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Assessment of Distribution System Margins Considering Battery Swapping Stations

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Abstract: Penetration of electric vehicles (EVs) into the market is expected to be significant in the near future, leading to an significant increase in EV charging demand, and that will create a surge in the demand for electrical energy. In this context, there is a need to find intelligent and cost effective means to make better use of electricity resources, improve the system flexibility, and slow the growth in demand. Therefore, swapping EV batteries rather than traditionally charging them can serve as flexible sources to provide capacity support for the power distribution grid when they are charged during off-peak periods prior to their swapping at the station. This paper presents a novel mathematical optimization model to assess distribution system margins considering different EV charging infrastructures. The proposed model maximizes the distribution system margins while considering the flexibility of battery swapping station loads and distribution grid limitations. To demonstrate the effectiveness of the proposed model, simulation results that consider the National Household Travel Survey data and a 32-bus distribution system are reported and discussed. Unlike charging EV batteries, swapping them would not affect system margins during the peak hours.

Keywords: battery swapping; flexibility; loading margin; mathematical model

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1. Introduction

The range and cost reduction of electric vehicles (EV) batteries have improved due to recent developments in its battery technology [1]. Electrifying the transportation sector will make the power and transport systems interdependent, and the increasing demand for EVs and their associated charging facilities will affect the distribution networks with increased peak load, increased losses, deterioration in voltage profile and change in load pattern. To mitigate these system issues, EV charging loads must be controlled while also considering customer preferences. However, EV rapid charging loads are inflexible and uncontrolled because of the very short stay of EVs at the charging station. In view of this, a battery swapping station (BSS) is considered as an alternative way of controlling EV charging loads at the charging station.

The BSS is a charging method, and currently, in operation in some Chinese cities, to serve personal vehicles, commercial vehicles and buses [2]. But, there are still problems preventing the wide-scale implementation of BSS, including the concern of battery ownership, standardization of batteries and the swapping process and safety [3]. Nevertheless, EV owners are open to the idea of using BSS according to [3,4], and it is therefore reasonable to assume, in the near future, they will be, a BSS serving EV arrivals.

With an increase in the EVs deployment to preserve the environment and reduce carbon emissions, the pressure on the power grid has significantly increased, which requires controlling the EVs charging process to reduce the increased system peak loads and the price of electrical energy. Controlling EV charging loads also helps in avoiding large waiting time for EV users at the charging stations. Recent developments in the BSS along with its futuristic perspectives on peak management were provided in [5], and it was highlighted that the BSS can be smartly coordinated with the power grid in such a way that the peak grid load is minimized. A linear programming model was developed in [6] to maximize the daily operation profit of a BSS while taking into account the BSS demand of users and the charging and discharging balance of batteries in the BSS. The problem of locating a BSS for electric buses on a passenger bus traffic network was studied in [7], with an objective of minimizing the number of stations needed. In [8], an optimization model was proposed for the BSS operating model considers the day-ahead scheduling process, so as to inform stakeholders on the design and operation of BSS stations, allowing market decisions that can exploit storage capabilities of the BSS. A method was proposed in [9] to maximize the net present value over the life cycle of the project while optimally planning of EV stations, especially BSSs, in the distribution system, including locations, sizes, and charging strategies of the BSS. Grid integration of a BSS considering battery charging strategies and renewable energy integration with the BSS were reviewed in [10]. A framework was developed in [11] to optimally determine the location of the EV charging among BSSs in the distribution system and the priority charging of the depleted batteries in each BSS. The optimal charging schedule in terms of cost and network constraints was obtained, and the load profile was levelled. In [12], a strategy was proposed to use the BSS in reducing the power outage loss and enhancing resilience of offshore-island renewable distribution systems. The results indicated that when the BSS participated in the gird power regulation, the system restoration cost reduced. In [13], a framework was proposed for improving the economy and reliability of the distribution network using a grid connected BSS with vehicle-to-grid (V2G). The results revealed that when the V2G of the BSS was exploited and managed in an orderly manner, the net profit of the network was increased by 11.97%, and the system expected energy not supplied was decreased by 14.34%. The impact of charging station loads on distribution systems was studied in [14], and a solution was presented to mitigate the effects of these loads and enhance distribution grid capability by planning and operating the charging station as a smart energy microhub.

