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Research Article

Resilience-Oriented Scheduling of Shared Autonomous Electric Vehicles: A Cooperation Framework for Electrical Distribution Networks and Transportation Sector

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As autonomous electric vehicles and car-sharing services are becoming more popular, the contribution of shared autonomous electric vehicles (SAEVs) to the future of urban transportation is getting more achievable. Like conventional electric vehicles, SAEVs can provide power grids with ancillary services. This article proposes a new scheduling scheme for SAEV fleets within a cooperative plan to let power distribution networks benefit from the energy storage of vehicle batteries in recovering critical loads after a predictable extreme event. According to a long-term contract, the detailed request of the distribution system operator (DSO), together with desired constraints and perquisites, is sent to the SAEVs aggregator (SA) prior to the landfall of a predictable extreme event. Afterward, SA runs a targeted algorithm to schedule trip assignments and charging cycles of SAEVs so that the required constraints of DSO are satisfied. The SAEV participants will continue carrying passengers within the scheduled time horizon in addition to delivering energy to the distribution network at the scheduling deadline declared by DSO. This deadline is the time instant when the capacity of the SAEV fleet may be no more applicable to enhance the system preparedness against the approaching event. Numerical results illustrated that the proposed scheme helps improve the power grid resilience by delivering 2396.1 kWh of energy to the distribution network in addition to increasing the total income of each participant SAEV by about 130%. Thus, it is implied that the proposed method offers a win-win situation for both entities.

1. Introduction

Climate change has turned out as a worldwide concern caused by greenhouse gas (GHG) emissions mainly due to the transportation sector, in particular, fossil-fuel-powered internal combustion engine vehicles (ICEVs) [1–3]. To alleviate this concern, governments have announced strict deadlines to replace ICEVs with electric vehicles (EVs). For instance, the European Union (EU) has introduced a plan to ban the sale of ICEVs by 2035 [4–7]. These policies have encouraged the automotive industry to invest in EVs, as it is reported that it will spend at least $ 300 billion over the next ten years to develop EVs [8]. Therefore, electric vehicles and related issues have received increasing attention in recent years. Among evolving EV types, Automated Electric Vehicles (AEVs) have attracted more attention since they employ artificial intelligence (AI) technology to improve service quality and driving flexibility. According to the

Society of Automotive Engineers, the level of car automation is graded from 0 to 5. The more the level of automation, the less the need for a driver to control the car. Ideally, vehicle automation of level 5 introduces a driverless vehicle [9–11]. In this regard, the automation revolution in the transportation sector has opened the door to a wide variety of applications. For instance, in [12], a new public transit (PT) system comprised of autonomous modular PT (AMPT) vehicles is introduced. In the modular service operation, the vehicle consists of smaller modular units/pods, which can be assembled/dissembled at some specially designed transit stations. This work focuses on accurately estimating the minimum number of vehicle modules required to perform a set of scheduled services. On this matter, another work in [13] aims to minimize the operator and passengers' total cost while determining the station's location and capacity and the maximum number of modular units to provide an optimal operation for future transit service systems with modular vehicles. Another potential application of automation in the transportation sector is Platoon operations that can affect energy consumption, elevate roadway capacity, and enhance traffic safety. This new emerging concept can potentially improve the efficiency of future transportation [14, 15].

As one of the most important applications of AEVs, a new type of urban transportation called car-sharing service has become popular recently. Among various companies providing car-sharing services, Uber and Lyft could be mentioned. Car-sharing service includes the shared use of a vehicle for traveling to a predefined destination while the car owner gets paid for providing this service [16, 17]. In such transportation services, the service aggregator runs a cost/profit optimization problem to schedule a fleet of shared electric vehicles (SEV) based on travel request data and vehicles' status. A group of researchers has presented fleet optimization models regarding technical considerations of Charging/Discharging Stations (CDSs) and parking lots [18–24]. References [25–28] have proposed a predictive fleet optimization model based on travel demand forecast data. References [29–31] have analyzed fleet size, pricing strategies, and fare level impacts to give detailed insight, which helps fit appropriate SEVs for a designated city or region. The modeling framework of car-sharing services is basically summarized in two categories, namely, first, modeling the car-sharing system with a single agent/aggregator [18–27, 29, 30]; second, modeling the car-sharing system with multiple agents/aggregators [32–35]. However, to avoid complexity and focus on the paper's main aim, a single aggregator model is presented in this work.

Recent advances in electric vehicle charging technology presented a solution for the long-standing challenge of EVs' slow charging. With Tesla's new generation chargers, Supercharger V3, EVs can be driven around 180 miles with a 15-minute charging process [36]. Such advances in charger and battery technology have accelerated the inevitable transition from ICEVs to EVs [37]. In this regard, car-sharing service companies have recently extended associated projects to electrify their fleets. For instance, Revel is launching the first all-electric fleet of car-sharing services [38]. In addition, two major companies, Lyft and Uber, have incentivized drivers and owners to electrify their vehicles. On the other hand, some governments and organizations have imposed strict restrictions on ICEVs [39], which in turn will lead to the faster growth of EVs for car-sharing services in the near future.

Regarding the concepts of AEVs and SEVs, a new concept called Shared Autonomous Electric Vehicle (SAEV) has been introduced, which is expected to significantly contribute to urban transportation. Similar to SEVs, the main function of SAEVs is to give service to passengers as a car-sharing service; however, the autonomous technology, along with real-time connection with fleet aggregators, enabled the operators to investigate the further application of this concept. Commercial companies such as Uber and Lyft have no control over their fleet members' charge/discharge process; moreover, the trips are assigned to the fleet members just in favor of the vehicle owner with no regard to the major objectives of the whole fleet. However, with the concept of SAEV, the fleet aggregator can coordinate the entire fleet concerning the real-time condition and primary objectives. Like conventional EVs, an important potential of SAEVs is the ability to deliver the electrical energy stored in their batteries to the power grid, called V2G capability. This feature of SAEVs can provide the power system with various ancillary services such as peak shaving [40–42], demand response [43, 44], mitigating renewables generation variability and intermittency [45, 46], voltage, and frequency regulation [47–52]. In addition, SAVEs can help distribution networks in emergency conditions to make the grid more resilient. In recent years, high-impact, low-probability (HILP) events have been happening more frequently due to global climate change [53, 54]. For instance, in 2022, Hurricane Ian caused widespread damage across western Cuba and the southeast United States. Heavy rainfall and flooding resulted in a nationwide power outage and severe damage to the infrastructure. It is reported that Hurricane Ian raised over $100 billion in economic losses [55]. The purpose of resilience-enhancement actions is to make the system bend rather than break in the face of HILP events [56]. The temporal performance of a power system against a HILP event is sketched in Figure 1. The system performance indicator is one of the key elements in each system which provides valuable information about the status of the system function. Supplied load, supplied critical load, and the number of connected customers have been selected as the performance indicator in resilience studies of power systems. The main purpose of the DSO in the proposed cooperative contract with the SAEV aggregator is to provide an additional source of energy to supply electrical loads at the event landfall as much as possible. Thus, the amount of supplied electrical load is mainly meant by the authors as the system performance indicator in Figure 2. In the avoidance phase, the system operator tries to identify potential risks and take proactive measures to lessen the effects of the upcoming event accordingly. Proactive measures may either include planning-oriented actions, such as hardening the assets, or short-term operation-oriented actions taken as the event alert is declared, such as increasing the scheduled energy reserves. In the survival phase, corrective measures help the system absorb the external shocks imposed by the HILP event. Finally, the system performance is rapidly recovered by adopting appropriate measures in the restoration phase [57]. In this work, at the avoidance phase, the proposed model tries to increase the system energy reserve by increasing the electricity stored in each SAEV before the event landfall while considering the SAEV fleet profits. It is evident that the distribution system with a higher level of energy reserve and enhanced preparedness will react to the HILP event more efficiently, resulting in a higher level of system resilience. However, the detailed resilience assessment indexes and measures of the electricity network side are out of the scope of this paper.

