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Impact of demand response management on chargeability of electric vehicles

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ABSTRACT

Large-scale penetration of electric vehicles (EVs) would significantly increase the load requirements of buildings in highly urbanized cities. EVs exhibit higher degree of charging flexibility when compared to other interruptible loads in buildings. Hence, EVs can be assigned lower priority and interrupted before interrupting any other loads. Any temporary interruption will have minimum impact on EV owner's satisfaction/comfort. However, it should be ensured that the EVs could be charged to the owner's required state of charge (SOC) by the time of departure. The scheduling algorithms that are used to manage the EV charging process ensure that the charging requirements are fulfilled even when there are temporary interruptions. The capability of the scheduling algorithms to manage mismatches decreases with the decrease in time available for charging. In this paper, the impact of demand response management (DRM) on the chargeability of the EVs while using different priority criteria is examined. Subsequently, the proportion of interruption for each EV with different priority criteria and the need for determining the chargeability of EVs before shedding them are studied. A scheduling driven algorithm is proposed which can be used for determining the chargeability of EVs and can be used in combination with DRM.

1. Introduction

Deployment of Electric Vehicles (EVs) is considered as one of the solutions for achieving cleaner and greener mobility in highly urbanized cities around the world. In the case of highly urbanized cities, EVs are generally parked in multi-storey car parks and is inevitable in commercial and office buildings. Hence, EV deployment will eventually increase the load demand of buildings from which EVs are electrically charged. The detrimental impact of EV penetration and uncoordinated charging on residential grid is clearly highlighted in Ref. [1]. The analysis presented in Ref. [2] gives an overview on the impact of EV penetration on investment as well as increment in energy losses. Furthermore, there is high risk that the total demand of building exceeding the limit imposed by utilities if the EV load demand added is not managed adequately [3,4]. However, if it can be ensured that the EVs can be charged to the desired SOC at the time of departure, lower priority could be assigned to EV load demand. This is owing to the fact that any temporary interruption in EV charging will have insignificant effect on satisfaction/comfort of the EV owner. Various dynamic charging algorithms such as [5] are available for managing the EV charging in parking lots. The capability of the dynamic charging algorithms decreases correspondingly with the decrease in time available for charging. Hence, ability of the dynamic charging algorithms to manage the mismatches in final desired SOCs is restricted in many cases. In Ref. [6], the authors have classified the customers and demand response (DR) programs into various categories namely large/small commercial and industrial, and residential. It is obvious that the EV owners prefer to charge their EVs using overnight off-peak power at cheaper prices. However, if EVs are used for auxiliary storage functions, discharging and charging of EVs can happen at commercial/office buildings as well [7,8]. Since there is a higher probability of the total load demand exceeding demand limits imposed by utility in commercial/office buildings, DRM functionality is much higher in such buildings. In residential buildings, chances that an EV load is shed using demand response management (DRM) are minimal while using appropriate scheduling algorithms.

2. Related work

EV charging algorithms presented in literature consider the

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Nomentclature

i	EV ID
j	time interval (j = 1,2,3…48)
α_i	priority parameter based on state of charge(SOC)
SOC_i	SOC of i^{th} EV
β_i	priority parameter based on slack time
$N_{dep,i}$	departure interval of i^{th} EV
$N_{req,i}$	actual number of time intervals (30 min) necessary to reach the desired SOC level
$t_{c,i}$	overall number of time intervals (30 min) required for charging i^{th} EV on a given day
δ_i	priority parameter based on allotted time
$N_{com,i}$	actual number of time intervals for which the i^{th} EV was charging before the current interval
$SOC_{initial,\ i}$	initial SOC of i^{th} EV
$SOC_{final\ previous\ day,\ i}$	final SOC required for the i^{th} EV on the previous day
μ_i	mean of the distance travelled by the i^{th} EV
σ_i^2	variance of the distance travelled by the i^{th} EV
P_n	load demand for any given day
P_i	load demand for j^{th} interval
$\overline{p_j}$	mean from load demands
$\overline{\sigma_j^2}$	variance from load demands
N	number of samples generated
p_j^k	k^{th} iid
σ_j^2	variance of generated samples
p_n^{limit}	power limits representing all intervals
p_j^{limit}	power limit of j^{th} interval
$PN(EV_i)$	overall probability that i^{th} EV is not charged to its desired SOC
$N(EV_i)$	number of events during which the i^{th} EV did not reach its desired SOC
N(S)	total number of charging events/days
$I(EV_i)$	number of events during which the charging of i^{th} EV will be stopped charging if DRM is invoked
$I(S)$	total number of interruptions.
$x_{i,j}$	charging command parameter
$p_j^{b,i}$	maximum power at which the i^{th} EV can be charged
Cd_n	chargeability matrix for ‘n’ EVs
cd_i	chargeability value for i^{th} EV

individual EVs parked in a residential building either as interruptible load (time coordinated charging) or as flexible load (power coordinated charging). The authors in Ref. [9] classify the residential loads as manageable and non-manageable, and EVs can be considered as manageable loads as their charging process is adjustable. Furthermore, the priority value assigned to the EV is pooled along with the priority of other residential loads [10–12]. However, in case of highly urbanized cities such as Singapore, most of the EVs will be charged together (in groups) in parking lots. Such a charging pattern is highly suitable for using EVs in DRM as flexible loads and offers a wide range for load demand control.