As EV charging stations are typically located along a highway to support long trips for EVs, they can coordinate with a wind generation farm and help mitigate wind power imbalances, particularly when the EV charging station are equipped with energy resources. Hence, a mathematical optimization framework was proposed in [15] to study the technical feasibility and viability of flexibility provisions from the EV charging station equipped with energy resources in wind integrated power grids. The developed framework determined the optimal design of the EV charging station with energy resources that provided upward and downward flexibility for mitigating wind power imbalances. It was revealed that, from the perspective of a wind generation farm owner, it was economical to invest in the design of an EV charging station with energy resources and avoid such penalties when wind imbalance penalties were high. On the other hand, it required high flexibility service prices to encourage an EV charging station owner to design its facility with energy resources to provide flexibility service to the gird to mitigate wind power imbalances. A Monte Carlo model was developed in [16] to study the service capability and profitability of the charging station and the BSS for taxis and buses. For the charging service provider, it was found that the BSS generally had more long-term economic benefits than the EV charging station. The authors of [17] developed a simulation model that took into account factors influencing charging behaviors and thereby estimated the EV charging demand under various circumstances. The simulation results facilitated a process of identifying optimal locations of EV charging station while maximizing the utilization of the charging infrastructure. An energy management framework was proposed in [18] for participating a BSS in the day ahead and real-time markets and ancillary services. A forecasting method was selected to incorporate the dynamicity of energy price and penetration of EVs loads in the developed framework. A detailed review on EVs control structures in charging stations, management and optimization methodologies for charging and discharging EVs in energy systems, was provided in [19]. A bi-level optimal dispatching model was developed in [20] for a community integrated energy system with an EV charging station in multi-stakeholder scenarios. The upper level of the developed model minimized the operating costs of the energy system while the lower level determined the least operating costs of the charging station. This model was also used to coordinate flexible loads with renewable generations uncertainties. The authors of developed [21] a planning model for swapping EV battery centralized charging station based on EV spatial-temporal load forecasting. An urban distribution system was considered to examine the effectiveness of the developed model using several case studies. Reddy et al. [22] developed an EV control strategy to achieve flat load profile and voltage regulation using EV's storage capacity in a distribution network. Utility and EV owner benefits through maximization of EV usage and customer revenue, were considered while scheduling EVs for grid support. Zeng et al. [23] developed a bi-level model that captured strategic decision making by EV owners, to optimize the design of an charging station with distributed energy resources. The upper level of the model determined the optimal configuration of the station and pricing schemes, whereas the lower level captured charging decisions by EV owners. In [24], an optimization model was developed to charge EV batteries in a BSS by assigning an optimized charging schedule for each incoming battery, with an objective of minimizing the BSS' operation cost. In [25], a cooperative operation approach was developed for a BSS, a EV charging station, and a group of residential buildings in a microgrid to minimize their operation costs, while trading electricity and carbon allowance in the central and local markets. The authors of [26] developed a framework for BSS planning in a centralized charging mode. It was noted that the power consumption of the station would be concentrated at certain times when high rates were used to charge the batteries at the a central charging station.

The concept of the Fuzzy with multiple criteria decision making method was used in [27] for determining the optimal location of BSS. An evaluation system was established based on existing research and literature, and different criteria from economic, technical, and social aspects were considered for location selection of the BSS. In [28], some problems of the modern economy associated with making decisions under uncertainty are analyzed based on the theory of approximations, which may be applied to the EV charging process since the charging behavior of EVs is dependent on a number of factors and their overall charging demand tends to be uncertain. In [29], a simulation model was developed to analyze the economics of the BSS, considering real data of different BSSs in Guangzhou, China. It was found that when the number of users increased, the service levels of the BSSs were notably reduced. An electric vehicle routing problem was studied in [30], while taking into account the constraints on battery life and battery swapping stations. It was concluded that carbon emissions and total logistics delivery cost could be reduced by a routing arrangement that accounted for power consumption and travel time. The authors of [31] presented a battery swapping-charging system in which EV batteries were centrally charged at charging stations and then delivered via truck to BSS, so as to provide battery swapping services and support local EVs in large cities. It was computationally demanding to consider each EV as a single entity for providing an optimal charging rate for every hour because of large size of decision variables involved when considering a significant number of charging loads. Hence, a combined state of charge based methodology was developed in [32] to estimate the aggregated EV charging loads while minimizing the computational time and memory requirements by reducing the number of decision variables involved.