Therefore, using the potential of SAEVs' fleet battery can be helpful to recover the power grid more rapidly after catastrophic HILP events such as extreme floods, windstorms, typhoons, and earthquakes. In this regard, [58] proposed a model to investigate the potential of shared autonomous electric vehicles (SAEVs) for improving the self-sufficiency and resilience of solar-powered urban Microgrids (MGs). The results demonstrated that depending on the SAEV fleet size, the MG self-sufficiency could be improved by up to 8.85%. However, this work merely concentrated on the benefit of the SAEV fleet for the power system, while the rescheduling of the transportation side, regarding the cooperation with the power grid, was ignored.

Relying on the intrinsic application of SAEV fleets in the transportation system for carrying passengers, several research works have been published that exclusively aim to optimally manage the SAEV fleet and transportation infrastructure so that the total fleet revenue is maximized. For instance, in [59], a single-stage decision-making framework has been designed and implemented to facilitate the operational performance of integrated fleet management. Results demonstrated that the proposed framework would result in substantially more responded ride requests and, consequently, more revenue. In addition, other potential benefits can be reached under different SAEV fleet sizes and charging downtime. Reference [60] proposed a neural network approach in which the SAEV fleet aggregator optimizes trip pricing and EV dispatching decisions dynamically to maximize the SAEV fleet revenue. Authors in [61] proposed a two-stage stochastic integer program to improve the system profit. In the first stage, the long-term charging facility deployment at the planning level (e.g., the sizing and configurations of charging facilities) is determined. In the second stage, the vehicle assignment, relocation, and charging decisions in the short-term are also optimized at the operational level. Numerical results showed that the proposed model could also increase the system's profit and improve its operational performance. Reference [62] utilized a deep learning-based algorithm to predict the optimal solution for idle vehicle relocation problems under various traffic conditions. The results demonstrated that the proposed strategy could drastically reduce operational costs and wait times for on-demand services.

As illustrated in Figure 3, considering the literature review on SAEV fleets, it can be concluded that there is a research gap for rescheduling the SAEV fleets regarding the limitations imposed on the transportation system by the electricity distribution network within the cooperation scheme. As illustrated in Figure 3, the recently published works focused on either the transportation side or power system infrastructure independently to highlight the SAEVs revenue while no cooperation between the two systems is studied. To fulfill this research gap, this paper presents a new scheme for the targeted scheduling of a fleet of SAEVs in cooperation with distribution networks in extreme conditions caused by HILP events. The proposed scheme introduces a new application of SAEVs to improve power grid resilience.

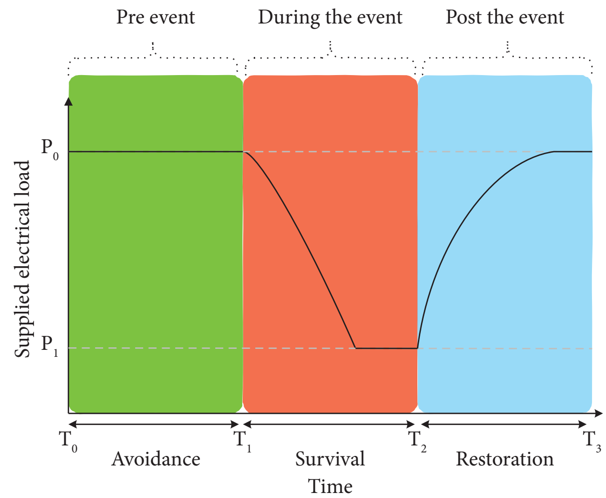

Figure 1: The temporal performance of a power system against an HILP event and the scope of this work (green area).

In this regard, a prior contract is signed by the DSO and the SA to benefit from the energy stored in vehicle batteries in exchange for a designated payment ahead of a predicted extreme HILP event. Accordingly, several constraints and perquisites are declared by DSO for the SAEV owners willing to participate in the cooperation a few hours ahead of the upcoming event. These constraints include the minimum cumulative energy storage required, the minimum state-of-charge (SOC) and discharge power rate of SAEVs, the location of CDS, and the deadline at which SAEVs are allowed to be present at the CDS. These constraints are basically extracted from the resilience-oriented proactive scheduling of the distribution system under the predicted contingency to enhance the system preparedness against the upcoming event, which is out of the scope of this paper. From the declaration of required constraints, the SAEVs aggregator runs a targeted algorithm to schedule the SAEV participants for passenger carrying and charging cycles so that the required constraints of DSO are satisfied. It will be shown via numerical simulations that the total income of each participant SAEV, including the income from carrying passengers and the income earned from energy delivery to CDS, is higher than that of other SAEVs. On the other hand, SAEV participants play an influential role in promoting resilience and rapid recovery of critical loads of the distribution system and earning more income compared with other SAEVs not involved in the contract.

The main contributions of this paper are listed as follows:

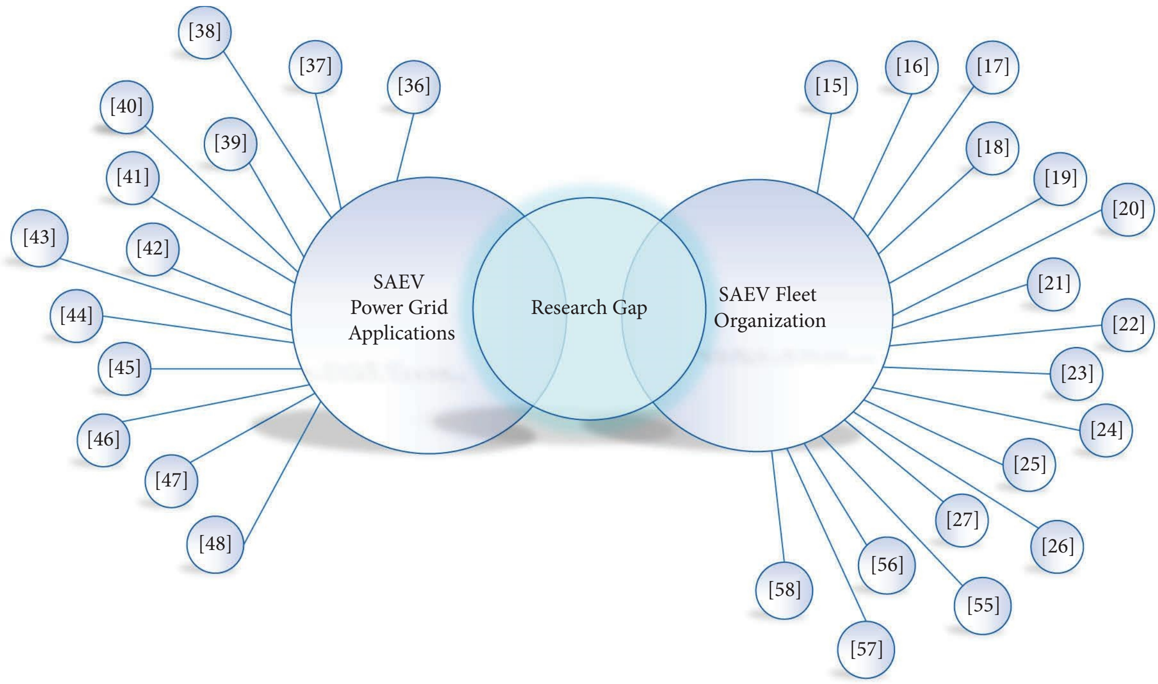

Figure 2: Literature review summary and research gap.

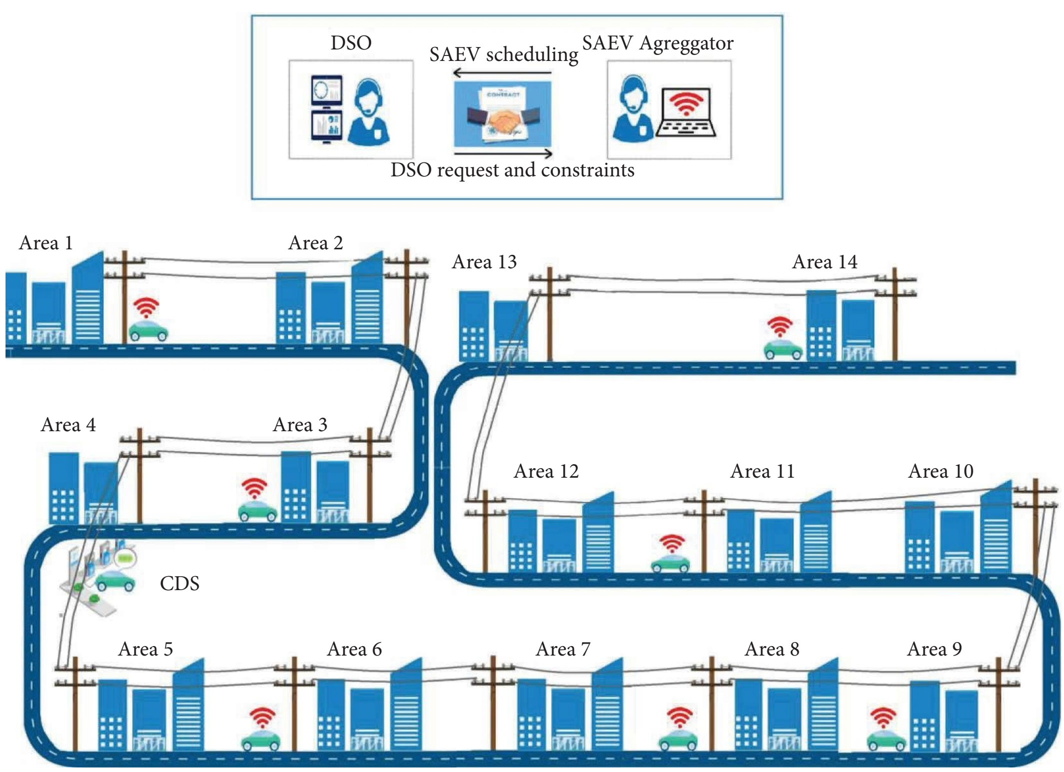

Figure 3: Conceptual schematic of the proposed methodology.

(i) Presenting a scheduling scheme for SAEV fleets considering joint transportation system revenue and power system resilience considerations.

(ii) Presenting concepts and paradigms of the potential application of SAEVs in resilience enhancement of distribution networks.

(iii) Proposing a new model for optimal scheduling of SAEVs concerning distribution network resilience considerations.

(iv) Tackling the stochastic parameters of the scheduling scheme by employing a Monte Carlo-based simulation algorithm and random values for uncertain parameters.

The rest of the paper is organized as follows: The proposed methodology is described in detail in Section 2. Numerical results and discussions are presented in Sections 3 and 4 to show the model's validity and efficiency. The sensitivity analysis is presented in Section 5. Finally, conclusive remarks are given in Section 6.

2. Materials and Methods

As the alert for the upcoming HILP event is declared a few hours ahead of the incidence, DSO runs a damage assessment analysis to find out the distribution system load supply performance under the predicted contingency. Proactive measures are then accordingly taken to enhance the system preparedness prior to the event's landfall. Among possible measures, the potential of SAEV batteries introduces a portable energy source for restoring critical loads post the event. This potential can be realized in practice through a mutual cooperation between DSO and SAEV aggregators. In this regard, relying on the results of the damage assessment analysis and the set of scheduled proactive measures, DSO determines the following constraints for the SAEV aggregator: (I) minimum cumulative energy storage required, (II) the minimum desired SOC and discharge power rate of SAEV participants, (III) the location of CDS, and (IV) the deadline at which SAEVs are allowed to be present at the CDS. It is noted that the damage assessment analysis of the distribution system is not within the scope of this paper, while the focus will be on the SAEV scheduling considering the DSO constraints. As depicted in Figure 4, relying on a long-term contract between DSO and the SAEV aggregator, the required negotiations will be made prior to the event to implement the contract.

The SAEV participants will continue carrying passengers in the scheduling time horizon in addition to delivering energy to the CDS at the deadline. The SAEVs will be paid for energy delivery based on a predefined fee close to the interruption cost of critical loads in the distribution system. In addition, they are paid for carrying passengers according to transportation tariffs. Thus, the primary purpose of the proposed model is to schedule trips and the charging/discharging of SAEV participants under the constraints received from the DSO. It is noted that the CDS shown in Figure 4 is a bidirectional charging/discharging point capable of supporting the grid-to-vehicle (G2V) mode as a charging station and the vehicle-to-grid (V2G) operation mode.

Moreover, the concept of car-sharing service implemented in this work is based on the one-way car-sharing framework [63]. In this framework, after assigning the trip request driver, drives through a trip origin to pick up the passenger and drop them off at the defined destination in the trip request. The common trip assignment used for the one-way car-sharing framework is the dynamic trip assignment [64]. In this method, contrary to first-come and first-serve method, the SAEV fleet moves on a road network, and trip requests arrive continuously.

The problem of dispatching SAEV fleets with dynamic trip assignments includes nonlinearity and numerous binary and nonbinary variables which makes it an NP-hard problemþ.þ In addition, the time-consuming process of optimization methods for NP-hard problems makes it rather impossible to exchange data within an acceptable time interval in SAEV scheduling problems [64–66]. Hence, in this work, a concise heuristic algorithm is considered to avoid complexity and focus on the main goals of the proposed model.

