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# Fairness and Utilitarianism in Allocating Energy to EVs during Power Contingencies Using Modified Division Rules

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***Abstract*— In order to maximize utilitarianism and fairness in allocating energy to electric vehicles (EVs) during outages, this study proposes an optimization method based on modified division rules. The idea of *essential energy demand* is introduced in this paper to maximize the number of EVs that are served during power contingencies. For EVs carrying out the time-critical task(s), the *essential energy demand* is defined as the amount of energy required by EVs to accomplish their upcoming task(s). For EVs carrying out delay-tolerant tasks, it is defined as the amount of energy required by EVs to travel to a nearby healthy charging station. To this end, an EV ranking mechanism is devised considering the full and essential energy demands along with the urgency of EVs. Subsequently, EVs with higher ranks are prioritized during energy allocation. The performance of the proposed method is compared with four existing division rules, i.e., proportional, constrained equal awards, constrained equal losses, and sequential priority rules. A utilitarianism index is proposed to analyze the performance of these methods and fairness is evaluated using existing indices, such as Jain's fairness index and cost of fairness index. The proposed method has outperformed existing division rules in both utilitarianism and fairness for the essential energy demand. Finally, a sensitivity analysis of uncertain parameters such as EV fleet size, available/required energy, and weight factors is carried out to analyze the performance of the proposed method under various conditions.**

***Index Terms*— Division rules, electric vehicles, energy allocation, fairness, power outage, resilience, utilitarianism.**

## I. Introduction

MODERN power systems are known to be reliable due to their ability to provide electricity to consumers during normal conditions and reliability-oriented events (planned or unplanned but small-scale outages). However, they still lack the resilience features, defined as their ability to sustain the major outages, which are commonly known as low-probability, high-impact events [1]. There has been a record increase in the number of resilience-oriented events (natural disasters, cyber-attacks, and extreme weather events) over the last few decades and the severity of these events has also increased. For example, among the ten major storms of the last 40 years, seven have occurred in the last 10 years [2]. The 2021 Texas outage is a recent example of an extreme weather event, which has caused the largest forced blackout in U.S history [3]. The increase in intensity and severity of extreme weather events is mainly due to climate change [4].

Meanwhile, the penetration of electric vehicles (EVs) is increasing in the transportation sector due to the reduction in the cost of batteries and related technologies [5]. EVs are a viable option to reduce the dependence of the transportation sector on fossil fuels, which is otherwise one of the major sources of global carbon footprint. However, transportation electrification will increase the interdependence of the transportation and power sectors. This interdependence can bring opportunities, on the one hand, to sustain the penetration of renewables. But it brings challenges, on the other hand, especially during power outages [6], [7]. EVs are projected to be the major source of transportation in the near future and they will be used for diverse purposes ranging from personal usage to emergency response. During resilience-oriented events, the locally available energy may not be sufficient to fulfill the needs of all EVs due to disconnection with the utility grid. The resilient operation of EVs is a crucial requirement and is a relatively new and less explored area. The literature describes several studies on enhancing the resilience of power systems, where EVs are used as resilience resources [8]–[10]. Studies on enhancing the resilience of EVs themselves are limited.

Due to the limited number of studies on energy allocation to EVs during outages, two of the closely related areas and their key differences are discussed. The first related area is load shedding in microgrids during power outages. The fundamental problem in both areas is to allocate limited energy to several claimants with diverse utilizations. Allocation of limited energy among different loads during outages is a nontrivial task and it arises fairness and utility-related issues. Several studies are conducted on the fair allocation of energy among different claimants (loads) during outages [11]–[14]. Division rules, also known as bankruptcy rules, are widely used in the allocation of limited resources among different claimants, such as solving water conflicts among territories [15], [16], allocating limited bandwidth in communication networks [17], and $CO_2$ emission permits allocation [18]. Recently, these rules have been applied to power systems as well, such as load shedding in microgrids [11], [13] and energy allocation to EVs during system overload [19]. However, there are some fundamental differences in allocating limited energy to EVs and load shedding in mi-

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crogrids. In the case of load shedding, any amount of energy allocated to claimants could be acceptable, but in the case of EVs, if the allocated energy is not sufficient to reach the destination, it may not be acceptable. Therefore, the existing division rules cannot be used directly in allocating energy to EVs.

The second closely related area is power/energy allocation to EVs during system overload. In both these areas, the net load of all EVs cannot exceed a certain threshold, i.e., the system capacity is shared by several EVs. Several studies have been conducted on prioritization and allocation of energy to EVs during system overload [19]–[22]. The impact of different priority criteria on the chargeability of EVs is analyzed in [19] and the weighted sum approach is suggested as the most suitable option. In [20], the least laxity first approach is proposed and demonstrated that proportional fairness can be achieved during system overload. Charging coordination among EVs within different charging stations is proposed in [21] to maximize the utilization of the deployed chargers. In [22], an adaptive neuro-fuzzy inference system is used to generate priority for EVs considering different factors such as energy level and departure time to avoid system overload. However, the methods devised for allocating system capacity to EVs during overload cannot be applied during outages due to the following reasons. First, the system overload intervals are usually a few hours and are known in advance, thus EVs can charge ahead of time or can be charged with a time delay. In case of outages, some of the EVs may not be recharged at all during the event time due to the scarcity of available resources. In addition, the occurrence of power outages (cyber-attacks, man-made events, natural disasters, etc.) cannot be precisely predicted. Second, during system overload intervals, EV owners tend to fully charge the EVs due to connection with the grid. However, during emergencies, the main objective is to survive the maximum number of EVs by allocating the amount of energy required for accomplishing critical tasks.

Therefore, during outages, EVs also need to be prioritized and allocate energy to vehicles that have greater value to society. Energy allocation to EVs during outages is relatively new but important research area for the adoption of EVs. A very limited number of studies have been conducted to date on this area. Different classes of EVs are considered in [23] and a priority factor is included in the utility function of each EV. The problem is modeled based on the non-cooperative game theory, and the demand fulfillment of higher priority EVs is ensured first. In [24], the prioritization of EVs is carried out considering the social welfare, community well-being, and individual satisfaction gained by allocating energy to EVs during outages. A two-level optimization model is developed in [25] to prioritize EVs and schedule power to them according to their priorities. The deviation between the actual and required energy of EVs is minimized and the emergency mode has also been considered.

This type of energy allocation mechanism can be beneficial for clustered EV charging stations where several EVs with different usage purposes share the same parking space. Few examples could be a muti-unit residential apartment building, a hospital building, or a college/university building with shared parking space. Automation in clustered EV supply equipment (EVSE) has been proposed by the International Renewable Energy Agency (IRENA) in the 2019 Innovation Outlook report on smart charging for electric vehicles [26]. Similarly, the EV energy management system (EVEMS) is suggested for multi-unit residential buildings in Canada in a report [27] on guidelines for charging demand management in the residential sector. In addition, several studies have recently considered the deployment of renewables and energy storage system in charging stations [28]–[30]. The EVEMS and the automated EVSE can also be used during power outages to allocate the locally available energy (energy storage and renewables) to EVs during outages. It is worth noting that during normal operation, the main focus is on cost minimization, but during emergencies, service reliability is prioritized above cost [31]. Especially, if the available resource is not sufficient to fulfill the needs of all claimants.