A day-ahead scheduling of a battery swapping and charging system for EVs, from a perspective of multiple decision makers, was studied in [33]. The battery swapping and charging processes were locally incorporated in the battery swapping and charging system, and were managed by a battery swapping operator responsible for receiving and serving the battery swapping requested from EV users, and a battery charging operator responsible for interacting with the power grid and controlled battery charging and discharging power. An EV battery management system, based on a blockchain technology, was presented in [34], to create a semi-decentralized network of EV and charging stations to share data of battery information and condition, with continuous monitoring. A layered decomposition model was proposed in [35] for considering decisions made by the main stakeholders in coordinating power transfers and assessing charging facility ratios. By using this coordinated management of EV charging facilities, a policy guide was provided for the ratio assessment of EV charging facilities, and demand-side management capability was demonstrated. When it comes to the management of EV charging facilities, an optimal management decision can be obtained based on a combination of an iterative randomized search algorithm, genetic algorithms and expert evaluation of linguistic variables and establishing a rank sequence of promising solutions [36]. In order to combine the operation of battery charging and swapping systems, a hybrid swapped battery charging and logistics dispatch model in continuous time domain was developed in [37]. By using this model, low operation costs were achieved by optimizing the departure time of each vehicle. In [38], a queuing network model was developed to obtain an optimal charging operation policy for a battery swapping and charging station to minimize its charging cost while ensuring its quality-of-service. It was concluded that the number of chargers in the station had an a notable impact in reducing the average charging cost when the system was operated under quality-of-service-guaranteed optimal policies.

From the aforementioned literature review, there are no reported works that take into account both the assessment of distribution system margins considering different EV charging infrastructures, namely EV rapid charging stations and the BSS. This paper therefore proposes a novel mathematical optimization model that maximizes distribution system loading margins while determining an optimal charging of EV swapping batteries at the BSS, with taking into account distribution grid limitations. In an earlier work [39], the author studied the impact of demand response provisions from the BSS on load flattening and capacity enhancement of a distribution system. The work in [39] is extended here to mathematically and optimally quantify the system loading margins considering different infrastructures of EV stations. The main contributions of the work presented in this paper, are as follows:

- Consideration of different EV charging infrastructures in the assessment of a distribution system capacity to accommodate EVs loads.
- Proposes a novel mathematical optimization model to maximize the distribution system margins, with taking into account the flexibility of the BSS loads and distribution grid limitations.
- Investigate whether the flexibility of BSS defers the need for system upgrades while accommodating EV loads in the distribution system.

The rest of the paper is organized as follows: Section 2 presents the proposed mathematical optimization model, followed by the test system and input data in Section 3. Numerical analysis and discussions are presented in Section 4. Conclusions are drawn in Section 5.

2. Proposed Mathematical Optimization Model

A new mathematical optimization model is proposed, with an objective of maximizing the distribution system loading margin while determining the optimal scheduling of BSS loads, with taking into account distribution system operations' constraints.

$$Max \sum_{s=1}^{n} LM_s \tag{1}$$

Power Flow Equations: The power injected at the substation bus and net of the load are constrained by traditional power flow equations.

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

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

EV Swapping Batteries State of Charge (SOC):

$$SOC_{a,s,h+1} = SOC_{a,s,h} + P_{a,s,h}^{BSS}\eta\Delta t - \lambda_{a,s,h}BS_{a,s} \qquad \forall a, \forall s, \forall h \tag{4}$$

$$SOC_{a,s,h} \le \gamma_{a,s}\sum_{h}\lambda_{a,s,h}\ \ BS_{a,s} \qquad \forall a, \forall s, \forall h \tag{5}$$

Availability of EV Batteries for Battery Swapping: This constraint determines the hourly available number of swapping EV batteries.

$$\beta_{a,s,h} = SOC_{a,s,h}/BS_{a,s} \qquad i\forall N, \forall h \tag{6}$$

Also, the arrived EVs for battery swapping does not exceed the available swapping batteries of EVs at the station.

$$\lambda_{a,s,h} \leqslant \beta_{a,s,h} \tag{7}$$

Limits of Feeder Capacity: The feeder capacity constraint ensures that the power flow through any distribution feeder is limited, as follows:

$$-V_{i,k}^2Y_{i,j}\cos\theta_{i,j} + V_{i,h}V_{j,h}Y_{i,j}\cos(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \leqslant S_{(i,j)}^{Fcap}cos\theta_{(i,j),h}^{F} \qquad \forall(i,j) \in N : \exists(i,j), \forall h \tag{8}$$

$$V_{i,h}^2Y_{i,j}\sin\theta_{i,j} - V_{i,h}V_{j,h}Y_{i,j}\sin(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \leqslant S_{(i,j)}^{Fcap}sin\theta_{(i,j),h}^{F} \qquad \forall(i,j) \in N : \exists(i,j), \forall h \tag{9}$$

Substation Capacity Limits: The constraint ensures the capacity substation is within its limit, given as.

$$(P_{u,h}^{Sub})^2 + (Q_{u,h}^{Sub})^2 \leqslant S_u^{Sub^{cap}2} \qquad \forall h \tag{10}$$

