fig. 4b. Typical market prices were obtained by averaging DA LMP prices for every Thursday from the period January-March 2013 in the PJM market [23], as shown in Fig. 5a. Thursday was chosen in order to show the effects on a typical weekday.

The model derives market offers, during high-cost periods, and bids, during low-cost periods, as illustrated in Fig. 5b. Fig. 6 displays the power transfer in different modes of operation. In Fig. 6a, the batteries discharge in B2G mode during high-cost periods, whereas they charge in low-cost periods in G2B mode. The B2G mode is enabled since the batteries charge in excess to transportation energy requirements. The BSS uses B2B mode as well, as shown in Fig. 6b. In B2B, stand-by batteries discharge and supply batteries due for swapping. In particular, in hours 7-11 and 18-22, batteries perform B2B for two reasons. First, the market prices are high which results in reduced electricity purchases, as shown in Fig. 5b. Secondly, the demand (Fig. 4b) is high in these periods. If B2B was not an option, the electricity would have been purchased in the DA market.

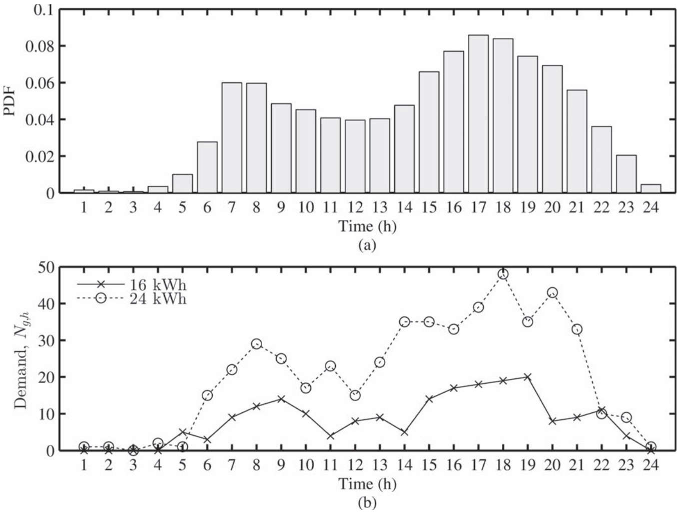

Fig. 4. (a) Distribution function of customer arrival at BSS. (b) Demand profiles for two groups of batteries.

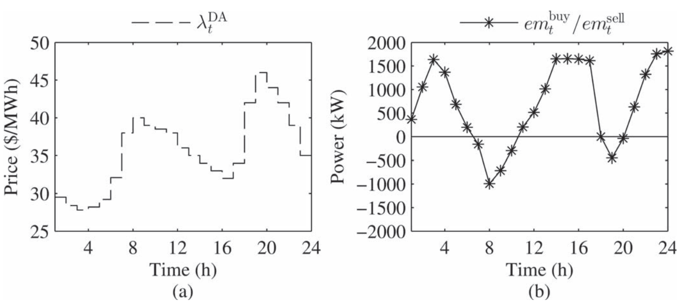

Fig. 5. (a) Market prices for PJM [23]. (b) DA market offers and bids.

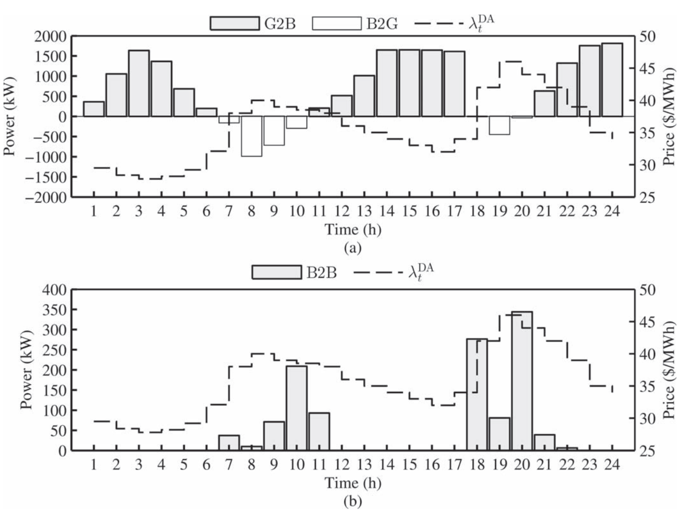

Fig. 6. (a) G2B and B2G, and (b) B2B actions scheduled by the BSS.

