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Optimal Scheduling of Battery-Swapping Station Loads for Capacity Enhancement of a Distribution System

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Abstract: A battery-swapping station (BSS) can serve as a flexible source in distribution systems, since electric vehicle (EV) batteries can be charged at different time periods prior to their swapping at a BSS. This paper presents an EV battery service transformation from charging to swapping batteries for EVs for the capacity enhancement of a distribution system. A novel mathematical model is proposed to optimally quantify and maximize the flexibility of BSS loads in providing demand response for the utility operator while considering technical operations in the distribution grid. Case studies and numerical findings that consider data from the National Household Travel Survey and a 32-bus distribution system are reported and discussed to demonstrate the effectiveness of the proposed model. Offering battery-swapping services helps reduce not only the peak load, but also the station operation cost.

Keywords: battery-swapping station; scheduling; optimization; mathematical model

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1. Introduction

With the deregulation of the power industry, environmental policy changes, advancements in technology, and the transformation into smart grids, distribution system paradigms have gone through significant changes in recent years. Concurrently, with the increase in gas prices driven by the foreseeable depletion of fossil fuel in the future, developments in the automotive sector, and environmental concerns, the penetration of electric vehicles (EVs) has been increasing. Electrifying the transportation sector impacts distribution networks with an increased peak load, increased losses, deterioration in voltage profiles, and changes in load patterns. To mitigate these effects, utilities need to adopt the right actions and policies and develop the associated infrastructure.

In the context of smart grids, a utility can control the EV charging demand while also considering customer preferences, which can lead to benefits such as deferment of decisions on reinforcement and other investments and the maximization of the use of existing infrastructure. Nevertheless, rapid charging demand is considered to be inflexible and cannot be controlled due to the very short stay of EVs at a rapid charging station. Unlike a rapid EV charging station, a battery-swapping station (BSS) can serve as a flexible source when EV batteries are charged at different time periods prior to their swapping at the BSS. The primary objective of this paper is to mathematically and optimally schedule BSS loads, to enhance the distribution system's capacity [1–3], and, thereby, to avoid system upgrades or increasing the spinning reserve [4].

There is a large and growing body of literature that has been devoted to integrating EV stations into power systems. A comprehensive literature review on the siting, sizing, and operation mechanisms of BSSs was provided in [5]. The optimal siting, sizing, and collaborative scheduling with microgrids and routing of EVs were highlighted and discussed. In [6], BSSs were optimally located and sized in a distribution system with the objective of maximizing the net present value over the life cycle of the project. Charging stations were planned and operated as a smart energy hub [7] to mitigate the effects of charging station loads and enhance the distribution grid's capabilities. In [8], the authors presented a strategy for integrating EVs into an electric grid with an intensive review of advanced smart metering and communication infrastructures. In [9], a framework was proposed for an electric vehicle charging navigation system with the objective of selecting the optimal route and electric vehicle charging station. An optimization framework was proposed in [10] for the operating model of a BSS in a day-ahead scheduling process in which the BSS could hedge against the market price and battery demand uncertainty. In [11], a bi-level scheduling framework was presented for optimal decision making for a microgrid and BSSs to minimize the total microgrid cost in the upper level while minimizing the total BSS cost in the lower level of the framework. In [12], an urban-scale integrated charging station system was proposed to examine the potential and technical benefits of using photovoltaic systems as the energy supplier vis-a-vis the external grid to charge EVs. A multi-objective collaborative planning model was proposed in [13] for the planning of an integrated power distribution system and charging stations with the minimization of the overall annual investment costs and energy losses and the maximization of the annual captured traffic flow.

A discrete cluster model was developed in [14] for the optimal operation of aggregated BSSs in day-ahead energy and reserve capacity markets. The main focus of the reported study was on optimally scheduling an aggregation of BSSs to meet their swapping demand, as well as making additional revenue by performing arbitrage in the day-ahead market and providing a reserve for the power system operator. To study the service capability and profitability of a charging station and a BSS for taxis and buses, a Monte Carlo model was developed in [15]. The findings revealed that the BSS generally had more long-term economic benefits for the charging service provider than the EV charging station. In [16], an EV control strategy was developed to achieve a flat load profile and voltage regulation by using EVs' storage capacity in a distribution network.