The chronological timeline of the proposed model is comprised of two phases as depicted in Figure 5. In the passenger delivery phase, by running the heuristic algorithm at $T = 0$, the SAEV aggregator dispatches the SAEV fleet considering joint transportation system revenue and power system considerations. In this regard, the SAEV participants will continue carrying passengers within the scheduled time horizon. However, as the energy delivery phase starts at the scheduling time horizon T_H, all SAEV participants are on standby in the CDS to deliver the stored energy to the distribution system.

As illustrated in Figure 5, the proposed framework for SAEV scheduling comprises three stages as follows: (1) data entry, (2) SAEV charge management and (3) SAEV trip assignment. The detailed procedure of the proposed model is illustrated in this figure and will be discussed in the following part: It is noted that stages 2 and 3 are repeated for all SAEVs. In this figure, the grey area describes the Monte Carlo simulation process. In order to randomize the initial parameters of SAEVs and trip requests, a Monte Carlo simulation is run for each case. Each iteration starts with a random initial value of SOC and location for SAEVs. In the next step, the three stages of the scheduling process are executed based on the randomized data entry; while having checked the iteration number, if the number reaches the predefined value of simulation samples, the simulation ends.

2.1. Data Entry. The trip request data, including trip origin/destination and trip fee, are sent to SA and updated at predefined time instances. Moreover, SA acquires needed information from DSO and SAEVs. In addition to contract constraints received from DSO, SA receives SAEVs parameters, including initial SOC, initial location, battery technical characteristics, and initial working state. It is noted that working states include 0, 1, and 2, indicating free, charging, and on a trip, respectively.

2.2. SAEV Charge Management. The main purpose of this stage is to recognize the working states of SAEVs so that they can be scheduled accordingly. In this regard, for each time slot within the scheduling horizon, $T \leq T_H$, the SAEV

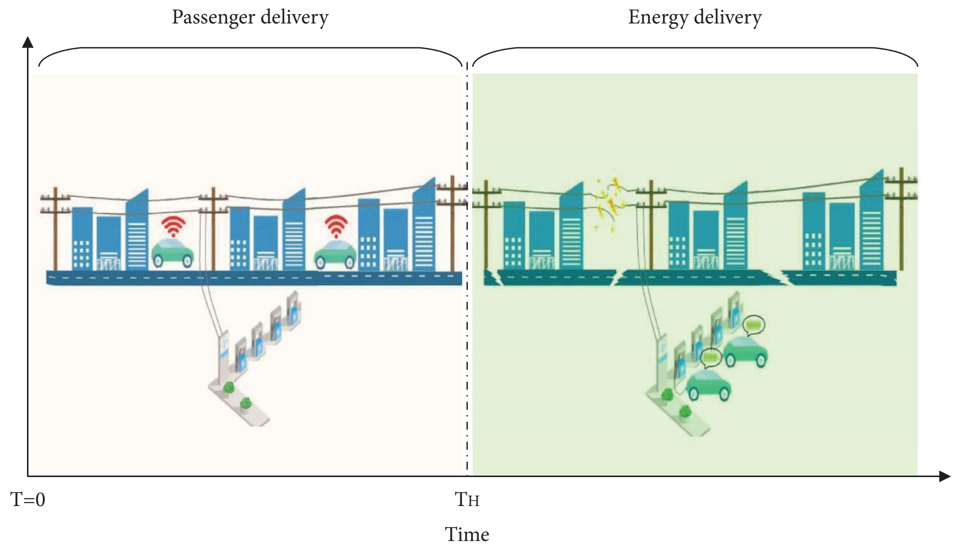

Figure 4: The chronological timeline of the proposed model.

parameters are first updated. Then, the working state of each SAEV is checked to recognize if the SAEV state is free ($S = 0$). If the SAEV state is free, then the SOC is checked to ensure that it is greater than the minimum technical level as shown as follows:

$$\mathrm{SOC} \geq \mathrm{SOC}_{\min}^{\mathrm{tec}}. \tag{1}$$

If SOC is lower than the minimum level, the SAEV is sent to the charging station and the SAEV state is set to 1 ($S = 1$). The SAEV can be either fully or partially charged according to the scheduling requirements. Otherwise, if SOC is greater than the minimum level, the SAEV could be considered for possible trip assignment in stage 3.

In addition to the minimum technical level, another critical constraint should be monitored in each time slot so that the desired minimum level of SOC declared by the DSO is guaranteed at the end of the scheduling horizon for each SAEV. In this regard, the potential level of SOC (SOC_p) at the end of the scheduling horizon is calculated for each time step as shown as follows:

$$\mathrm{SOC}_p = \mathrm{SOC}_a + \delta_e. \tag{2}$$

In this equation, (SOC_a) is the level of SOC at the arrival to CDS if the SAEV is instantly assigned to make a hypothetical trip to CDS. Moreover, (δ_e) denotes the SOC increment if the SAEV is charged from the hypothetical arrival till the end of the scheduling horizon. Then, the potential level of SOC is bounded to the minimum desired level declared by DSO and the maximum technical level of the battery as shown as follows:

$$\mathrm{SOC}_{\min}^{\mathrm{DSO}} \leq \mathrm{SOC}_p \leq \mathrm{SOC}_{\max}^{\mathrm{tec}}. \tag{3}$$

If this constraint is satisfied, the SAEV is sent to CDS to participate in the contract, and the SAEV state is set to 1 ($S = 1$). Otherwise, if the constraint is not satisfied, the SAEV could be considered for trip assignment in stage 3.

2.3. SAEV Trip Assignment. The trip requests contain origin, destination, and trip fee, which are randomly generated for each SAEV. Hence, in this stage, all active trip requests are investigated to assign the most profitable set of trips satisfying the associated constraints. In this regard, the level of SOC at the end of the requested trip (SOC_h^m) is checked if it will be kept over the minimum technical level as shown as follows:

$$\mathrm{SOC}_h^m \geq \mathrm{SOC}_{\min}^{\mathrm{tec}}. \tag{4}$$

If the constraint is not satisfied, the trip request is ignored, and the algorithm checks the same constraint for the subsequent trip request. However, if the constraint is satisfied, the trip request is checked for an additional constraint for a possible trip assignment. In other words, it should be guaranteed that the SOC will be kept over the DSO desired minimum level by the end of the scheduling horizon if the trip request is assigned to the SAEV. In this regard, the hypothetical potential level of SOC (SOC_v^m) is defined as follows:

$$\mathrm{SOC}_v^m = \mathrm{SOC}_u^m + \delta_f^m, \tag{5}$$

where (SOC_u) is the hypothetical SOC level of SAEV at the arrival to CDS after an instant trip from the trip destination to CDS as shown as follows:

$$\mathrm{SOC}_u^m = \mathrm{SOC}^T - \left(\varphi_T^m + \varphi_a^m\right). \tag{6}$$