Limits on Voltage: The limit of the bus voltage is included, as follows:

$$\underline{V} \leqslant V_{i,h} \leqslant \overline{V} \qquad i\forall N, \forall h \tag{11}$$

3. Test System and Input Data

The well-known 32 bus radial distribution system presented in [40] is employed in this study, as shown in Figure 1. The system peak demand is 4 MW, with a base voltage of 12.66 kV. Profiles of the system loads are from the IEEE Reliability Test System [41], and it is also assumed that all loads to be residential loads. To calculate the number of houses at each bus, the house peak load is assumed to be 2.08 kW [42]. Four arbitrarily locations for the EV stations are selected in this study, which are locations-12, -20, -23 and -30; the system load profiles for two of which are shown in Figure 2. Considering the penetration level of EVs [14], number of houses, and average number of vehicles per household, the number of electric vehicles in the system is determined.

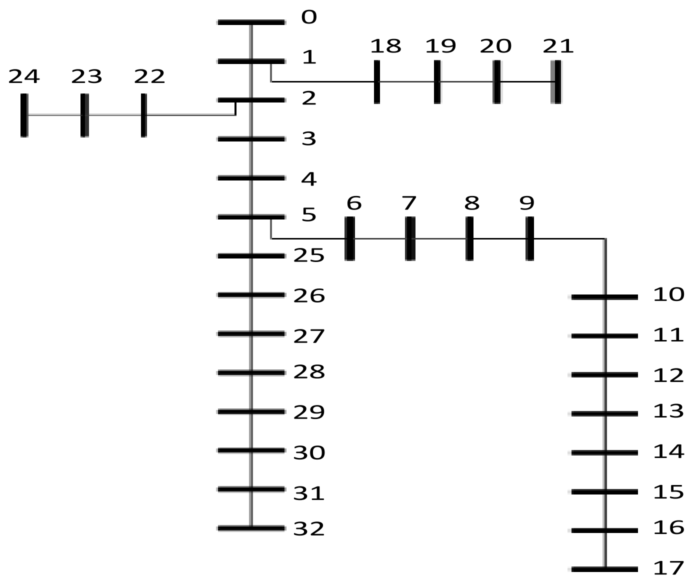

Figure 1. 32-bus distribution system.

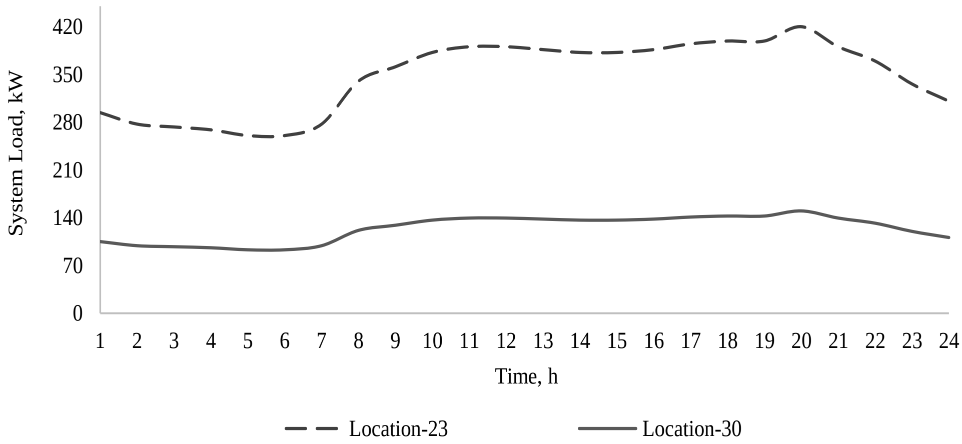

Figure 2. Distribution system load at locations-23 and -30.

The daily behavior of drivers (e.g., traveled distances, and number and times of trips) must be considered in modeling the arrival rate of EVs at the BSS. A detailed transportation data, i.e., the National Household Travel Survey (NHTS) data [43] is used to infer the main features pertaining to the driver behavior. The distribution of trip distances, the time-of-day distribution of the trips, and the number of trips associated with each vehicle are extracted from [43], to be used for predicting the arrival times for EVs at the BSS. A developed method in [44], is adopted in this work to track trip information for each vehicle and determine the arrival time for each EV at the BSS. The SOC of an EV is checked considering its distance-driven mileage for each trip, and when the vehicle depletes the entire SOC window, either the begin time or the finish time of that trip is recorded For instance, the begin time of that trip will be recorded for a battery swapping when the EV depletes its SOC before finishing the trip. However, the finish time of that trip is instead recorded if the trip is completed prior to depletion, which helps to avoid trip interruptions. Hence, using this method, the arrival rate of EVs is predcited at the BSS, as shown in Figure 3, considering a mix of 30% EV20 vehicles, 40% EV40 vehicles, and 30% EV60 vehicles.