The service and operation of electric vehicle power stations were reviewed in [17]; the results of the analysis obtained through their literature review and future research directions were presented and discussed. In [18], a hybrid charging management framework was proposed for optimal selection between battery charging and swapping for urban EV taxis, with the objective of reducing the trip delay of a public urban electric taxi system. The authors of [19] proposed a site selection framework for a BSS based on a multi-criteria decision-making method so as to assist investors in selecting the most appropriate alternative. A method for a battery-swapping technology with a Tesla BSS as a case study was reviewed in [20]; technical challenges that were prevalent in commercially implementing this technology were identified. The authors of [21] proposed a framework for studying the impact of BSSs on the reliability of distribution networks. It was reported that BSSs could improve reliability to a certain extent and reduce the adverse impact on the reliability of the distribution network. A scheduling model for EVs in the time dimension was established in [22], with the objective of minimizing the system's equivalent load fluctuation while maximizing the charging capacity of the EVs. The authors of [23] established a bi-level model that considered profit-driven decision making by plug-in electric vehicle owners. The model was used to minimize the installation and operation investments of a charging station with distributed energy resources while fully capturing EV users' decisions. In [24], a two-layer optimization model was built for simultaneously determining dynamic pricing policy for a system operator and the demand response strategies for EV parking lots. It was observed that dynamic pricing with demand response from EVs could lower the daily average consumer cost. An optimal scheduling model was developed in [25] to minimize the operation cost of a microgrid that included distributed generation and

BSSs. The authors of [26] developed a dynamic operation model for BSSs in an electricity market and formulated it based on a short-term battery management and energy bidding strategy in the electricity market.

From the aforementioned literature review, there were no reported works that took into account the flexibility of BSS loads for demand response provisions in distribution grids. Moreover, the effects of a BSS with a minimum number of EV batteries in stock on a distribution system's operations and system loading capabilities have not been investigated. Therefore, there is a need to develop a new mathematical model for optimally quantifying and maximizing the flexibility of BSS loads in providing demand response for the utility operator while considering the distribution grid's technical operations. There is also a need to determine the minimum number of EV batteries in stock that would result in the optimal demand response provisions while ensuring the stability of a BSS to avoid unserved EVs at that BSS.

The main contributions that characterize the work presented in this paper are as follows:

- A new mathematical model is proposed to quantify the flexibility of swapping EV batteries at a BSS while considering the distribution grid's technical operations. The proposed model also determines the minimum number of EV batteries in stock for the system stability of the BSS and to avoid unserved EVs at that BSS.
- The presented BSS load is compared with a traditional charging station's load in terms of peak reduction and operation costs to demonstrate the effectiveness of transforming from a charging service to a battery-swapping service at an EV station in the distribution system.
- The effects of the BSS loads on the distribution system's operations and the extent to which they can enhance the system's loading capability and defer the need for system upgrades are investigated.

The rest of this paper is organized as follows. Section 2 describes the EV arrival rate model. A novel mathematical optimization model is proposed in Section 3 for quantifying the optimal demand response provisions from the BSS loads for the peak reduction and capacity enhancement of a distribution grid. Section 4 presents the test system and input data, followed by a discussion of the results in Section 5. Finally, Section 6 presents the conclusions.

2. Modeling of the EV Arrival Rate at a Battery-Swapping Station

Many factors have to be taken into consideration when modeling EV loads at an EV station; a key factor of this is the daily behavior of drivers (e.g., traveled distances and the number and times of trips). In order to infer the main features pertaining to driver behavior, detailed transportation data, *i.e*, the National Household Travel Survey (NHTS) data [27], were used. The distribution of trip distances, the time-of-day distribution of the trips, and the number of trips associated with each vehicle were extracted from [27] for use in predicting the required times for rapid EV charging. The Vehicle Decision Tree (VDT) method developed in [7] was used in this work to track the trip information for each vehicle and determine the arrival time for each vehicle at the charging station. The state of charge (SOC) of the battery of an EV was checked by considering its distance-driven mileage for each trip, and when the EV depleted the entire SOC window, either the start time or the end time of that trip was recorded. Figure 1 demonstrates an EV's calling time for a rapid charge or battery swapping by using the developed VDT method. Let us assume that, for an EV with a battery capacity of 100 kWh, the SOC is initially 40 kWh, and the energy consumption per km is 0.3 kWh/km. After accumulating two trips, the SOC reaches its minimum, i.e., 20%. It should be mentioned that the hour, rather than the minute, at which the EV calls for a rapid charge is considered for estimating the probability of an EV's arrival at an EV station each hour based on the assumption that the EV will definitely reach the local EV station within that one-hour calling window. The EV charging load depends on the required SOC and the EV battery type. A queuing model is used to represent the overall charging process of EVs at the charging station. The reader may refer to [7] for further discussions of the VDT method and queuing models.