The two primary challenges in the allocation of the limited resource among different claimants are utilitarianism and fairness, none of these aspects is considered by any of these studies [23]–[25]. These aspects are more crucial during outages due to the use of EVs for diverse purposes and the scarcity of energy resources. This fairness in allocations of scarce resources is required to gain long-term commitments from the users with the network. In addition, all these studies have prioritized EVs based on the total required energy by EVs. This may result in demand fulfillment of a limited number of EVs, raising issues of both fairness and utilitarianism. This is due to the direct application of division rules, for example, sequential priority rule is used in all these studies. Instead, modification of these rules is required to maximize the number of EVs with their essential energy demand fulfilled. Therefore, techniques are required to rank EVs and allocate energy in such a way that can increase utilitarianism and fairness during outages.

To address the challenges mentioned in the previous paragraphs, an energy allocation method for EVs during power contingency is proposed in this study. The proposed method can enhance utilitarianism and fairness among EVs during outages. Fairness is defined as the amount of energy received by an EV relative to the amount of energy required by that EV. The required energy could be the total energy demand or the essential energy demand depending on the nature of the EV (critical service or non-critical service EV). Similarly, utilitarianism is defined as the number of EVs that have their energy demands (total or essential) fulfilled relative to the total number of EVs that require a recharge during the same period. The main contributions of this study in comparison to existing studies are as follows.

- In contrast to most studies, where energy allocation to EVs during system overload is considered [19]–[22], power allocation during outages is considered in this study. Power allocation during outages is more crucial due to the absence of connection with the grid and is more dynamic.
- Compared to existing studies on energy allocation during outages, where only total demand is considered for prioritizing EVs [23]–[25], the concept of *essential energy demand* is introduced in this study. Consideration of essential energy demand can enhance utilitarianism and fairness in

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power allocation to EVs during outages.

- The performance of the proposed method is compared with four existing division rules, including proportional (PR), constrained equal awards (CEA), constrained equal losses (CEL), and sequential priority (SP) rules.
- An index is proposed to analyze the utilitarianism of different allocation methods, including the proposed method. In addition, different existing indices are used to analyze the performance of all methods, such as Jain's fairness index and cost of fairness index for analyzing fairness.

In addition, a sensitivity analysis of different uncertain factors, such as the number of EVs, available and required energy, and weight parameters, is carried out.

The organization of the remainder of the paper is as follows. The proposed energy allocation scheme along with the overview of division rules is presented in Section II. The formulated optimization model is discussed in Section III and Section IV discusses the indices used for the performance evaluation of the proposed and existing methods. Simulation results are presented in Section V, and sensitivity analysis of uncertain parameters is presented in Section VI. Finally, conclusions and future research directions are summarized in Section VII.

## II. Energy allocation to EVs during contingencies

During contingencies, the available energy needs to be allocated among the EVs to enhance utilitarianism and fairness. In this section, the preliminaries of the proposed method are discussed, which include the charging management system, framework for implementation of the proposed method, conventional division rules, and essential energy demand modeling of EVs. The proposed utilitarianism-oriented model is discussed in the next section.

### A. Proposed Charging Station Management System

A charging management system is required to optimize the operation of charging stations during normal and emergency operations. The configuration of the proposed charging station management system is shown in Fig. 1. It comprises the energy allocation module, the energy and demand adjustment module, and the database module. The database module contains the information of EVs registered with the charging station and other charging stations in the vicinity. The load profile of EVs can be estimated by using the historical data related to the arrival and departure times of EVs. The charging station is in islanded mode (when grid-connection is lost) and only locally available energy can be allocated to EVs, i.e., grid-to-vehicle (G2V) mode is considered for charging EVs.

The charging station contains renewables and battery energy storage systems (BESS), which can provide energy to EVs during emergencies. The load profile of some of the EVs can be shifted (demand response, DR) to better utilize the renewables. Similarly, BESS can be used to store excess energy from renewables and used to charge EVs during deficit intervals. Information about available energy, EV demand (full and essential), and EV information are provided to the energy allocation algorithm during each interval. The energy allocation algorithm

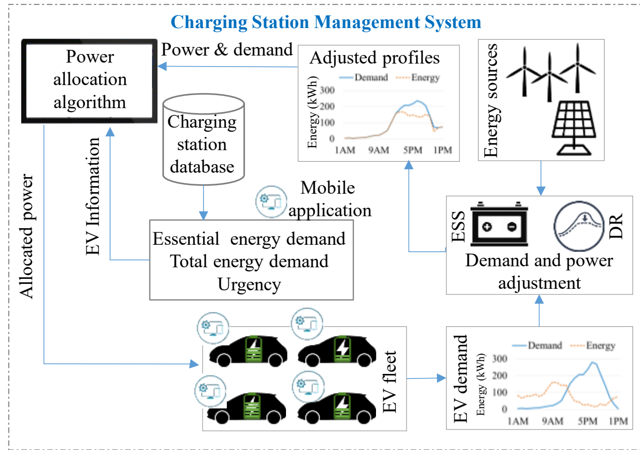


Fig. 1. Configuration of the proposed charging management system.

allocates energy to EVs based on the proposed optimization model, which is discussed in the next section.

### B. Framework for Implementation

To implement the proposed energy allocation scheme in automated clustered EV charging stations, the following infrastructure/services are required. The infrastructure discussed below can also be used to manage the power/energy of the charging station under normal conditions. However, the focus of this study is on energy allocation during outages; therefore, it is discussed with reference to outage scenarios.

- A charging station management system (CSMS) to receive EV information, locally available energy information, and execute the proposed energy allocation scheme.
- EVSE with communication capabilities to receive commands from the CSMS and execute them.
- A mobile application/website to communicate between EV owners and the CSMS.
- A contract (smart contract) between the charging station managers and the EV owners on categorization of EVs (critical service or non-critical service), pricing mechanism during outages, and energy allocation policy during power outages.

During outages, EV owners that require recharge will choose a destination/direction of travel for the upcoming trip, using the mobile application/website. The application will determine the *essential energy demand* using the information of a healthy charging station in the vicinity (based on the chosen destination /direction of the next trip). Then, a number will be assigned (by the application) to the EV based on the location of the nearest healthy charging station, the total energy demand of the EV (based on the current state-of-charge: SoC), and nature of the EV (critical service or non-critical service). The discussion of these factors and the ranking mechanism is presented in Section III. Then, the aggregated number will be sent to the CSMS using the mobile application /website. Due to the aggregation of different factors, the private information (destination of the next trip, current SoC, etc.,) will be masked and not visible to the CSMS. There is a possibility that EV owners may not be

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truthful when selecting the direction/destination of the upcoming trip to gain favorable outcomes. There are two possibilities (1) Changing the destination to a farther location to gain a higher amount of energy. Since the EV owners are aware of the power allocation mechanism (smart contract) that higher demand EVs will be ranked lower, this option will not be chosen. (2) Changing destination to a closer location to gain higher rank in the system. It is also less likely since the allocated energy will not be sufficient to reach the actual destination. Therefore, they will be naturally forced to report the correct destination, since cheating in either way is not beneficial. The SoC will be read directly by the application from the EV or by using a screenshot of the dashboard. In addition, the nature of EV is pre-settled between the EV owner and the CSMS (smart contract). Therefore, there is no room for misrepresentation in these two aspects.