In addition, (δ_f^m) denotes the hypothetical amount of charge that the SAEV can receive if it instantly starts to get charged from the arrival to CDS till the end of the scheduling horizon as shown as follows:

$$\delta_f^m = \left(T_H - \left(T_d^m + T_a^m\right)\right) \times U. \tag{7}$$

To guarantee the DSO's desired minimum level of SOC at the end of the scheduling horizon, the following constraint should be satisfied:

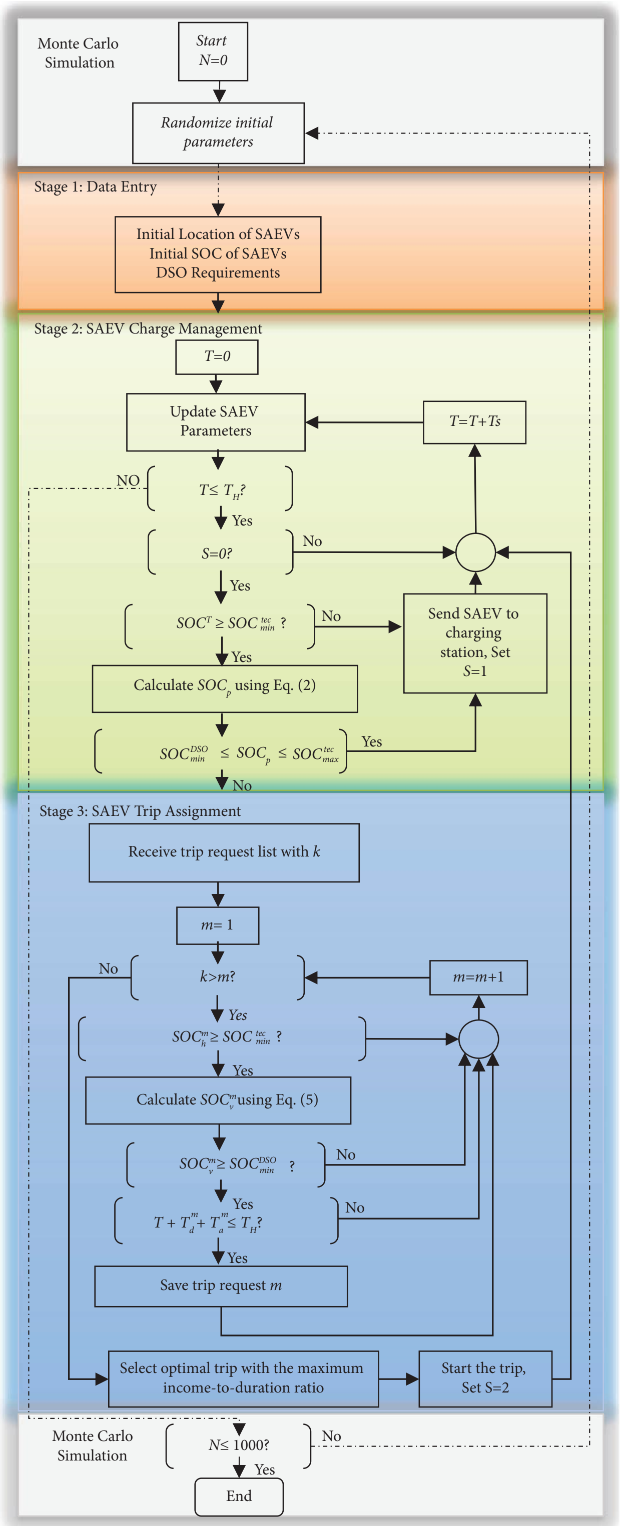

Figure 5: Detailed algorithm of the three-stage proposed model.

$$\mathrm{SOC}_v^m \geq \mathrm{SOC}_{\min}^{\mathrm{DSO}}. \tag{8}$$

The trip request is passed to the next constraint only if constraint (9) is satisfied; otherwise, the request is ignored, and the algorithm will check other trip requests for this constraint.

In order to make sure that the SAEV will be in the free state by the end of the scheduling time horizon, the following constraint should be satisfied:

$$T + T_d^m + T_a^m \leq T_H. \tag{9}$$

According to this constraint, considering the trip duration, T_d^m, and the hypothetical duration of instant travel from the trip destination to the CDS, T_{EDS}^m, the deadline of the scheduling horizon should be observed. If constraint (10) is not satisfied, the trip request is ignored, and the algorithm checks for the subsequent available trip request. Otherwise, the trip request is saved, and the algorithm is continued to check the next trip request. Having investigated all trip requests, the one with the highest income-to-duration ratio, $\max\{I^m/L^m\}$, is assigned to the SAEV. The algorithm is repeated for all SAEVs till the end of the time horizon.

3. Results

3.1. System Description. As illustrated in Figure 6, a minimal linear transportation network consisting of 14 areas is considered with a pairwise distance of 10 km between areas [67]. For the sake of simplicity, it is assumed that the trip request in each area is abundant, and therefore, the repositioning problem of car-sharing services is ignored in this study. The SAEVs can drive with a mean speed of 61.2 km/h through the network, and each area can be a possible origin or destination for a designated trip. Moreover, it is assumed that the targeted charging/discharging station of this work has enough capacity for SAEVs to connect. In this way, there is no concern about the charging behavior and relative constraints of other SAEVs and stations. In this model, each SAEV's balance in the program is composed of the sum of trip income and contract income subtracted by charging cost. Meticulously, the trip income is the predefined fee paid by the passenger after arriving at the destination, while the contract income is the fee paid to each participant of SAEV in the contract at the expense of delivering energy stored in the vehicle battery. The trip income for SAEVs is considered a standard normal distribution with an average of 0.2 \$/km and a standard deviation of ±0.013 \$/km to simulate real conditions. All SAEVs have a battery capacity of 50 kWh with a charge rate of 0.075 kWh/second and a power consumption rate (PCR) of 0.4 kWh/km. It is assumed that 4 hours prior to the event landfall, DSO receives the event prediction alert. Consequently, the request for activating the contract is instantly sent to SA by the DSO. The request details are summarized as follows: (I) Provision of at least 1 MWh energy storage from SAEVs fleet. (II) A deadline of 4 hours to provide the energy at CDS. (III) Payment fee of 2 \$/kWh for energy delivery to the distribution network. (IV) The minimum SOC level of 51 kWh or equivalently 85% at the deadline of the end of the scheduling horizon for each SAEV participating in the contract.

The following assumptions are applied to the model presented in this work:

(i) The HILP event landfall is predictable with an acceptable range of a few hours.