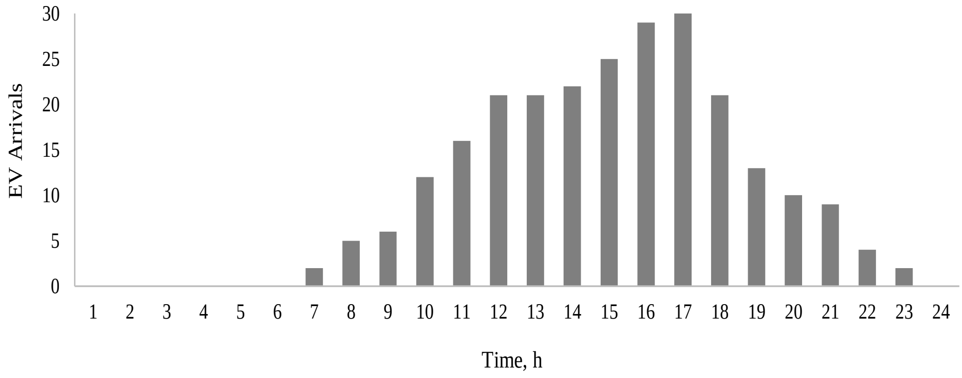

Figure 3. EV arrival rate within a typical day.

To describe the overall process of charging multiple EVs served at an EV station, queuing theory is thereafter employed. The EV loads of charging station are estimated using the method developed in [44]. For a detailed explanation and discussion of modeling EV loads using a battery charging service, the reader may refer to [44].

4. Results and Discussion

The system loading margin is used to measure the ability of the distribution system to meet any future daily required energy, considering distribution grid limitations. If the system margin becomes very low or zero, it is an indication that the distribution system would not be able to accommodate any new loads, such as EV loads, and hence the local distribution company must upgrade the distribution grid. On the other hand, when the system margin is high, then the grid is able to withstand any new loads and thereby accommodate EV loads. Using the proposed model, the optimal system margin is firstly determined without including any types of EV stations, as shown in Figure 4 for locations-23 and 30, respectively. It is observed that, in both locations, the system margin varies from one hour to another, and it decreases during the peak hours, such as hour-20. The system loading margin at location-30 is lower than that of location-23 during most of the day hours and mainly during the peak hour, hour-20, due to the fact that the location-30 is far away from the substation, and is affected by the feeders capacity limits, voltage limits, and/or substation capacity limits. In view of this, there is a need to improve the system margin, mainly during the peak hours, or at least avoiding the occurrence of additional loads at those hours, so as to defer the need for system upgrades.

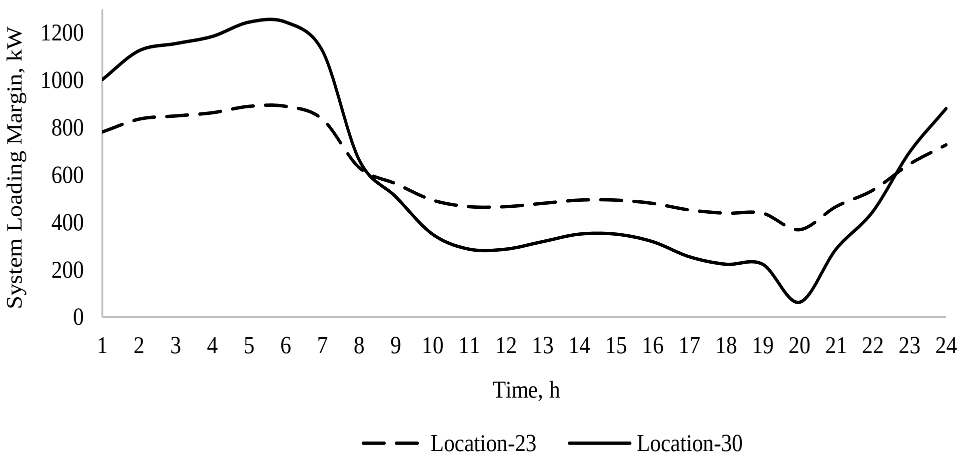

Figure 4. Optimal system margin of different locations without EV station loads.

The effects of EV battery charging and swapping services on distribution system margins are examined using the proposed mathematical model, as presented in Figures 5 and 6, respectively, considering different locations.