### C. Overview of Division Rules

Division rules have been used since ancient times to allocate scarce resources among different claimants in a fair way [32] and are applied in several fields. For example, water resource allocation [8], bandwidth allocation [17], $CO_2$ emission permits [18], load shedding in microgrids [33], resource allocation in microgrids during outages [14], and energy allocation to EVs during system overload [19]. The three most widely used division rules are the PR rule, CEA rule, and CEL rule. The allocation in these three rules, grouped as Young rules [32], is based on the amount claimed by the claimant. Another category of commonly used division rules is SP rules, where the allocation is based on the priority of claimants, irrespective of their claims. The performance of the proposed method is compared with these four division rules in the simulation section; therefore, an overview of these rules is presented here. In a classical division problem, there are $N$ claimants ($N \geq 2$) with individual claims $c_n$. The total resource, known as endowment ($E$), is less than the total claimed amount ($C$) and is allocated to claimants.

*1) PR Rule*: This rule, where awards are proportional to claims [32], is generally quoted as being proposed by Aristotle. Mathematically, it can be written as in (1), where $\rho$ is the total available energy to total required energy ratio and $x_n^{pro}$ is the amount of energy allocated to the $n^{th}$ EV using the proportional rule. The allocations based on this rule are generally considered fair in many disciplines due to the absence of bias for small/ large claimants.

$$x_n^{pro} = \rho.c_n \text{ where } \rho = E / C \tag{1}$$

*2) CEA Rule*: In this rule, all claimants are awarded an equal amount of share, but they cannot receive more than their claims. It can be mathematically modeled as (2), where $\lambda = E / N$. However, $E$ and $N$ need to be updated after each allocation, if $\lambda > c_n$. $x_n^{cea}$ is the amount of energy allocated to the $n^{th}$ EV using the CEA rule. This rule is generally known to be more favorable for claimants with lower claims.

$$x_n^{cea} = \min\left\{\lambda, c_n\right\} \text{ where } \sum_{n \in N} \min\left\{\lambda, c_n\right\} = E \tag{2}$$

*3) CEL Rule*: In this rule, the loss ($C$-$E$) is equally shared among all claimants, but the loss cannot be negative. It can be mathematically modeled as (3), where $\upsilon = (C - E) / N$. Similar to CEL, $C$, $E$, and $N$ need to be updated after each allocation, if $c_n - \upsilon < 0$. $x_n^{cel}$ is the amount of energy allocated to the $n^{th}$ EV using the CEL rule. This rule is generally known to be more favorable for claimants with higher claims.

$$x_n^{cel} = \max\left\{0, c_n - \upsilon\right\} \text{ where } \sum_{n \in N} \max\left\{0, c_n - \upsilon\right\} = E \tag{3}$$

*4) SP Rule*: In this rule, the claimant with the highest priority is served fully first. It is then followed by the second and so on. It can be mathematically modeled as (4), where $m \prec n$ implies that claimant $m$ has priority over claimant $n$. $x_n^{sp}$ is the amount of energy allocated to the $n^{th}$ EV using the sequential priority rule. This rule may not be considered fair in normal circumstances, but during emergencies, allocations based on this rule are perceived as reasonable.

$$x_n^{sp} = \min\left\{c_n, \max\{E - \sum_{m \in N: m \prec n} c_m, 0\}\right\} \tag{4}$$

### D. Essential Energy Demand Modeling

In contrast to existing studies [23]–[25], where the fulfillment of the total demand is considered, the concept of essential energy demand is introduced in this study. During major outages, it may not be possible to fulfill the total demand of all EVs. Therefore, the objective of this study is to maximize the number of EVs fulfilling their essential energy demand during large-scale outages. The essential energy demand will be equal to the amount of energy required to fulfill the upcoming task(s) for EVs carrying out time-critical tasks. However, in the case of EVs with flexibility in time, the essential energy demand is defined as the amount of energy required for traveling to a healthy charging station in the vicinity. Healthy charging stations refer to stations that operate normally, i.e., their connection with the grid is alive and they can buy power from the grid.

To compute the essential energy demand, the amount of energy remaining in any EV ($e_n^{rem}$) is required, which can be computed using (5). It has been noted in [34] that the daily mileage of vehicles follows a lognormal distribution. Therefore, in this study also, the distance covered by EVs is assumed to follow a lognormal distribution with a mean of $\mu_n$ and a standard deviation of $\sigma_n$. The energy consumption of EVs can be computed using the traveled distance (computed using the lognormal distribution) and the efficiency (energy consumption per km) of EVs ($e_n^{pkm}$). Finally, $e_n^{st}$ represents the amount of energy available in the $n^{th}$ EV at the beginning of the day. It is worth noting that the remaining energy is computed at the time of the occurrence of the event, i.e., data of travelled distances before the occurrence of the event are used. In addition, resilience events can be categorized as disasters (natural disasters, extreme weather events, accidental events, and terrorist attacks on the grid), cyber-attacks, and man-made cascaded events [35], [36]. Except for natural disasters and extreme weather events, the travel pattern of public generally does not change significantly, i.e., evacuation is not required [37].

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The distance between the location of the charging station of the $n^{th}$ EV and the nearby healthy charging stations is taken as a random variable, similar to [6]. The random variable follows a lognormal distribution function and data of gas stations is used to compute the statistical parameters, due to the absence of the widespread deployment of charging stations until now. The amount of energy required to travel to the nearest healthy station ($e_n^h$) can be computed using (6), where $d_n^{hcs}$ is the distance to the nearest healthy charging station (km) and $e_n^{pkm}$ is the EV efficiency. Finally, the essential energy demand of the $n^{th}$ EV is calculated using (7), considering the amount of energy required and available for the EV.

$$e_n^{rem} = e_n^{st} - random(\mu_n, \sigma_n^2).e_n^{pkm} \tag{5}$$

$$e_n^h = d_n^{hcs}.e_n^{pkm} \tag{6}$$

$$e_n = \begin{cases} e_n^h - e_n^{rem} & if \quad e_n^h > e_n^{rem} \\ 0 & else \end{cases} \tag{7}$$

## III. Utilitarianism-oriented optimization modeling

### A. EV Ranking

To maximize the utilitarianism of EV owners during outages, a ranking of EVs is required. In this study, three factors are considered to rank the EVs and allocate the available energy based on the ranking of EVs. The step-by-step process of EV ranking and energy allocation is shown in Algorithm I.

The first factor considered for the ranking of EVs is the claim factor ($f_n^{cl}$), where EVs with higher claims are ranked lower and vice versa. The total required energy ($c_n$) is reported to the application/website and all other EVs also report their required energy amount. The identities of EVs are not visible to other EV owners, the total amount of all EVs is visible as an accumulated energy amount. Based on the relative demand of all EVs, the application computes the claim factor for the EV, as shown in (8). The second factor is the essential energy demand factor ($f_n^{en}$), and EVs with higher essential energy demand are ranked lower and vice versa. EV owners select a destination or direction of travel for the next trip from the map, populated in the mobile application. The value of the essential energy demand ($e_n$) is determined by the application using (5)-(7). An aggregated value of the total essential energy demand of other EVs is also visible to all EVs. Then the value of this factor ($f_n^{en}$) is determined using (9). The objective of these two factors is to maximize the number of EVs with their demands