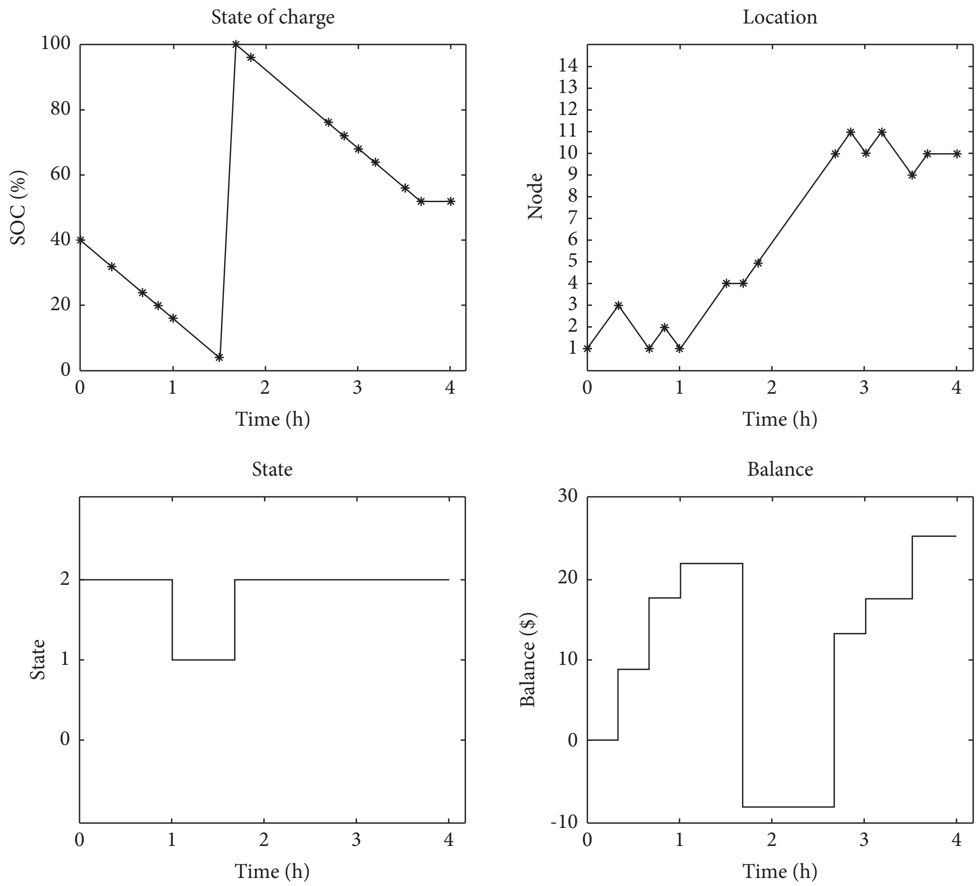

Figure 6: Parameters of a sample SAEV in case 0.

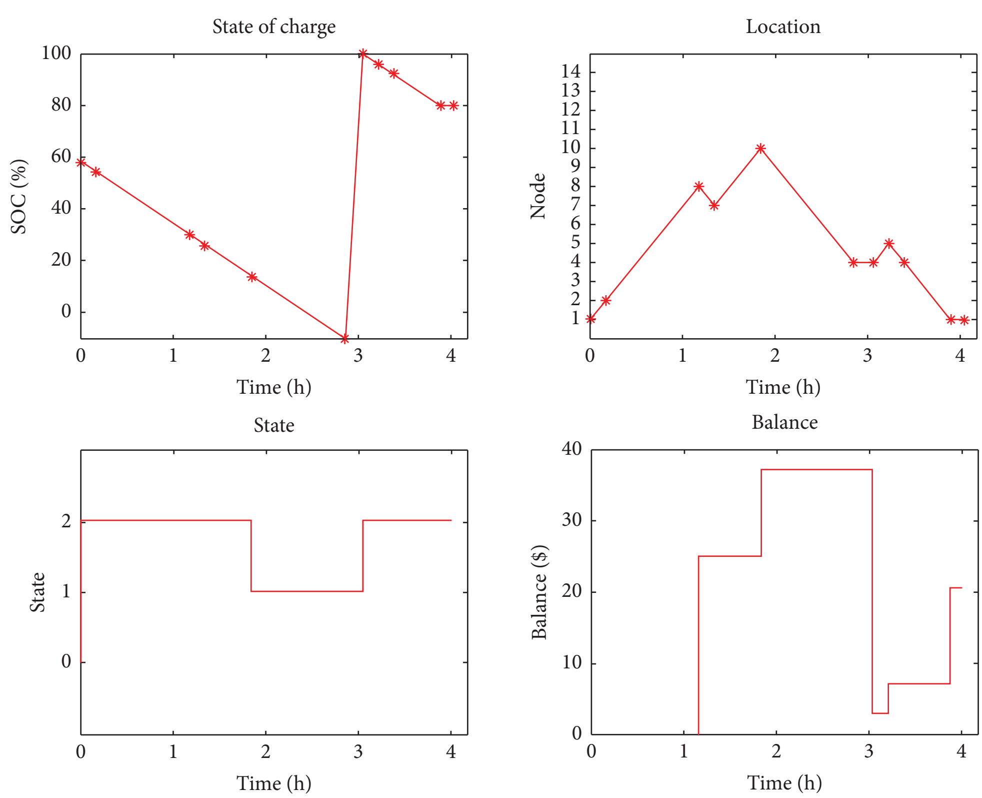

Figure 7: Parameters of a sample SAEV in case 1.

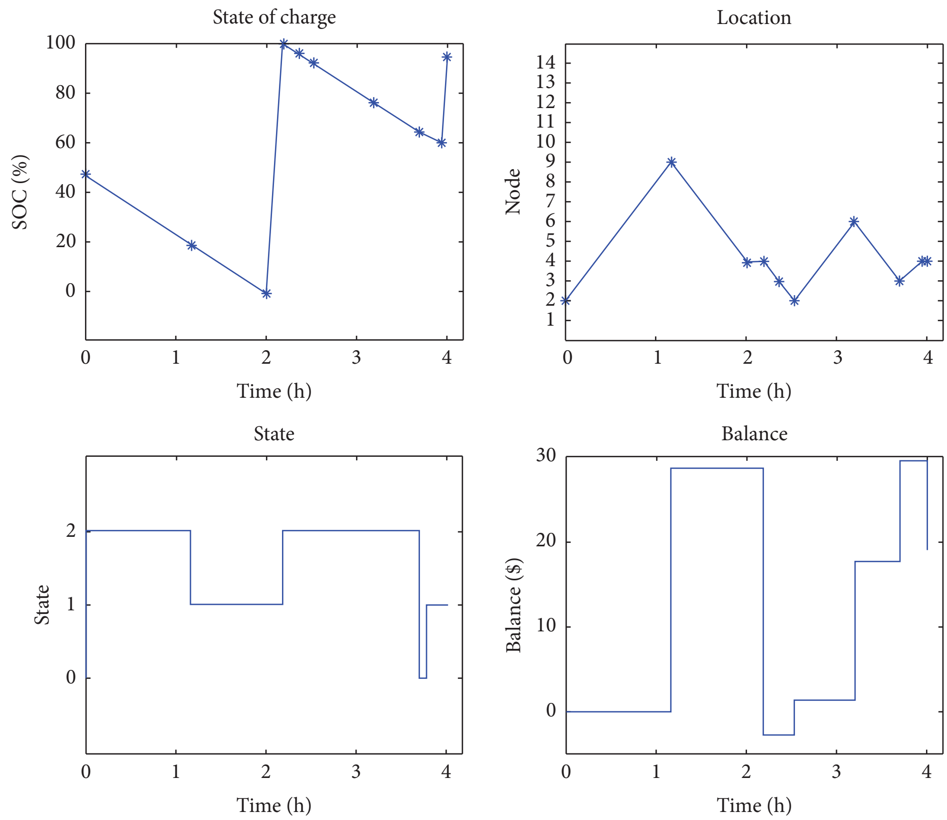

FIGURE 8: Parameters of a sample SAEV in case 2.