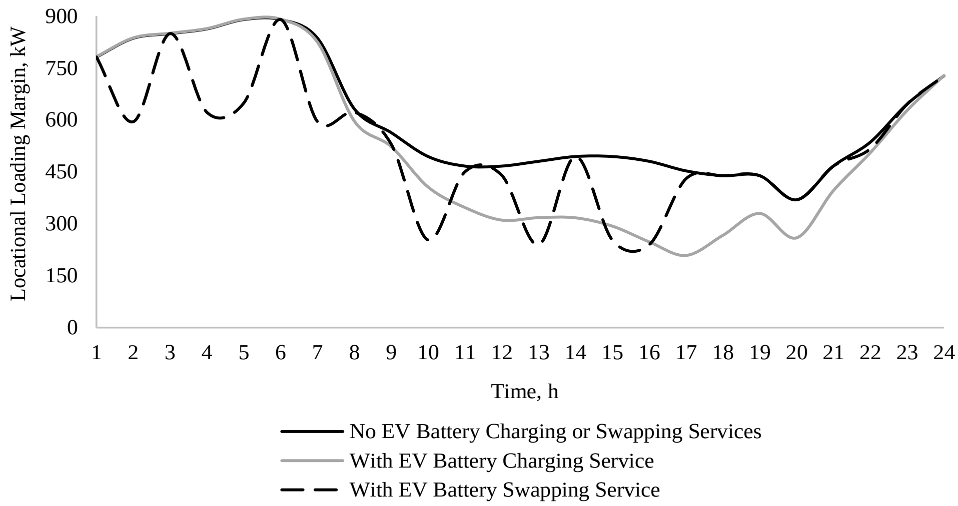

Figure 5. Optimal system margin at location-23, considering EV battery charging and swapping services.

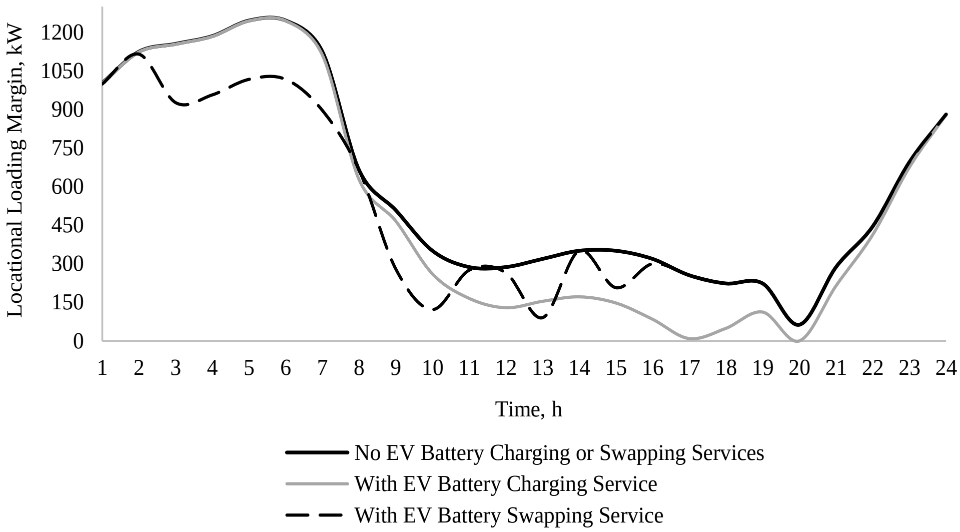

Figure 6. Optimal system margin at location-30, considering EV battery charging and swapping services.

It is noted that the EV charging battery service decreases the system margin during off-peak and on-peak hours, and at location-30, the system margin reaches zero during the peak hour, hour-20. On the other hand, the EV battery swapping service decreases the system margin during off-peak hours, while it remains the same during peak hours. This demonstrates that the flexibility of the BSS would help defer the need to upgrade the system components to accommodate the EV loads, thereby avoiding a high financial burden on the local distribution company.

Figures 7–9 present the optimal power charging of EV20, EV40, and EV60 batteries, for battery swapping, respectively. The power charging varies from one location to another based on both the types of EV swapping batteries and distribution system operations' limits.