**Algorithm I** Interval-wise EV ranking and energy allocation.

Get input data (required energy, urgency level, available energy, and essential energy demand)
Compute ranking factors for EV: Equations (8)-(10)
Compute the final ranking factor (11) and inform CSMS
Sort EVs in descending order based on the final rank (CSMS)
In case a, $\varphi_n = c_n$ and in case b, $\varphi_n = e_n$ (refer to Fig.2 for cases)
**for all** $n \in N$ **do**
  **If** $E \geq \varphi_n$ **then**
    Allocate energy to EV $n$: $x_n = \varphi_n$
    Update remaining energy: $E \leftarrow E - \varphi_n$
  **else**
    Allocate energy to EV $n$: $x_n = E$
    Update remaining energy: $E = 0$
  **end if**
**end for**

fulfilled. For example, allocating 5kWh of energy to four EVs will be preferred over allocating 20kWh of energy to one EV. The third factor is the urgency factor ($f_n^{ur}$), which signifies the priority of EVs. In (10), $u_n$ is the urgency identifier. This factor ($f_n^{ur}$) takes positive values for EVs which are responsible for carrying out critical tasks, such as fire departments, ambulances, first responders, etc. It takes a value of zero for all other EVs. The decision about categorization of EVs as critical service EVs and their relative importance is pre-agreed, contract between CSMS and EV owners. The application in each EV aggregates all three factors and determines final factor ($f_n^{tot}$), as given by (11). The weight factors ($\alpha, \beta, \gamma$) can be chosen by the charging station operators based on the significance of each factor and are accessible for the mobile application. Based on the values of the weight factors, the outcome of the optimization problem may change, i.e., Pareto optimal points. However, due to the consideration of power allocation to EVs during outages (in this study), the relationship among these weights will be in this order: $\alpha < \beta < \gamma$ .

$$f_n^{cl} = 1 - \left( c_n \Big/ \sum_{n \in N} c_n \right) \tag{8}$$

$$f_n^{en} = 1 - \left( e_n \Big/ \sum_{n \in N} e_n \right) \tag{9}$$

$$f_n^{ur} = 1 - \left( u_n \Big/ \sum_{n \in N} u_n \right) \tag{10}$$

$$f_n^{tot} = \frac{\alpha \cdot f_n^{cl} + \beta \cdot f_n^{en} + \gamma \cdot f_n^{ur}}{(\alpha + \beta + \gamma).(N-1)} \tag{11}$$

### B. EV Modeling

The battery size and charging efficiency of different EVs is not the same and so is the rating of chargers. Therefore, EVs are modeled using equations (12)-(16). Equation (12) implies that the amount of charging power of $n^{th}$ EV in time interval $t$ ($P_{t,n}^{ec}$) is restricted by the SoC of the EV battery in the previous interval *t-1* ($SoC_{t-1,n}$), capacity ($P_n^{cap}$), and charging efficiency ($\eta_n^{ec}$). Similarly, the charging power is constrained by the power rating of the charger connected to the $n^{th}$ EV ($P_n^{cha}$), as given by (12). Finally, EVs can only be charged during the parking period ($\tau$), i.e., $t \in \tau$ , as shown in (13). The SoC of the $n^{th}$ EV can be updated at each interval $t$ using (14) and the SoC at arrival time ($t_a$) can be computed using remaining energy ($e_{t,n}^{rem}$) as given by (15). The estimation of the remaining energy is discussed in Section II-D. Finally, the SoC of EVs must be within the specified upper ($SoC_n^{\max}$) and lower ($SoC_n^{\min}$) bounds, as given by (16). These constraints need to be met while allocating energy to EVs, which is discussed in the following section.

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$$0 \le P_{t,n}^{ec} \le P_n^{cap} \cdot \left(1 - SoC_{t-1,n}\right) \cdot \frac{1}{\eta_n^{ec}} \tag{12}$$

$$P_{t,n}^{ec} \le P_n^{cha} \text{ , } P_{t,n}^{ec} = 0 \;\forall t \notin \tau \tag{13}$$

$$SoC_{t,n} = SoC_{t-1,n} + \frac{1}{P_n^{cap}} \cdot \left(P_{t,n}^{ec} \cdot \eta_n^{ec}\right) \tag{14}$$

$$SoC_{t,n} = e_{t,n}^{rem} \big/ P_n^{cap} \qquad \forall t = t_a \tag{15}$$

$$SoC_n^{\min} \le SoC_{t,n} \le SoC_n^{\max} \tag{16}$$

At each interval, the SoC of arriving EVs is estimated first and then the amount of power required to reach the upper SoC limit ( $SoC_n^{\max}$ ) is estimated. The charging power for each EV during each interval is determined considering the rating of the converter and SoC of the EV battery. EVs are charged until they reach the upper SoC limit or until their departure time, whichever comes earlier. Then, the charging power of all EVs is accumulated for each interval *t* to determine the net load of the charging station for that interval (*t*). Details of the EV load estimation can be found in [6].

### C. Problem Formulation

The objective of the proposed optimization model is to meet the energy demand of the maximum number of EVs based on the normalized rank factor developed in the previous section. In the objective function (17), $x_n^{opt}$ is the decision variable, which is the optimal amount of energy allocated to the $n^{th}$ EV by the proposed method. The rank factor ( $f_n^{tot}$ ) is an input parameter to the optimization problem and it does not contain any decision variable. Therefore, the formulated model is a linear problem, and thus the convexity of the problem is guaranteed. Constraint (18) imposes efficiency [38], the sum of energy allocated to all EVs must be equal to the available energy, i.e., no energy remains unallocated. Constraint (19) implies that the energy allocated to EVs cannot be negative and it should not exceed the required energy, i.e., individual rationality. Equation (20) is a feasibility constraint, and it implies that any individual allocation cannot exceed the available energy. It is worth noting that constraint (20) is complimentary and, due to the physical significance of this constraint, it is generally mentioned in division rules [15], [16]. In (21), a slack variable ( $x_n^{slack}$ ) is introduced to keep the solution feasible if the available energy is less than the essential energy demand. It can be seen from (22) that the slack variable will take a value of zero if the available energy is greater than or equal to the essential energy demand.

$$\max \sum_{n \in N} x_n^{opt} \cdot f_n^{tot} \tag{17}$$

Subject to

$$\sum_{n \in N} x_n^{opt} = E \tag{18}$$

$$0 \le x_n^{opt} \le c_n \tag{19}$$

$$x_n^{opt} \le E \tag{20}$$

$$x_n^{opt} + x_n^{slack} \ge e_n \tag{21}$$

$$x_n^{slack} = 0 \;\, if \;\sum_{n \in N} e_n \le E \tag{22}$$

$$E^{rem} = \begin{cases} 0 \;\, if \;\sum_{n \in N} e_n > E \\ E - \sum_{n \in N} e_n \quad else \end{cases} \tag{23}$$

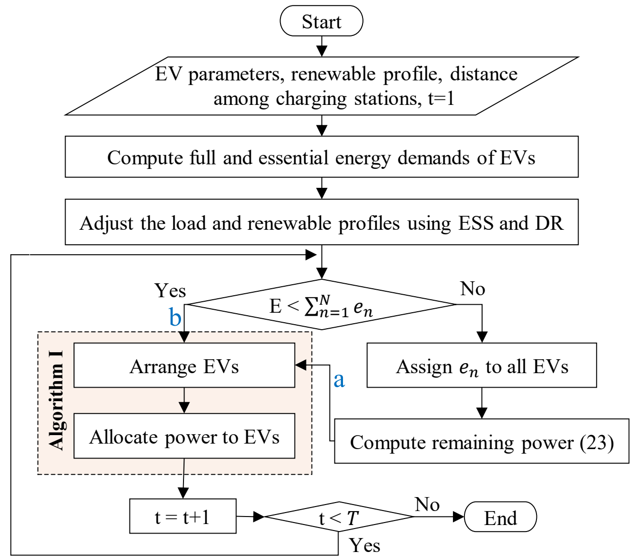

Fig. 2. Flowchart of power allocation to EVs during outage period.