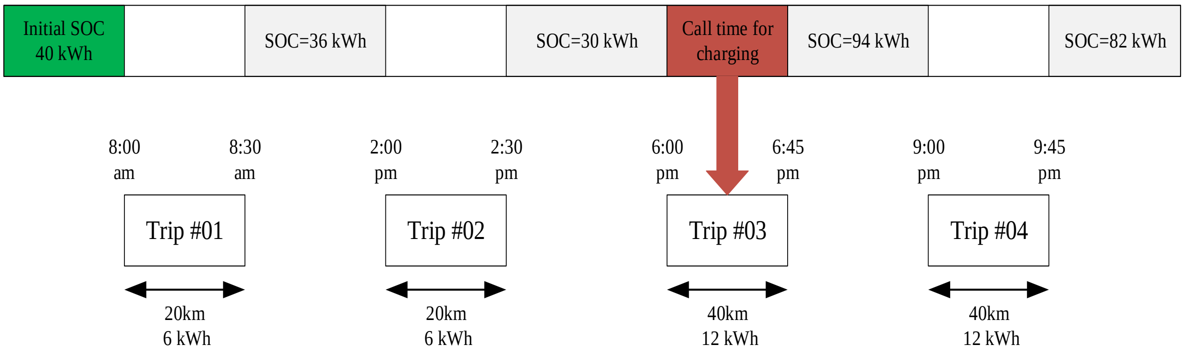

Figure 1. Demonstration of an EV's calling time for rapid charging or battery-swapping services.

3. Proposed Mathematical Optimization Model

This section proposes a novel mathematical optimization model with the objective of minimizing the peak BSS demand (PK_{st}^{BSS}) while optimally scheduling the operation of swapping batteries for EV arrivals and considering the distribution grid's network and load constraints.

$$Min \sum_{st=1}^{n} PK_{st}^{BSS} \tag{1}$$

where st = the number of the BSSs in the distribution system.

Power flow equations: These ensure that the power injected at the substation bus, the net of the system load, and the BSS loads are constrained by the active power flow equations. The reactive power injected at the substation bus and the net of the reactive load are governed by the reactive power flow equations.

$$P_{u,h}^{Sub} - Pd_{i,h} - Pd_{st,h}^{BSS} = \sum_{j\varepsilon N} V_{i,h} V_{j,h} Y_{i,j} \cos(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \qquad \forall i \in N, \forall h \tag{2}$$

$$Q_{u,h}^{Sub} - Qd_{i,h} = -\sum_{j\varepsilon N} V_{i,h} V_{j,h} Y_{i,j} \sin(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \qquad i\forall N, \forall h \tag{3}$$

where P^{Sub} and Q^{Sub} denote the active and reactive power drawn at the substation bus. Pd^{BSS} represents a BSS load. Pd, Qd are for active and reactive loads in the distribution system.

The battery-swapping system's constraints are as follows.

State of charge (SOC) of swapping batteries:

$$SOC_{bt,st,h+1} = SOC_{bt,st,h} + Pch_{bt,st,h} \eta \Delta t - \lambda_{bt,st,h} RBS_{bt,st} \qquad \forall bt, \forall st, \forall h \tag{4}$$

$$SOC_{bt,st,h} \leq \gamma_{bt,st} \sum_{h} \lambda_{bt,st,h} \; RBS_{bt,st} \qquad \forall bt, \forall st, \forall h \tag{5}$$

where $Pch_{bt,st,h}$ represents the power charging of EV batteries prior to swapping. λ denotes the hourly EV arrival rate; Δt is the time duration in hours; η is the charging efficiency; RBS represents the required EV battery capacity. $\gamma_{bt,st}$ denotes the percentage of battery types of EV arrivals that are in stock.