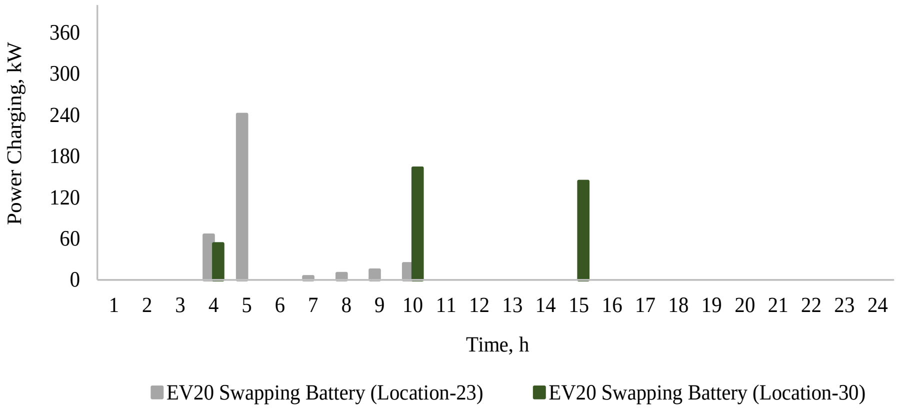

Figure 7. Optimal power charging of EV20 swapping batteries considering different locations.

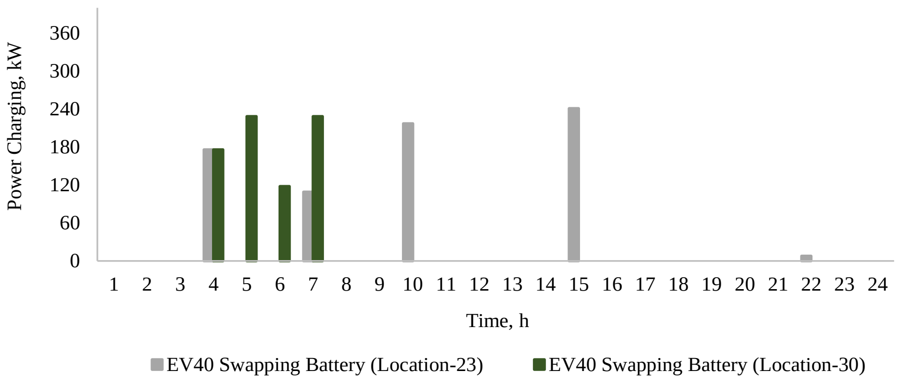

Figure 8. Optimal power charging of EV40 swapping batteries considering different locations.

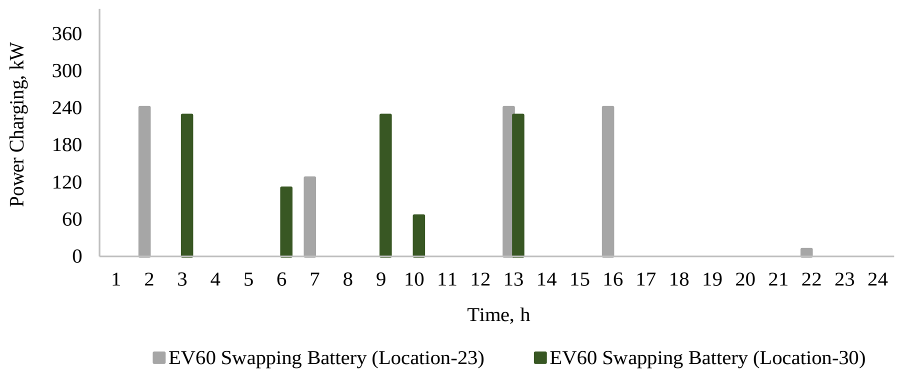

Figure 9. Optimal power charging of EV60 swapping batteries considering different locations.

It is observed that the power charging of EV swapping batteries takes place during off-peak hours, so as to avoid reducing system loading margin during the peak hours. It is noted that a battery capacity type of EVs would affect the frequency and magnitude of the power charging of swapping batteries. Hence, the power charging is frequent and higher for swapping batteries of EVs with larger battery capacities, and vice versa.

Load profiles of different infrastructures of EV stations are shown in Figures 10 and 11. The EV charging station is considered to be identical at both locations, and therefore they have the same load profile, while the BSS loads are different at theses location as they are optimally scheduled for maximizing the distribution system margin, considering distribution grid technical operations' limits. There is no occurrence of EV loads at the BSS after hour 16 at location-30, to avoid reducing the system margin, whereas the fast charging station has no control over its charging loads, which often coincide with the system peak load, and that further reduces the system margin. It can be concluded that the flexibility of the BSS in scheduling its loads would not affect the distribution system margin, mainly during the peak hours, thereby deferring the need for system upgrades.