The step-by-step process for ranking and allocation of energy to EVs during the outage period is shown in Fig. 2. After estimating the full and essential energy demands, the load and energy profiles are adjusted using DR and BESS, where possible. EVs can voluntarily delay their charging time, thus reducing charging demand, i.e., load profile adjustment via DR. Similarly, during renewable excess intervals, BESS can store the excess energy amount, i.e., energy profile adjustment via BESS. It is worth noting that the objective of this study is to allocate the energy available to EVs that require recharge during outages. Therefore, the available energy in the BESS is estimated at the beginning of each interval and is taken as input for the energy allocation algorithm. The management of renewable power and charging/discharging of BESS can be carried out by using existing algorithms such as [39]. Then, the essential energy demand of EVs is fulfilled first and the remaining energy is updated according to (23). The remaining energy is allocated to EVs based on their rank, according to Algorithm I (case a). This contrasts with the sequential priority rule, where the full demand of EVs is fulfilled considering their rank/priority. If the available energy is smaller than the essential energy demand, the essential energy demand is allocated according to the EV rank, Algorithm I (case b).

## IV. Performance Evaluation Indices

### A. Fairness Evaluation Index

In contrast to normal operation, where cost minimization or profit maximization is focused, service reliability is focused during emergencies. Fairness is one of the major issues in allocating scarce resources among different claimants during outages. It is essential for charging station operators to ensure fairness during emergencies to attract more consumers and make them feel treated fairly, which will ultimately increase their revenue. It is also necessary to have a contract and agree on some rules for prioritization during emergencies. In addition, the perception of fairness varies with the prevailing conditions. For example, equal allocation of power to all EV could be considered fair during normal conditions, but prioritization of critical service EVs will be perceived as fair during emergencies. Similar studies are conducted in the fields of communication [40] and medicine [41]. To quantify the fairness of different algorithms, a unified index is required. The desired properties of any fairness index are [42]: a) population size independence, b) scale and metric independence, c) boundedness, and d) continuity. Jain's fairness index [42] has all the desired properties. It measures the equality of allocation among different claimants. It was originally proposed to evaluate fairness in congested communication networks, but it is being widely used in different fields, including power systems [13], [20], [43]. It is used in [13] to evaluate the fairness in power allocation to loads during outages and in [20] to evaluate the fairness in allocating energy to EVs during overload. Similarly, fairness in quality of service for prosumers in networked microgrids is evaluated in [43] using Jain's fairness index. Due to the desired traits and usage in similar problems, Jain's fairness index is used in this study to evaluate the fairness in energy allocation to EVs during outages. Jain's fairness index for the full claim ($J$) is formulated in (24), where the fulfilled service ratio ($xr_n$) is used as a fairness measurement criterion, equation (25). Similarly, the Jains fairness index for the essential energy demand ($J'$) is formulated in (26) and the essential energy demand fulfillment ratio ($er_n$) is defined in (27). These indices are continuous; thus any slight change in the service ratio will change the indices. They are bounded in the range of [0,1] and take the value of 1 only when all users get the same service ratio. With an increase in the disparity, their values decrease.

$$J = \left(\sum_{n\in N} xr_n\right)^2 \Big/ N \cdot \sum_{n\in N} xr_n^2 \tag{24}$$

$$xr_n = x_n / c_n \tag{25}$$

$$J' = \left(\sum_{n\in N} er_n\right)^2 \Big/ N \cdot \sum_{n\in N} er_n^2 \tag{26}$$

$$er_n = min\{x_n, e_n\} / e_n \tag{27}$$

### B. Price of Fairness and Utilitarianism Indices

Price of fairness and utilitarianism are also important aspects in allocating limited resources, especially during emergencies [44]. An allocation may be perceived as fair under normal circumstances, but the perception may change during emergencies [45]. A fair allocation does not necessarily enhance utilitarianism, and during emergencies, utilitarianism is preferred over fairness. To analyze the relative system efficiency loss under different allocation schemes, this study adopts the price of fairness index proposed in [46]. The price of fairness index ($P$) evaluates the relative reduction in utility under different allocation rules compared to the utilitarian-oriented schemes (proposed method), as given by (28). Where $N^{Opt}$ is the number of EVs that survived under the utilitarianism - oriented scheme and $N^s$ is the number of EVs that survived under another allocation scheme $s$.

During outages, optimal utilization of available resources is required to maximize utility, i.e., utilitarianism enhancement. The objective is to maximize the service reliability to EV owners during outage periods (under a scarce resource). To quantify utilitarianism, an index ($U$) is proposed to analyze the performance of different allocation schemes, as shown in (29). This index evaluates the ratio of EVs survived by different allocation schemes ($N^s$) compared to the total number of EVs that require recharge ($N$) at that interval. The range of both these indices is [0,1] and is continuous.

$$P = 1\text{-}\left(N^s / N^{Opt}\right) \tag{28}$$

$$U = 1\text{-}\left((N - N^s)/N\right) \tag{29}$$

## V. Fairness and Utilitarianism Analysis: Comparison Between Proposed Method and Existing Division Rules

In this study, a single charging station is considered where EVs can communicate with the charging management system through a mobile application. A scheduling horizon of 24-hours with a time step of 1-hour is considered. Simulations are performed in the Java NetBeans environment with the integration of the optimization tool CPLEX 12.7. The performance of the proposed method is compared with the four division rules, i.e., the PR, CEA, CEL and SP rules, in terms of utilitarianism and fairness in allocating energy to EVs.

As stated in the introduction section, energy allocation to EVs during outages is not a well-explored area, and a limited number of studies are available in the literature. In the existing literature, only the sequential priority rule has been applied to the EV energy allocation problem during outages [23], [24]. The remaining three division rules have been applied to the two closely related areas (EV energy allocation during system overload and load shedding in microgrids), discussed in the introduction. For example, the proportional rule has been used in [19] for energy allocation to EVs. Similarly, the CEA and CEL rules have been used in [11] for the allocation of the load-shedding amount in microgrids during outages. Therefore, in this section, the performance of all four rules is analyzed.

### A. Input Data

To estimate the load of EVs, driving pattern data and EV-related data are required. The data related to the vehicle travel pattern is taken from [6] and the data of EVs is taken from [47]. In addition, similar to [48], vehicles are categorized into three groups, i.e., private vehicles used by the working class, commercial vehicles, and private vehicles used by the non-working class. A residential parking lot is considered for the study, and the proportion of vehicles arriving at home during different hours of the day is shown in Fig. 3a. Similarly, the total number of EVs present at the charging station at different times of the day $t$ is shown in Fig. 3b. In each interval, 20% of EVs are assumed to be critical service EVs. For the sake of visualiza-

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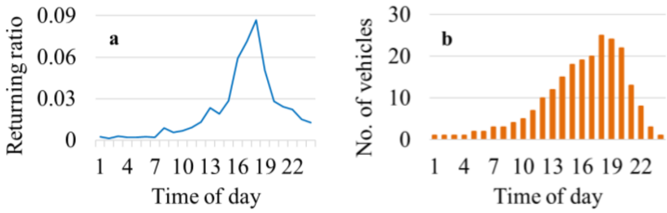


Fig. 3. Hourly data of EVs returning home: a) proportion; b) total number.