Number of EV batteries in stock: This constraint ensures that the number of batteries in stock for each EV type does not exceed the daily EV arrivals at the station.

$$\sum_{bt} (\gamma_{bt,st} \sum_{h} \lambda_{bt,st,h}) \leq \omega \lambda_{st}^{Daily} \tag{6}$$

where λ^{Daily} is the daily EV arrival rate; ω represents the percentage of daily EV arrivals.

Limits on the power charging of swapping batteries: This limit ensures that the power charging of swapping batteries does not exceed the power charger of the station.

$$Pch_{bt,st,h} \leq P_{st}^{Cap} \tag{7}$$

Charging and swapping EV batteries: To guarantee that the EV batteries that are being swapped are already filled and not being charged at the same time, the empty EV batteries that are dropped off at the station after battery swapping will not be charged in the same hour, but can be charged starting from the next hour.

$$Pch_{bt,st,h} \leq ([\gamma_{bt,st} - \lambda_{bt,st,h}]RBS_{bt,st})/\eta\Delta t \tag{8}$$

Determination of BSS loads: The BSS loads resulting from the battery-swapping service for arriving EVs are determined as follows:

$$Pd_{st,h}^{BSS} = \sum_{bt} Pch_{bt,st,h} \tag{9}$$

Demand response of BSS loads: The upward and downward demand response of BSS loads is quantified as follows:

$$DR_{st,h}^{BSS} = \sum_{bt} Pch_{bt,st,h} - Pd_{st,h}^{EV} \tag{10}$$

$DR_{st,h}^{BSS}$ is positive and in an upward state when the BSS adds an extra load (more than a charging station's load) on the distribution system. When $DR_{st,h}^{BSS}$ becomes negative, this means that the BSS is in a downward state and supports the distribution system by scheduling the operation of swapping batteries during other times that are favorable to the utility with respect to grid availability. In an idle state, $DR_{st,h}^{BSS}$ becomes zero, and there is no change in the BSS's load from its baseline load (charging service).

Peak BSS load constraint: The following constraint ensures that the peak BSS load is minimized in conjunction with (1).

$$Pd_{st,h}^{BSS} \leqslant PK_{st}^{BSS} \qquad \forall st,\ \forall h \tag{11}$$

Feeder capacity limits: The power flow through any distribution feeder should be within the limit of the feeder capacity.

$$-V_{i,k}^2 Y_{i,j} \cos\theta_{i,j} + V_{i,h}V_{j,h}Y_{i,j}\cos(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \leqslant S_{(i,j)}^{Fcap} cos\theta_{(i,j),h}^{F} \qquad \forall (i,j) \in N : \exists (i,j), \forall h \tag{12}$$

$$V_{i,h}^2 Y_{i,j} \sin\theta_{i,j} - V_{i,h}V_{j,h}Y_{i,j}\sin(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \leqslant S_{(i,j)}^{Fcap} sin\theta_{(i,j),h}^{F} \qquad \forall (i,j) \in N : \exists (i,j), \forall h \tag{13}$$

Limits of substation capacity: The capacity limit of the substation is included as follows.

$$(P_{u,h}^{Sub})^2 + (Q_{u,h}^{Sub})^2 \leqslant S_u^{Sub^{cap}2} \qquad \forall h \tag{14}$$

Voltage limits: This ensures that the bus voltage is within its limit as follows:

$$\underline{V} \leqslant V_{i,h} \leqslant \overline{V} \qquad i\forall N, \forall h \tag{15}$$

BSS operation cost: The following equations are included in the model to assess the effect of swapping batteries for the PEV arrivals on the operation cost of the charging station.

$$Co_{st}^{OP} = \sum_{h} \rho_h^{TOU} Pd_{st,h}^{BSS} n_d \tag{16}$$

It should be mentioned that there is a possibility of power exchange between the BSS and the main grid, but it would somehow be similar to the concept of an energy storage system; therefore, it is out of the scope of the work presented in this paper.

The proposed mathematical optimization model is a nonlinear programming model and was solved by using the SNOPT solver in the General Algebraic Modeling System (GAMS) environment [28]. The SNOPT solver is suitable for nonlinear programming problems, and it uses a sequential quadratic programming algorithm that obtains search directions from a sequence of quadratic programming sub-problems.

4. Test System and Input Data

The 32-bus radial distribution system shown in Figure 2 and described in [29] is considered in this study. The system peak demand was 4 MW, with a base voltage of 12.66 kV. The profiles of the system loads are from the IEEE Reliability Test System [30]. The house peak load was assumed to be 2.08 kW [31] to calculate the number of houses at each bus, and it was also assumed that all loads were residential loads.