Unlike traditional gasoline stations, which receive weekly (or even daily) gasoline refills, occurring in a matter of hours or less, the BSS is limited by the batteries maximum charging/discharging power rating. The optimal schedule is more crucial for the BSS as compared to traditional gasoline stations. With the optimal schedule, the BSS needs to ensure it generates sufficient profits to maintain its business. In Fig. 7a, the profits are shown periodically and cumulatively. The cumulative profit is \$44,033 with revenue of \$48,510. The total losses accrued are \$4,477. The itemization of the losses is shown in Fig. 7b. When batteries perform B2G, the BSS is selling electricity and hence, obtains a cumulative profit in the market of \$107.37. Though, when performing G2B, the BSS profit is reduced by \$632.08 due to purchased electricity.

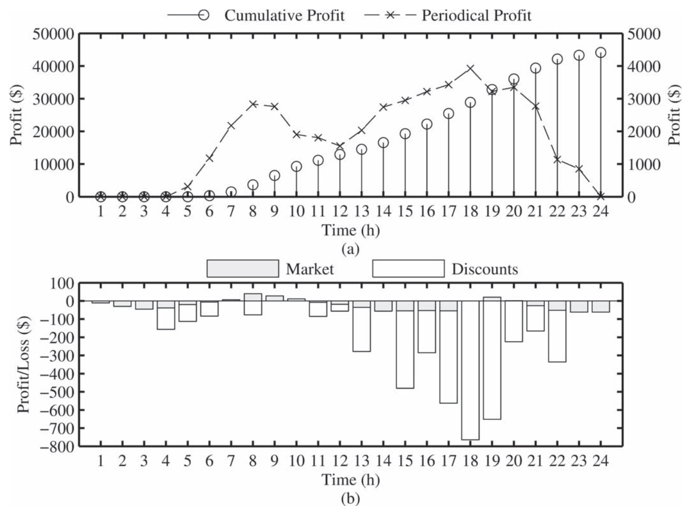

Fig. 7. (a) Cumulative and periodical profit, and (b) itemized costs for the BSS.

Most of the economic losses of the BSS are due to discounts for not meeting the nominal eSoC of swapped batteries. Due to high *VoLC* value, the model favors discounts over losing customers. Ideally, after replacement of a large number of batteries in a high-demand hour, the BSS should have enough capacity in batteries to manage the subsequent high-demand hours. However, after replacement, the initial eSoC of batteries are low and require several hours of charging to be available for another replacement. This entails discounts to be given to customers which are visualized in Fig. 7b, indicating large discounts being given at high-demand hours. The cost due to discounts for the BSS is \$3,952.50. Furthermore, the *VoLC* loss is not amassed in this situation since it is perceived as the worst-case situation of not providing a battery to customers.

From a customers' perspective, a decision needs to be made, as to take the battery replacement with the discount and lower eSoC or utilizing residential charging. From the BSS perspective, it can invest in more batteries to minimize discounts or continue using a first-come first-serve business model. As the cost of batteries decrease, the former approach for the BSS will be beneficial. Nonetheless, it is crucial for the BSS to decide which group of batteries to invest in. This can be identified by visualizing the frequency of discounts given per battery group as displayed in Fig. 8. Group 2 (24 kWh) has higher frequency of discounts as compared to Group 1 (16 kWh). This is caused by the larger demand (Fig. 4b) of Group 2 batteries. As for the value of discounts itemized by battery group, Group 2 (24 kWh) incurs cost of \$2,735.40, whereas Group 1 (16 kWh) incurs cost of \$1,217.08. Therefore, investing in Group 2 batteries will allow for reduction in discounts accrued by the BSS.

Additional benefit of investing in Group 2 batteries is for B2G and B2B mode since larger storage capacity is available.

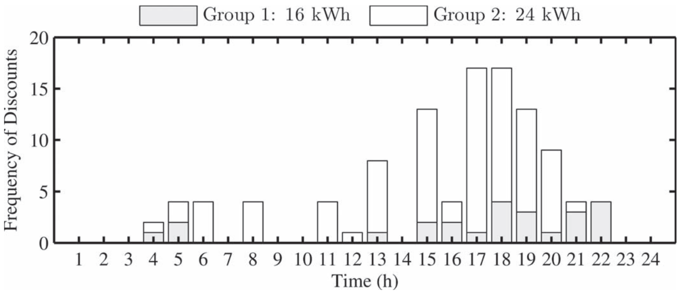

Fig. 8. Frequency of discounts itemized by group of batteries.

V. Conclusion

This paper presents a business case and an optimization model for a battery swapping station. The BSS can alleviate customer concerns related to long charging times and range anxiety. Not only does the BSS benefit customers financially but also benefits the power system by participating in electricity markets and by avoiding or deferring expensive infrastructure upgrades. To be profitable, the BSS needs to ensure that the fees it charges, the risk it takes of not satisfying its customers, and the discounts it offers are properly designed. Results show that the utilization of market prices allows batteries to pre-charge during low price periods (G2B), partially discharge during high price periods (B2G), and transfer electricity between batteries when purchasing energy from the electricity market should be avoided (B2B).

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