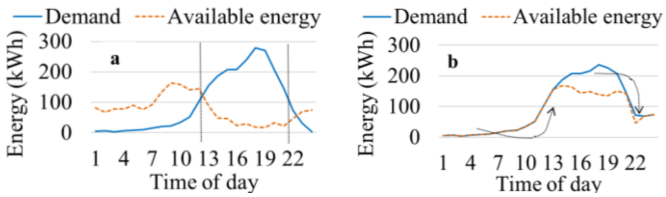


Fig. 4. Hourly EV demand and available energy profiles:
a) before adjustment; b) after adjustment.

TABLE I
INPUT PARAMETERS OF ADJUSTED PROFILES IN KWH.

| Interval | Available energy | Total energy demand | Essential energy demand |
|---|---|---|---|
| 14 | 168.4 | 186.7 | 77.5 |
| 15 | 165.1 | 207.4 | 99 |
| 16 | 143.65 | 207.4 | 105.5 |
| 17 | 148.6 | 237.9 | 105.5 |
| 18 | 138.7 | 279.7 | 129.5 |
| 19 | 135.4 | 270.3 | 123 |
| 20 | 151.9 | 207.4 | 103.5 |
| 21 | 122 | 145.2 | 71 |
| 22 | 66.2 | 72.6 | 43.5 |

tion, the number of EVs considered in [6] is scaled down in this section. However, in the next section, the performance of the proposed method is analyzed for different penetration levels of EVs.

The charging station contains renewables and BESS to provide energy to EVs during outages, as shown in Fig. 1. To analyze the impact of DR and BESS, two cases are considered in this study. The first case is without BESS and DR, where adjustments to load and energy profiles are not possible. The original load and available energy profiles are shown in Fig. 4a. In the second case, the adjustment of load and renewable energy is possible due to the presence of DR and BESS. 5% of the load is assumed to be shiftable (EVs' participation in the DR program) for the load profile adjustment. A price signal is generated for each interval based on the difference between net EV demand and available energy, similar to [49]. Similarly, 1.3MWh of battery is considered to absorb excess energy from renewables (for energy profile adjustment). It can be observed from Fig. 4a and 4b that excess energy is absorbed by the BESS during intervals 1-12 and it is discharged during intervals 13-21. A total of 1.02MWh of energy was charged during low load intervals and 0.92MWh of energy (excluding battery losses) was provided during peak load intervals. It can also be observed from these figures that the peak load is reduced during the intervals 17-19 (peak load intervals). A total of 108kWh of load is shifted from these intervals to the last two intervals (23 and 24), which is about 5% of the total load.

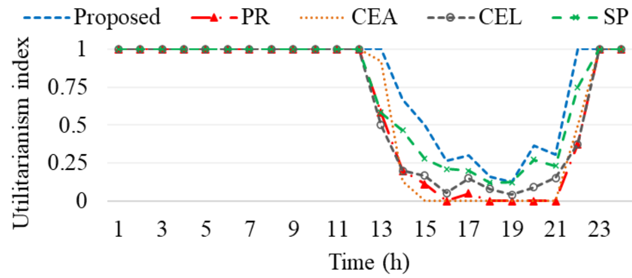


Fig. 5. Utilitarianism comparison before load and power adjustment.

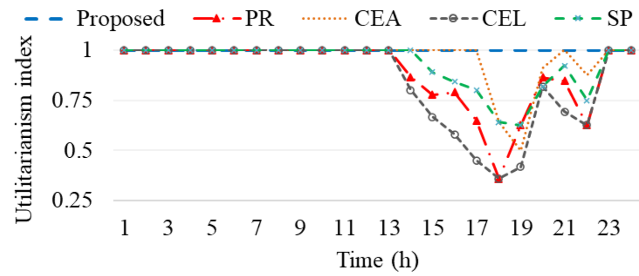


Fig. 6. Utilitarianism comparison after load and power adjustment.

The essential energy demand is computed using the distance data of nearby charging stations, similar to [6]. The urgency factor is set to zero for non-critical service EVs and it takes a positive value (> 0) for critical service EVs in each interval. In the following sections, adjusted profiles are focused on during energy deficit intervals. Relevant information (interval-wise essential energy demand, full energy demand, and available energy for the adjusted case) is shown in Table I.

### *B. Utilitarianism Analysis*

The utilitarianism comparison of the four division rules and the proposed method is carried out for both (before adjustment and after adjustment) available energy and demand cases. The demand and available energy profiles are the same as in Fig. 4, and the number of EVs at the charging station during different intervals of the day is the same as in Fig. 3b. The utilitarianism index formulated in equation (29) is used to compute the essential energy demand fulfillment ratio in all cases for all rules/ methods. The range of this index is between 0 and 1, and higher values refer to better utilitarianism and vice versa.

It can be observed from Fig. 4a that the available energy is higher than the load demand during intervals 1-12, 23, and 24. Therefore, during those intervals, utilitarianism is the maximum (one) for all rules. However, as a residential charging station, most EVs start returning home in the afternoon and the maximum number of EVs return in the evening hours. Therefore, during intervals 13-22, the amount of available energy is smaller than the energy demand (Fig. 4a). It can be observed from Fig. 5 that the proposed method has outperformed all four division rules, i.e., utilitarianism is higher during all these intervals (13-22). Utilitarianism has even reduced to zero for the PR and CEA rules during most of the intervals, i.e., none of the EVs has received its essential energy demand. This is due to the allocation based on the claimed amount in the case of division rules. The SP rule has performed better in comparison with the

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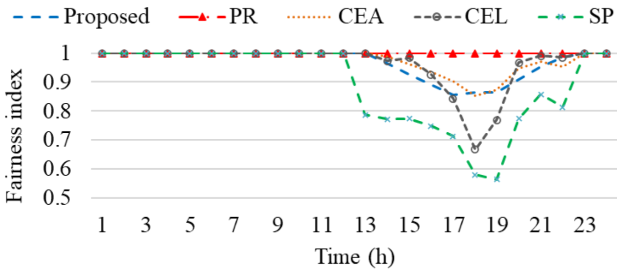


Fig. 7. Fairness comparison in full energy demand (claim).

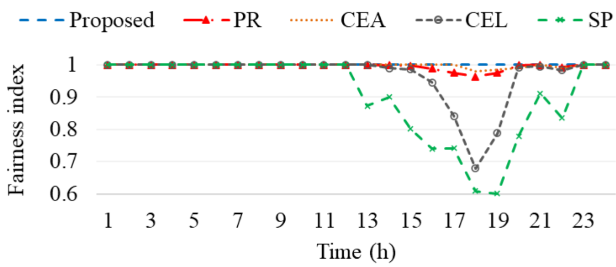


Fig. 8. Fairness comparison in essential energy demand.

other three division rules, which is in line with the idea of priority-based sharing during emergencies [45]. However, the performance of the SP rule is still inferior to that of the proposed method due to consideration of the full claim only.

Fig. 6 shows a similar trend where the available energy amount is smaller than the required demand during intervals 14-22. Due to demand and load adjustment, the performance of all rules has improved. However, the proposed method has outperformed all four rules in this case as well and maximum utilitarianism is achieved throughout the day (one). This implies that all EVs have received at least the essential energy demand throughout the day. In the case of the other division rules, the utilitarianism index is as low as 0.36 for the PR and CEL rules.

### C. Fairness Analysis

The division rules allocate energy based on the full energy demand, while the proposed method considers both full and essential energy demands. Therefore, the fairness of all methods is analyzed for both the full and the essential energy demands. In this section, Jain's fairness indices defined in equations (24)-(27) are used to analyze fairness for the case of adjusted energy and demand (Fig. 4b).