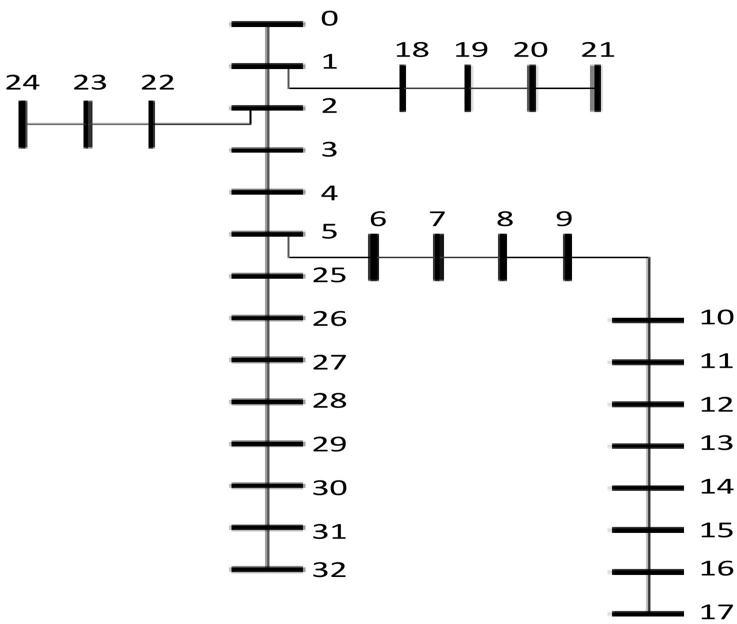

Figure 2. The 32-bus distribution system.

The number of electric vehicles in the system could be determined based on knowledge of the EV penetration level [7], number of houses, and average number of vehicles per household. The average number of vehicles per household was estimated to be 1.9 according to [27]. Three years of Hourly Ontario Energy Price (HOEP) data were used to generate the average price profile for a typical day.

5. Results and Discussion

5.1. BSS Loads for Demand Response Provisions

Prior to executing and solving the proposed model, the EV arrival rate at an EV station needed to be determined. In the absence of historical data on the arrival percentages of EV arrival types, the EV arrival rates were assumed based on the different EV battery capacities. Hence, the EV arrivals were assumed to comprise a mix of 30% PEV20 vehicles, 40% EV40 vehicles, and 30% EV60 vehicles, and they were determined by using the developed VDT, as shown in Figure 3. The expected EV charging demand was estimated based on these percentages.

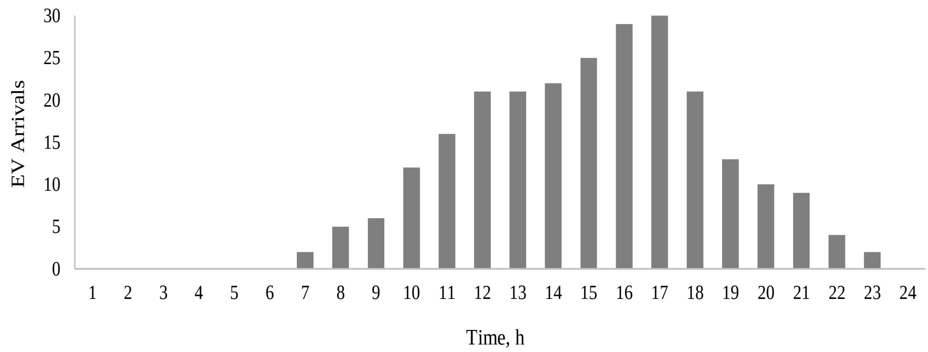

Figure 3. EV arrival rate within a typical day.

Using the proposed model, the power charging when swapping EV batteries was optimally scheduled to minimize the peak BSS load and provide the demand response for enhancing the distribution grid's capacity. Figure 4 shows the optimal power scheduling of EV batteries for battery swapping, which varied from one hour to another based on the total number of EV batteries in stock, as well as the distribution grid's operation constraints. It is to be noted that, in total, a minimum of 74 EV batteries were required to be in stock (30% of all PEV arrivals) for the system stability of the BSS and the avoidance of unserved EVs at the BSS. It was also observed that power charging of all EV batteries took place at all hours of the day, except for hours 23 and 24 because there are only 74 EV batteries in stock, and when they were already swapped, there was a need to charge the empty ones and make them available for battery swapping later during the day. It should be mentioned that when the number of EV batteries in stock was large enough, the power charging of EV batteries would take place only during the early period of the day, hence further reducing the peak system load.