(ii) The implementation environment of the model is equipped with a robust protocol for uninterruptable communication between SAEVs, DSO, and the SAEV aggregator.

(iii) The CDS remains undamaged from the adverse impacts of the HILP event.

3.2. Case Studies. To verify the proposed methodology, three case studies were defined as follows:

(i) Case 0: A fleet of private nonautonomous conventional SEV, including 50 vehicles, is considered. It is noted that SEVs do not participate in the contract with the DSO.

(ii) Case 1: A fleet of SAEVs, including 50 vehicles, is considered. SAEVs are free to make trips or get charged with no attention to DSO constraints. In other words, SAEVs do not participate in the contract with the DSO.

(iii) Case 2: A fleet of SAEVs containing 50 vehicles is scheduled for participation in the contract.

In this section, the proposed model is demonstrated on a test system with an Intel i7-3840QM processor and 8 GB memory in MATLAB R2021a. The computation time for case 0, case 1, and case 2 is reported as 6.1, 7.2, and 15.3 seconds, respectively.

In this work, a Monte Carlo simulation is run with 1000 iterations to randomize the initial parameters of SAEVs and trip requests.

4. Discussion

Figures 7 and 8 illustrate the parameters of two sample SAEVs in cases 1 and 2. Regarding the SOC diagram, it is evident that there are two charging cycles for SAEVs in case 2. The former is related to the minimum technical level of SOC, and the latter is associated with the DSO's desired minimum level of SOC at the deadline. In contrast, the SOC diagram in case 1 has one charging cycle related to the minimum technical level of SOC. The location of SAEVs changes as they make a trip or travel to the charging station to get charged, as shown in Figures 8 and 9. Accordingly, the state of SAEVs varies between 0, 1, and 2. The SAEV balance varies according to its working state, meaning getting paid for making a trip increases the balance while paying for the battery charging decreases the balance. It is evident from the balance diagram of Figure 9 that the balance of the SAEV in case 2 decreases at the end of the scheduling horizon since it gets charged to increase the level of SOC so that the DSO-desired minimum level is satisfied.

Figure 9 illustrates Monte Carlo simulation results for a sample SAEV. Each dot in this 3-D diagram represents the result of an iteration of the simulation. As shown in this figure, the average trip income of case 1 is about 2.6% higher

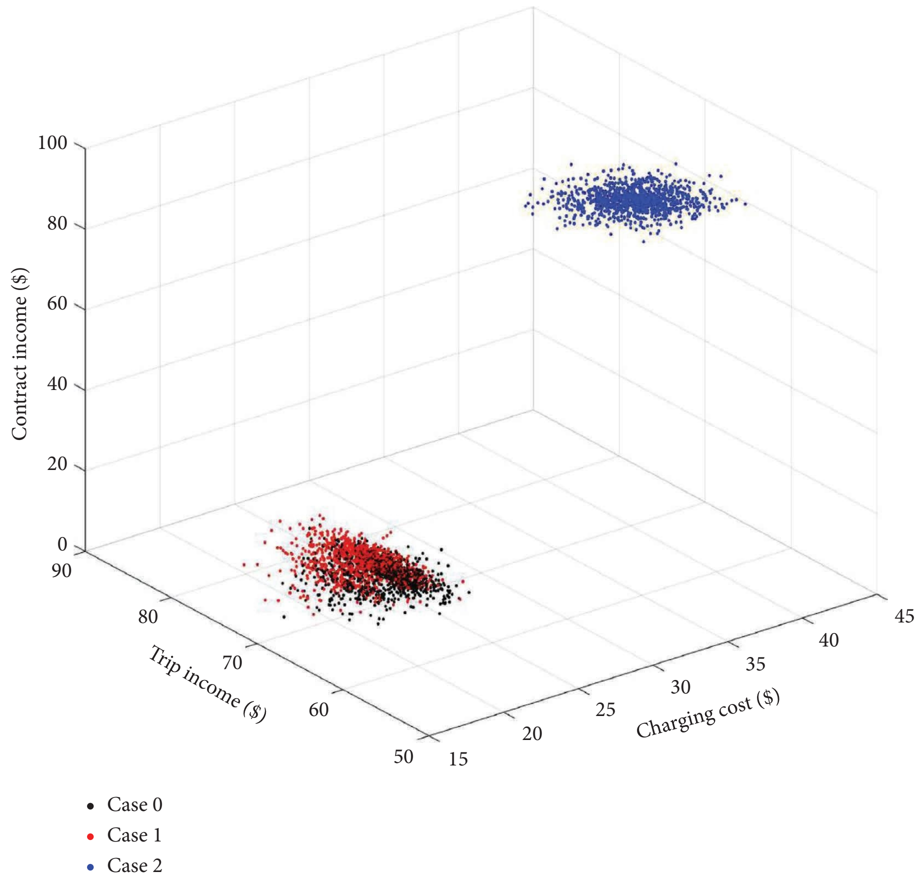

Figure 9: Monte Carlo simulation results for different case studies.

than case 0, since the automation level of vehicles in case 1 helps choose the most profitable trip request instantly while the private human-driven vehicles in case 0 lack this advantage resulting in lower trip income. SAEV parameters for case 2 are spotted in a confined zone with a higher charging cost and lower trip income compared to case 1. It is because SAEVs in case 2 are scheduled to satisfy the minimum desired level of SOC declared by the DSO in the contract. Thus, fewer trips are made, and more charging cycles are run. However, the SAEV in case 2 benefits from selling energy to DSO based on the contract, while the SAEV in case 1 has no income from the contract.

Figure 10illustrates a cost/benefit analysis for a sample SAEV. Accordingly, it can be implied for the SAEV in case 2 that the significant contract income compensates for higher charging costs and lower trip income compared to the SAEV in case 1. Thus, the net income earned by the SAEV in case 2 is higher than that of case 1. According to Figure 10, the net income in case 2 increased by about 130% compared to case 1, indicating the profitability of participation in the contract.

Regarding technical cooperation with the DSO, the SAEV fleet under study in case 2 delivers 2396.1 kWh of energy to the distribution network, which can help recover critical loads after the event's landfall.

Table 1presents values of the average, standard deviation, minimum, and maximum of the SAEV fleet parameters to give insight into the statistical distribution of numerical results. It is implied that the SAEV parameters lie within a narrow range of values maintaining the validity and applicability of the proposed scheduling method for all SAEVs.