It can be observed from Fig. 7 that the full energy fairness index is highest for the PR rule during energy deficiency intervals (13-22), as expected. The PR rule allocates energy to EVs relative to their full demand without consideration of utilitarianism. It can be argued that this increase in fairness is at the cost of utilitarianism. Analysis of the cost of fairness is discussed in the next section. Even in the case of full energy demand fairness, the proposed method has performed better than the CEL and SP rules during most of the energy deficit intervals.

Fig. 8 shows that in the case of the essential energy demand fairness, the proposed method has outperformed all other rules. The unity fairness index is achieved throughout the day, which implies that all EVs have received at least their essential energy

TABLE II
PRICE OF FAIRNESS IN DIVISION RULES.

| Time interval | Full energy demand | | | | Essential energy demand | | | |
|---|---|---|---|---|---|---|---|---|
| | PR | CEA | CEL | SP | PR | CEA | CEL | SP |
| 14 | 1.00 | 0.08 | 1.00 | 0.08 | 0.13 | 0.00 | 0.20 | 0.00 |
| 15 | 1.00 | 0.08 | 1.00 | 0.25 | 0.22 | 0.00 | 0.33 | 0.11 |
| 16 | 1.00 | 0.42 | 1.00 | 0.25 | 0.21 | 0.00 | 0.42 | 0.16 |
| 17 | 1.00 | 0.42 | 1.00 | 0.33 | 0.35 | 0.00 | 0.55 | 0.20 |
| 18 | 1.00 | 0.00 | 1.00 | 2.20 | 0.64 | 0.36 | 0.64 | 0.36 |
| 19 | 1.00 | 0.00 | 1.00 | 3.67 | 0.38 | 0.50 | 0.58 | 0.38 |
| 20 | 1.00 | 0.17 | 1.00 | 0.50 | 0.14 | 0.09 | 0.18 | 0.18 |
| 21 | 1.00 | 0.20 | 1.00 | 0.20 | 0.15 | 0.00 | 0.31 | 0.08 |
| 22 | 1.00 | 0.25 | 1.00 | 0.50 | 0.38 | 0.13 | 0.38 | 0.25 |
| Average | 0.38 | 0.07 | 0.38 | 0.33 | 0.11 | 0.04 | 0.15 | 0.07 |

demand. The fairness results validate the utilitarianism results discussed in the previous section. In terms of fairness, the SP rule has the worst performance due to the allocation of most of the available energy to a few top-ranked EVs while allocating no energy to low-ranked EVs.

### D. Price of Fairness

In this section, the price of fairness of each division rule is computed by using the index formulated in equation (28). The price of the fairness index for only the energy deficit intervals (14-22) of the adjusted case is shown in Table II. However, the last row shows the average index for the entire day (24 hours). The price of fairness must be analyzed together with the fairness index to fully evaluate any division rule. Some rules might provide fair divisions at the cost of utility reductions.

It can be observed from Table II (left half) that the average price of fairness is the highest for the PR and CEL rules. The price of fairness of these rules is one (1) for the entire energy deficit period, which implies that none of the EVs has received its full demand. It can be observed from Fig. 7 that the fairness index of these two rules is relatively higher for the same case (full energy demand). This proves our argument that the increase in fairness in these rules is at the cost of utilitarianism.

The right half of Table II shows the price of fairness for the essential energy demand case. It can be observed that the corresponding index values are lower compared to the full demand values, which implies that some EVs are getting their essential energy demand. However, the positive average values for all rules imply that the utilitarianism of all these methods is lower compared to the proposed method. The price of fairness is zero for the proposed method, since $N^s$ is the same as $N^{Opt}$ in (28). It can be observed from Table II and Fig. 8 that the performance of CEA is better than the other three division rules, i.e., it can be ranked as second (after the proposed method).

## VI. Sensitivity Analysis

There are some uncertain factors and decision parameters involved in the formulation of the proposed method. These factors include the available energy (renewable and BESS state-of-charge) and the energy demand of EVs. Similarly, the decision parameters include the number of EVs registered with the charging station and the weight parameters used for different ranking factors. In this section, a sensitivity analysis of these uncertain factors and decision parameters is carried out to analyze the performance of the proposed method. For the sake

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TABLE III
ESSENTIAL AND FULL ENERGY DEMAND FOR EACH CASE.

| No of Evs | 25 | 50 | 100 | 150 | 200 | 250 |
|---|---|---|---|---|---|---|
| Essential energy | 115 | 250 | 474 | 756 | 964 | 1214 |
| Full energy | 388 | 780 | 1501 | 2290 | 3048 | 3781 |

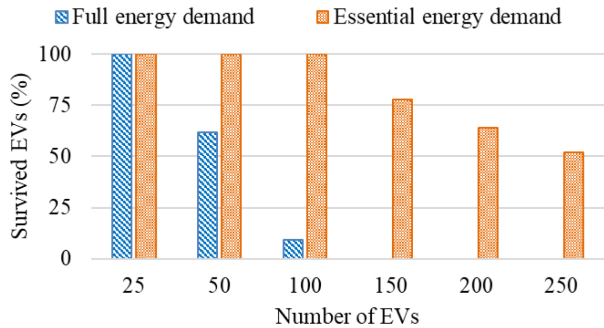


Fig. 9. Energy allocation results with different EV fleet sizes.

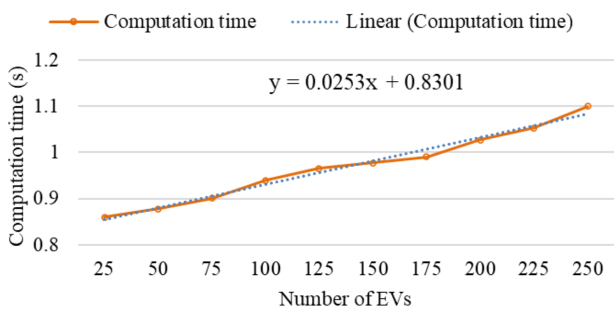


Fig. 10. Computation time under different EV fleet sizes.

of visualization, only one interval is analyzed in the following sections.

## A. *Size of EV Fleet*

In this section, the size of the EV fleet is varied from 25 to 250 and six cases are devised while keeping the available energy the same (550kWh). The weight parameter values for the three ranking factors (full energy demand, essential energy demand, and urgency) are also kept the same for all cases, i.e., $\alpha=1$, $\beta=2$, and $\gamma=3$. The number of survived EVs is computed in percent for each case by multiplying the utilitarianism index formulated in equation (29) by 100.

The essential and full energy demands for different EV fleet sizes are shown in Table III. It can be observed from Fig. 9 that in the first case (EVs=25), all EVs get their essential and full energy demands fulfilled (100% of EVs served) due to lower full demand compared to available energy. In the second and third cases (50 and 100), the served EVs for essential demand are 100% while the served EVs for full demand decrease. This is because in these cases, the available energy is higher than the essential energy demand, but lower than the full energy demand. Therefore, after fulfilling the essential energy demand of all EVs, the remaining energy is allocated to EVs based on their rank. In the last three cases, the available energy amount is lower than the essential energy demand of the entire fleet. Therefore, none of the EVs has full energy while the essential energy demand is allocated according to the EV rank. This analysis shows that the proposed method can allocate energy to EVs in a meaningful way with any number of EVs.