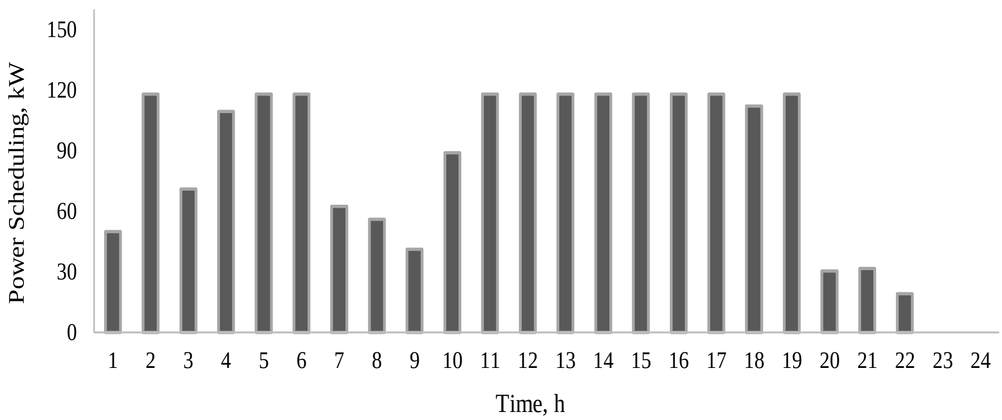

Figure 4. Power scheduling for swapping EV batteries at the BSS.

The scheduling of the BSS for demand response provisions was determined by using the proposed model, as shown in Figure 5. The downward demand response varied from one hour to another based on the number of EV arrivals in each hour for battery swapping instead of battery charging, and this took place in hours [11–18] and hours [20–23] in order to reduce the peak BSS load and, thereby, reduce the peak system load. However, an upward demand response occurred during the off-peak times—hours [1–8]—as a result of charging the EV batteries during the early hours of the day for the swapping of EV batteries during the later hours of the day at the BSS. It is to be noted that there were no differences between the EV charging and battery-swapping services during the idle states, such as in hours 9 and 10.

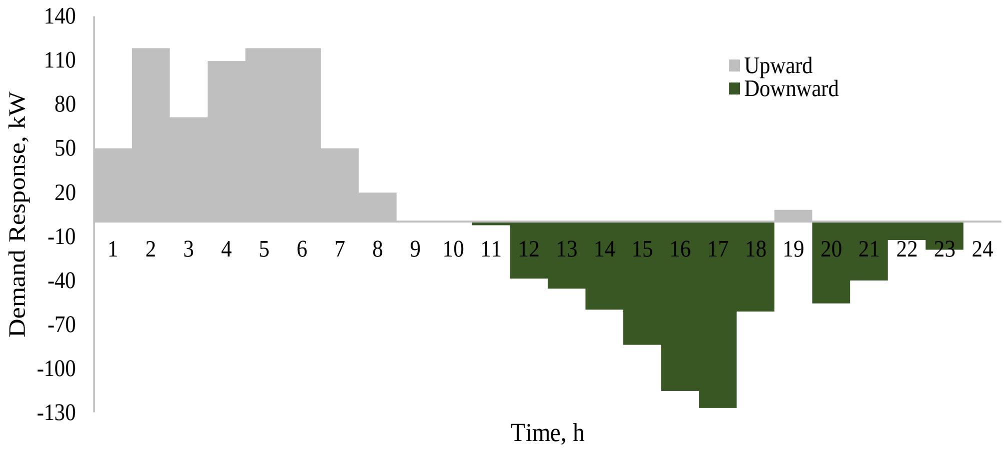

Figure 5. Demand response of the battery-swapping station.