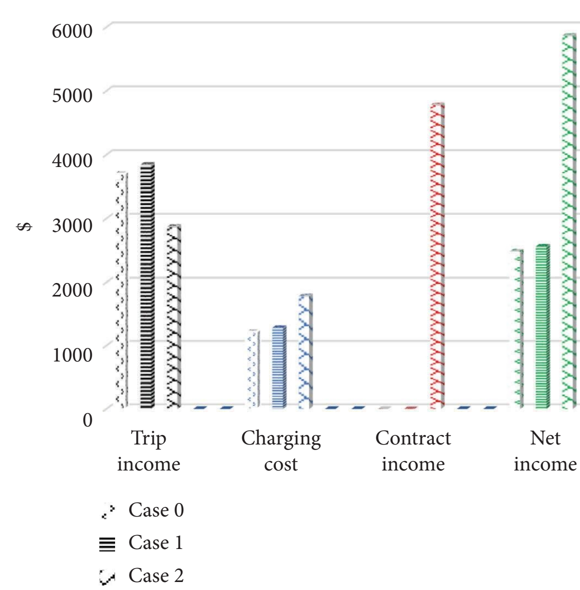

Figure 10: Cost/benefit analysis for different case studies.

Table 1: Statistical distribution of numerical results.

Cost type	Statistical parameter	Case 0	Case 1	Case 2
Trip income ($)	σ	2.33	2.51	2.12
	μ	73.6	76.2	61.5
	Min	65.1	66.27	55.19
	Max	81.4	75.6	61.2
Charging cost ($)	σ	1.54	1.32	1.73
	μ	25.4	25.5	35.3
	Min	18.13	18.73	29.86
	Max	30.11	25.5	35.5
Contract income ($)	σ	0	0	0.53
	μ	0	0	95.3
	Min	0	0	93.4
	Max	0	0	97.5
Net income ($)	σ	2.95	3.07	3.6
	μ	48.6	50.7	116.7
	Min	39.4	40.24	92.65
	Max	57.24	60.64	131.44

Table 2: Results of sensitivity analysis on the main SAEV parameters.

		Total income ($)	Delivered energy (kWh)
Fleet size	20	2360.2	955.4
	50	5928.8	2396.1
	100	11680.1	4805.8
Battery capacity (kWh)	30	3875.0	1438.0
	50	5928.8	2396.1
	70	7803.5	3350.6
Power consumption rate (kWh/100 km)	0.3	6447.8	2395.1
	0.4	5928.8	2396.1
	0.5	5442.7	2396.4

5. Sensitivity Analysis

In this work, sensitivity analysis is employed to assess the uncertainty of the SAEV parameters and their impacts on the total income and delivered energy of the scheduled SAEV fleet. In this regard, three main parameters, i.e., fleet size, battery capacity, and power consumption rate (PCR), are considered. As illustrated in Table 2, the fleet size directly affects the results. For instance, by a 150% increase in the fleet size from 20 vehicles to 50, the total income and delivered energy have increased by about 151.2% and 150.8%, respectively. However, with a 40% increase and reduction in the battery capacity, the delivered energy alters at the same rate while the total income changed by 31.6% and −34.6%, respectively. Moreover, the variation of the PCR with a percentage of 25% resulted in almost no change in the delivered energy. Finally, changing the PCR by 25% imposed an 8% variation in total income. Thus, it can be concluded that changes in the fleet size and battery capacity can majorly influence the model outcomes while the impact of PCR is negligible.

6. Conclusions

This paper proposes a new scheduling scheme for SAEV fleets within a cooperative contract to let distribution networks benefit from the energy storage of vehicle batteries in recovering critical loads after a predictable extreme event. The proposed method comprises three stages, namely, (i) data entry, (ii) SAEV charge management, and (iii) SAEV trip assignment. Once the adverse impacts of the predicted extreme event are analyzed, the DSO request for the required minimum energy storage, associated constraints on technical features of SAEVs, and the deadline for delivering energy are sent to SA. Then, SAEV participants are scheduled so that the DSO constraints are satisfied while the total income of each SAEV is enhanced. In order to verify the proposed methodology, three case studies were defined; (i) case 0 represented a fleet of human-driven SEVs, (ii) case 1 resembled a fleet of non-scheduled SAEVs that do not participate in the contract with the DSO, and (iii) case 2 indicated a fleet of scheduled SAEVs that participate in the contract with the DSO. Numerical simulations demonstrated that the average trip income of case 1 is about 2.6% higher than case 0 because an increment in the automation level of vehicles could result in trip income improvement. In case 2, the total income of each participant SAEV, including the income from carrying passengers and the income earned from energy delivery to the distribution network, increased by about 130% compared with other SAEVs. The scheduled SAEV fleet under study delivered 2396.1 kWh of energy to the distribution network, which plays an effective role in the rapid recovery of critical loads and enhancing the resilience of the distribution network. Moreover, a sensitivity analysis is implied to investigate the influence of the SAEV fleet's main parameters on the model outputs. In conclusion, the model presented in this work can be commercially developed as a software package. Obtaining the required data from real fleets, the software package can provide the SAEV's aggregators with a higher profit in addition to a reliable source of energy for the DSO in face of HILP events. In future works, the proposed algorithm might be implemented on a large-scale real transportation network to examine the potential and shortcomings of the proposed method in practical applications.

Abbreviations

Sets and Indices

n: Number of SAEVs
m: Trip request

Parameters

k: Number of trip requests
TH: Scheduling time horizon
TS: Scheduling time slots
V: SAEV mean speed
U: SAEV charging rate
$\mathrm{SOC}_{\mathrm{max}}^{\mathrm{tec}}$: SAEV maximum technical level of SOC
$\mathrm{SOC}_{\mathrm{min}}^{\mathrm{tec}}$: SAEV minimum technical level of SOC
$\mathrm{SOC}_{\mathrm{min}}^{\mathrm{DSO}}$: DSO desired minimum level of SOC for SAEVs

Variables

S: SAEV status (binary) indicating 0 for free, 1 for charging, and 2 for discharging on a trip
δ_e: SOC increment of SAEV from the hypothetical arrival to CDS till the end of the scheduling horizon
δ_f^m: SOC increment of SAEV from the hypothetical arrival to CDS after making trip m till the of the scheduling horizon
$\mathrm{SOC}^{\mathrm{T}}$: SAEV SOC at time slot T
$\mathrm{SOC}_{\mathrm{a}}$: SOC level after a hypothetical travel to CDS
$\mathrm{SOC}_{\mathrm{p}}$: The potential level of SOC at the end of the horizon
$\mathrm{SOC}_{v}^{\mathrm{m}}$: The potential level of SOC at the end of the scheduling horizon in case of making trip m
$\mathrm{SOC}_{u}^{\mathrm{m}}$: Hypothetical SOC level of SAEV after instant travel from the destination of trip m to CDS
$\mathrm{SOC}_{h}^{\mathrm{m}}$: SAEV level of SOC at the end of trip m
ϕ_T^m: SOC decrease of SAEV in trip m
ϕ_T^m: SOC decrease of SAEV in instant travel from the destination of trip m to CDS
T_d^m: Duration of trip m
T_a^m: Duration of the travel from the destination trip m to CDS
I^m: SAEV income from trip m
$L_{\ m}$: Distance of trip m.

Data Availability

The data used to support the findings of the study are available from the corresponding author upon request and within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

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