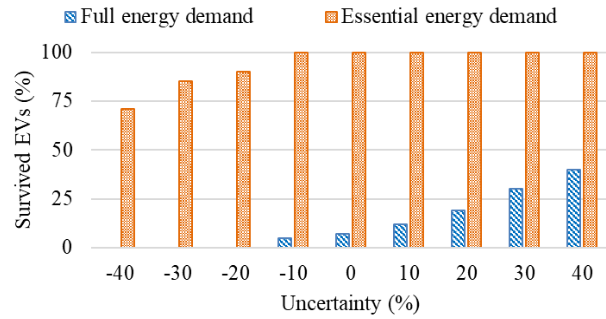


Fig. 11. Energy allocation results under uncertain energy gap.

To analyze the scalability and computation complexity of the proposed method, the computation time is analyzed for different EV fleet sizes, as shown in Fig. 10. It can be observed that the proposed method has a polynomial running time. In addition, the computation time was around 1.1 seconds even for 250 EVs. This is due to the linear and convex nature of the problem, as discussed in Section III-C.

## B. *Uncertainty in Energy Gap*

The uncertainty in available energy could arise due to uncertainty in renewables and errors in the estimation of the BESS state-of-charge. Similarly, the estimated EV load is also uncertain due to the uncertainty in the arrival and departure times of the EVs. Therefore, the difference in available energy and estimated EV load is named energy gap and nine cases are simulated by varying this energy gap in the range of ±40%. A total of 100 EVs are considered for this case (essential energy 483 kWh and full energy 1537 kWh) and the available energy corresponding to the 0% case is taken as 550 kWh.

It can be observed from Fig. 11 that with an increase in the uncertainty in the negative direction (0% case as reference), the percentage of survived EVs for full energy decreases due to the reduction in the available energy. In the last three cases (-20% to -40%), the percentage of survived EVs for essential energy demand is also below 100% due to the lower energy availability. On the contrary, with an increase in the uncertainty in the positive direction, 100% of the essential energy demand is fulfilled, and the percentage of EVs with full energy demand being fulfilled also increases. It can be observed from this analysis that the proposed method allocates the available energy to EVs in the desired fashion, i.e., the essential energy demand is met first, and then the remaining energy is allocated based on the EV rank.

## C. *Sensitivity to Weight Parameters*

The factors used for the ranking of EVs are multiplied by user-defined coefficients to define the precedence of different parameters. In this section, the impact of these parameters on the outcome of the proposed method is analyzed. In particular, interval 22 is analyzed where the total number of EVs is 8, with a full demand of 73 kWh and an essential energy demand of 44 kWh. The energy available for this interval is 66 kWh. Different cases are analyzed and only those cases where the outcome has changed are shown in Table IV.

Fig. 12 shows the EVs with full energy demand that are fulfilled, the essential energy demand of all EVs is fulfilled;

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TABLE IV
WEIGHT PARAMETERS FOR DIFFERENT CASES.

| Case | α | β | γ | Case | α | β | γ |
|---|---|---|---|---|---|---|---|
| a | 1 | 1 | 1 | e | 1 | 20 | 1 |
| b | 2 | 1 | 1 | f | 1 | 100 | 1 |
| c | 100 | 1 | 1 | g | 1 | 1 | 100 |
| d | 1 | 2 | 1 | | | | |

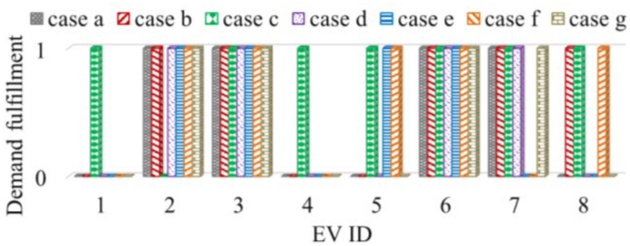

Fig. 12. Full energy demand fulfillment in different cases.

TABLE V
CHANGE IN POWER ALLOCATION IN DIFFERENT CASES.

| EV ID | a | b | c | d | e | f | g |
|---|---|---|---|---|---|---|---|
| 1 | 7 | 7 | 8 | 7 | 7 | 7 | 7 |
| 2 | 16 | 16 | 9 | 16 | 16 | 16 | 16 |
| 3 | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
| 4 | 8 | 8 | 11 | 8 | 8 | 8 | 8 |
| 5 | 7 | 6 | 9 | 7 | 9 | 9 | 7 |
| 6 | 5 | 5 | 5 | 5 | 5 | 5 | 5 |
| 7 | 11 | 11 | 11 | 11 | 9 | 8 | 11 |
| 8 | 5 | 6 | 6 | 5 | 5 | 6 | 5 |

therefore, it is not shown in this section. It can be observed from Table V that with an increase in the value of α, the energy from EV5 is reduced (case b). In case b, more energy is allocated to EV8 and EV8 receives full energy demand, as shown in Fig. 12. This is due to the change in the rank of EVs, i.e., it changed from [0.086, 0.085] in case a to [0.096, 0.097] in case b. Similarly, in case c, the energy from EV2 is reduced and more energy is allocated to EV1, EV4, EV5, and EV8. On the contrary, in case e, with an increase in the value of β, the energy from EV7 is reduced and more energy is allocated to EV5. The original ranks of EV7 and 5 were [0.128, 0.086], which changed to [0.121, 0.129] in case e. Similarly, in case f, the energy from EV 7 is further reduced and allocated to EV5 and EV8. The outcome has remained the same with an increase in the value of γ. This is due to the higher rank of EVs with positive γ, i.e., critical service EVs. This is desirable, since critical service EVs need to be served first. In all cases, the essential energy demand of all EVs was met. It implies that the proposed method successfully allocates essential energy to all EVs first, and the remaining energy is allocated to EVs based on their rank. The ranks can be controlled by policymakers through the values of α, β, and γ, considering their local situation.

## VII. Conclusion

In this study, an energy allocation method for EVs is proposed, which enhances utilitarianism and fairness (in case of essential energy demand) among EV users during major outages. Three factors are considered to rank the EVs and a unified normalized factor is formulated to allocate energy during contingencies. The performance of the proposed method is compared with four existing division rules in terms of utilitarianism and fairness in allocating energy to EVs. The proposed method has outperformed all the rules in terms of utilitarianism by maximizing the number of electric vehicles with their essential and full energy demands being met. In addition, fairness has also improved in allocating essential energy demand to EVs, i.e., more vehicles receive energy close to their essential energy demand. In some of the division rules, the fairness in full energy demand increased at the cost of a reduction in utilitarianism, which is not desired, especially during emergencies. Sensitivity analysis has confirmed that the proposed method can successfully allocate energy to EVs under different EV penetration levels and supply/demand ratios in a reasonable way. In all cases, the essential energy demand was fulfilled first and the remaining energy was allocated to EVs based on their rank, which is the desired performance during emergencies. Finally, scalability and computational complexity analysis have shown that the proposed method has a polynomial running time, thus it can be easily applied to large fleets of electric vehicles.

The focus of this study is on energy allocation in a single charging station in islanded mode. The application of the proposed method to multiple charging stations in outage areas while considering grid constraints and power transfer among different charging stations will be a valuable extension of this study. This will also make it possible to utilize electric vehicles for supporting grid/homes (vehicle-to-grid), where possible. Similarly, acquisition and processing of more granulated data from electric vehicle owners during contingencies while ensuring privacy preservation and truthfulness in data reporting (through incentive mechanisms) could further enhance the useability of the proposed method.

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