5.2. A Comparison of Charging and Battery-Swapping Services

A battery-swapping service at the BSS was compared with a traditional EV charging station in terms of the peak load and operation cost, as presented in Table 1. The expected daily EV arrivals were 248 EVs, all of which were charged their batteries at the EV charging station, while they swapped their batteries at the BSS. It was observed that with a minimum number of 74 EV batteries in stock, the BSS station's peak load was 118 kW, while the peak load of the EV charging station was 245 kW. Hence, the peak station load was reduced by 48% when transforming the service from charging to battery swapping at the EV station. It was observed that providing the swapping service helped reduce the BSS's operation cost with respect to that of the charging service as a result of reducing the peak BSS load, charging the EV batteries during periods with off-peak prices, and avoiding charging them during periods with on-peak prices.

Table 1. EV station's operation cost and peak load.

Type of EV Stations	Charging Station	Battery Swapping Station
Charged EV Batteries	248	-
Swapped EV Batteries	-	248
Station Peak Load (kW)	245	118
Annual Operation Cost of Station ($)	94,109	82,580

Figure 6 shows the EV load profiles of the BSS and the traditional EV charging station, and it can be observed that their load profile shapes were significantly different from each other. It is clear that the battery-swapping service helped reduces the peak station load and flatten the EV loads.

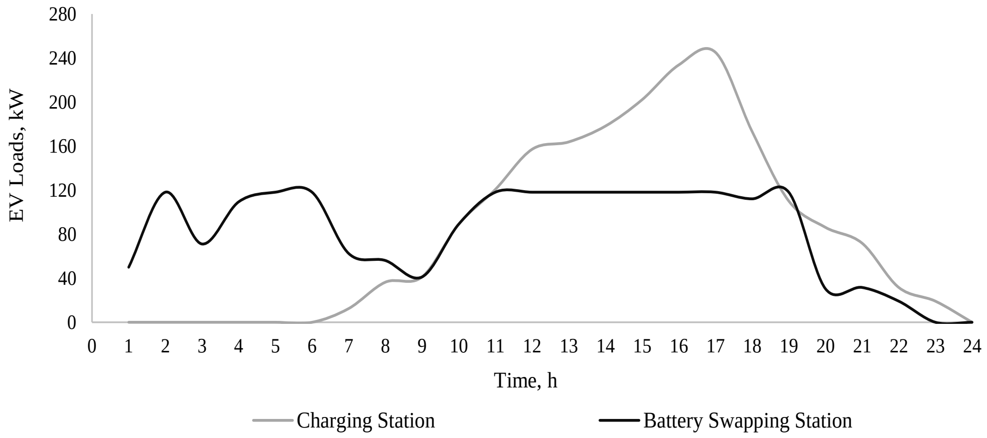

Figure 6. EV load profiles of the charging and battery-swapping stations.

5.3. *Effects of BSS Loads on the Distribution System's Loading and Capacity*

This section presents the effects of having multiple EV stations of different types serving the EVs on the distribution system's loading (Figure 7), system capacity (Figure 8), and peak load (Figure 9). It was observed that the system load (Figure 7) and the power of the substation (Figure 8) in the case of the BSS were higher during off-peak hours, while they were lower during on-peak hours. In contrast, those of the EV station were higher during the on-peak hours and lower during the off-peak hours; hence, this impacted the distribution system's operations and increased its peak load. The peak system load when the distribution system included charging stations was found to be 4.75, whereas having the BSSs in the distribution system reduced the peak system load (Figure 9) to about 4.22 MW. The power imported by the substation increased when including EV charging stations in the system, as shown in Figure 8. It can be concluded that the BSSs helped reduce the system's load, the peak load, and the power imported by the distribution substation, thereby deferring the need for system upgrades.

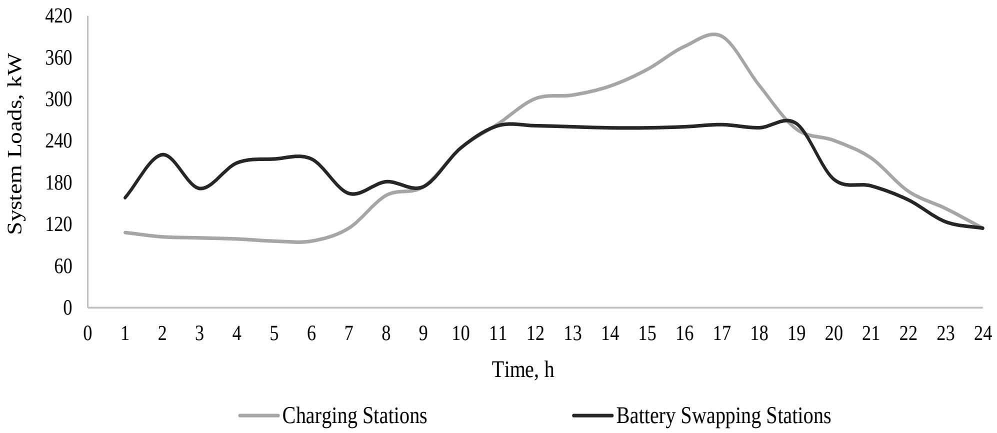

Figure 7. The distribution system's load at location 31 considering charging and battery-swapping stations.