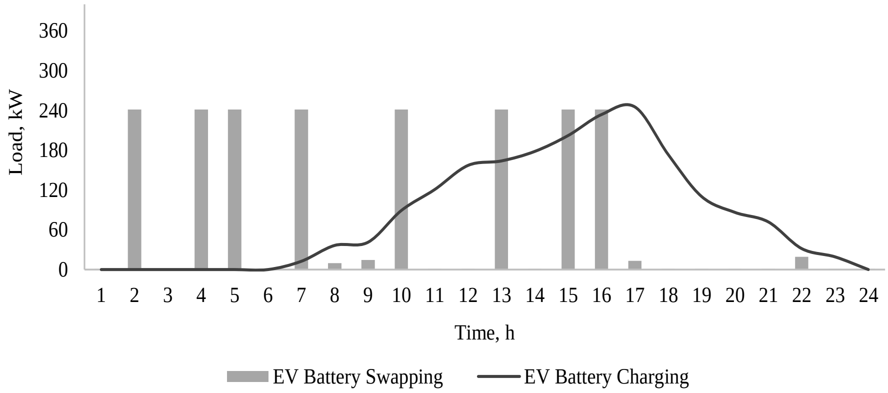

Figure 10. EV charging station and BSS loads at location-23.

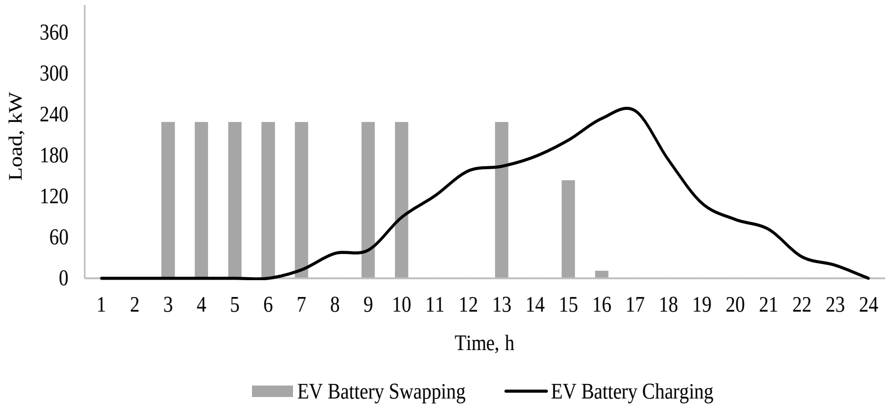

Figure 11. EV Charging station and BSS loads at location-30.

5. Conclusions

The paper assessed distribution system margins considering battery swapping stations. A new mathematical model was proposed to quantify the power flexibility of BSS for maximizing system margins, while accommodating EV loads considering distribution grid limitations. Case studies along with numerical results were presented to demonstrate the performance of the proposed model. Different types of EV batteries were considered for battery swapping at the BSS. Using the proposed model, the optimal system margin was obtained without including any EV station infrastructure. Load profiles of different infrastructures of EV stations were determined, and the BSS load was compared with the charging station load in the assessment of distribution system margins. It was observed that the optimal power charging of EV swapping batteries varied from one location to another based on both the types of EV swapping batteries and the distribution system operations' constraints. Furthermore, the power charging was frequent and higher for swapping batteries of EVs with larger battery capacities, and vice versa. It was noted that the power charging of EV swapping batteries took place during off-peak hours, so as to avoid decreasing the system margins during the peak hours. It can be concluded that the EV charging station load deceased the distribution system margins during both on-peak and off-peak periods, whereas the BSS loads decreased the system margin during off-peak hours only, which can defer the need for system upgrades, thereby avoiding a high financial burden on the local distribution company. Last but not least, the battery swapping for EV batteries at the BSS takes a shorter time with respect to battery charging of EVs at the charging station, that takes a long time to charge. Equipping a rooftop photovoltaic generation with the BSS and its impact on enhancing the capacity of a distribution system will be considered and studied in future work.

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Abbreviations

The following abbreviations are used in this manuscript:

i, j	Buses, $i, j \varepsilon N$
h	Time, $h \varepsilon H$
u	Location of distribution substation, $u \varepsilon U$
s	Location of charging stations, $s \varepsilon S$
a	Type of EV swapping batteries
Δt	Duration time, hour
λ	Hourly arrival rate of EVs
η	Charging efficiency, %
Pd	Active load of a distribution system, p.u.
Qd	Reactive load of a distribution system, p.u.
γ	Number of EV swapping batteries in stock for each type
BS	EV swapped battery energy capacity
LM	Locational loading margin, p.u.
P^{Sub}, Q^{Sub}	Active and reactive power drawn, p.u.
P^{BSS}	Power charging of EV swapping batteries, p.u.
P^F, Q^F	Feeder active and reactive power flow, p.u.
SOC	State of charge of swapping batteries, p.u.
V	Voltage magnitude, p.u.
δ	Voltage phase angle, rad

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