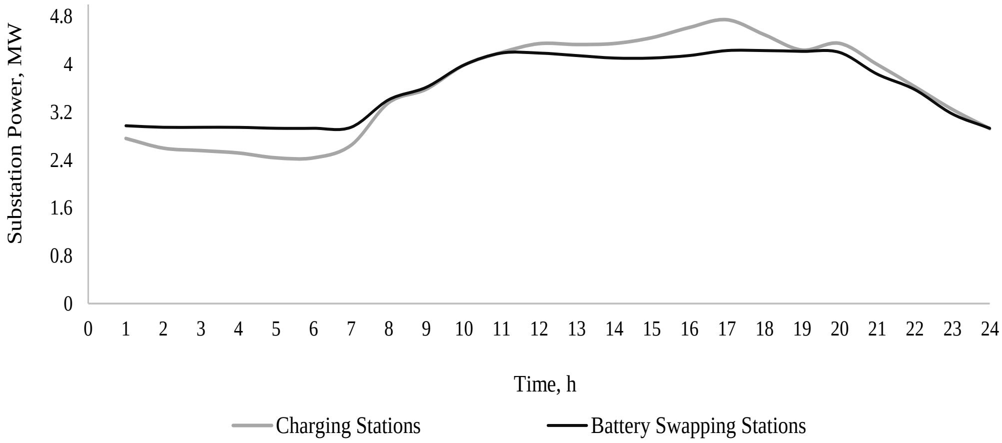

Figure 8. The power of the distribution substation at location 1 with charging and battery-swapping stations.

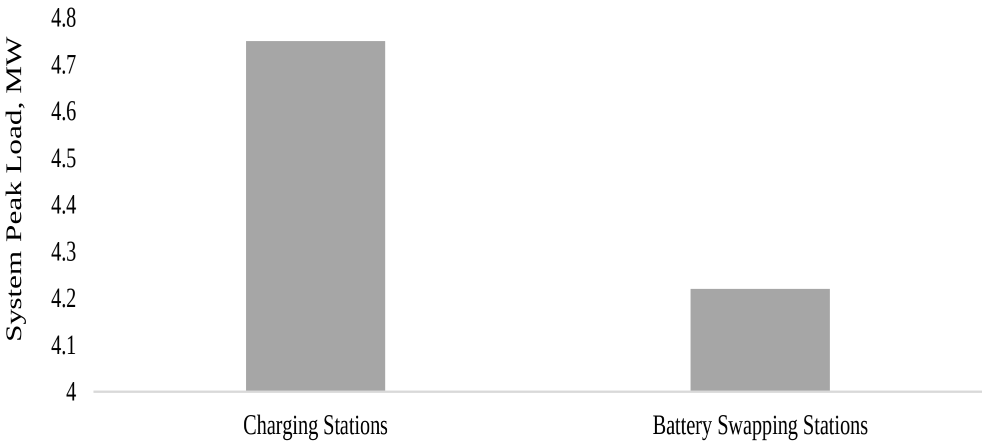

Figure 9. The distribution system's peak load considering charging and battery-swapping stations.

6. Conclusions

The paper presented a new mathematical model for the optimal scheduling for swapping EV batteries at a BSS for demand response provisions in distribution systems. The proposed model also determined the minimum number of EV batteries in stock for the system stability of the BSS, thereby avoiding unserved EVs. The BSS's load was compared with a charging station's load in terms of peak reduction and operation costs to demonstrate the effectiveness of transforming from charging into battery-swapping services at an EV station. The minimum number of EV batteries in stock was found to be 30% of the daily EV arrivals, which would result in a 48% reduction in the peak station load. The BSS helped reduce the peak system load and, thereby, deferred the need for system upgrades.

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