In Ref. [13], investigation for DRM using various charging methods in a car park environment was carried out. Statistical data was used to obtain arrival times and durations for which the EVs are parked. The charging of individual EVs is assumed to be controlled by the car park operator. With the above conditions, the effect of DRM on the total charging cost of the system was analyzed. In Ref. [14], a methodology for managing quasi-time EV charging was presented. The authors considered the participation of EV aggregators in electricity markets as well as the technical restrictions of the electricity grid components. In Ref. [10], a DR strategy was proposed to minimize the impact of EV charging on a distribution circuit of a smart distribution network. Severity indices were used for executing the demand response of EVs. In Ref. [15], a new model of DRM for the future integration of EVs and renewable distributed generators into a smart grid network was proposed. In Ref. [16], a DR strategy to increase the potential for adding new load with minimal infrastructure investments was proposed. It also served as a load-shaping tool for improving the usage of the distribution transformer. The consumers' preferences, load priorities, and privacy were also taken into account.

In Ref. [17], two DR programs were presented, namely the trip reduce DR and trip shifting DR. The DR models were activated whenever the energy price reaches the cutoff value set by users. In Ref. [18], the authors investigated dynamic DR for intelligent EV charging. A detailed hybrid model was proposed to handle problems that cannot be properly handled by traditional tools. In Ref. [11], a distributed framework for DR and user adaptation in smart grid networks was proposed. The authors applied the concept of congestion pricing developed for internet traffic control to regulate the user demand and balance the load of a network. The authors of [19] demonstrated the applicability of a novel ‘pool market mechanism’ for re-schedulable demands such as EVs having flexible charging capability. In Ref. [3], a novel scheduling driven DRM utilizing time coordinated scheduling was proposed. Group of EVs were combined to form a load demand which is both flexible and interruptible. The degree of fairness obtained using the above method is better owing to the fact that the EV with highest probability to charge before departure is shed first while invoking the DRM for EV load demand. The DRM was implemented as a part of the Building Energy Management System.

In Ref. [20], the authors carried out an analysis on the influence of various priority parameters on the chargeability of EVs and fairness accorded to all EV users. In this paper, the impact of interruption due to DRM on the chargeability of the EVs is examined for various priority criteria. Subsequently, the proportion of interruption for each EV (when various priority criteria are employed for DRM) and the need for determining the chargeability of EVs before shedding them are studied. A novel scheduling driven algorithm is also proposed for determining the chargeability of EVs before shedding them using DRM. The major contributions of the paper are the analyses on the impact of DRM on chargeability and the proposed novel scheduling driven chargeability algorithm for determining the suitability of the EVs for DRM in any given interval.

3. Impact of DRM on EV chargeability

In commercial/office buildings when the DRM is invoked, various priority criteria as proposed in Refs. [3,7,20–25] can be used to determine which EV's charging has to be interrupted for managing the load demand. All the above priority criteria can be consolidated into state of charge (SOC) of the EV battery [22–24], slack time available [22,24,25] and time allotted [3,7] for charging, and can be represented by Equations (1)–(3) given below,

$$\alpha_i = 1 - \left(\frac{SOC_i}{100}\right) \tag{1}$$

$$\beta_i = 1 - \left(\frac{N_{dep,i} - N_{req,i}}{t_{c,i}}\right) \quad (2)$$

$$\delta_i = 1 - \left(\frac{N_{com,i}}{t_{c,i}}\right) \quad (3)$$

where i represents the EV number. α_i is the priority parameter based on battery SOC. SOC_i is the SOC of i^{th} EV. β_i is the parameter based on slack time. $N_{dep,i}$ is the number of intervals (30 min) available for charging i^{th} EV. $N_{req,i}$ is the actual number of time intervals (30 min) necessary to reach the desired SOC level for the i^{th} EV. δ_i is the priority parameter based on time allotted to i^{th} EV for charging. $N_{com,i}$ is the actual number of time intervals for which the i^{th} EV was charging before the current interval. $t_{c,i}$ is the overall number of time intervals (30 min) required for charging the i^{th} EV on a given day.

Either individual priority criterion or group of priority criteria is employed to determine the interruption of EVs' charging. The impacts of such interruptions are evaluated by determining the chargeability of the EVs to the desired SOC after DRM is invoked. Furthermore, the percentage of interruptions for each EV is also analyzed. Using different combination of priority criteria will have different types of impact on EVs having different battery capacities and travel distances. The building load demand based on stochastic simulations [26] and EV load demands based on [7] are used to carry out the analysis for an EV system with 15 EVs. The EV system is designed such that 3 EVs have 7 kWh battery capacity (EV1, EV2, EV3), 3 EVs have 24 kWh battery capacity (EV13, EV14, EV15), and 9 EVs have 16 kWh battery. Singapore's data on the number personal vehicles and population [27], and penetration level of 33% are considered to obtain the number of EVs for the EV system.

To analyze the influence of various priority criteria/parameters it is inevitable to consider different EV models (different battery capacities). It is crucial to setup a system consisting of EVs with different battery capacities and different energy requirement/day for a detailed analysis. The battery capacity of each EV is selected based on the typical distance travelled/day and EV models available in market with corresponding travel range/charge. Furthermore, such a configuration consisting of different EV models is more realistic. The battery capacities of EV model such as Renault Twizy, Nissan Leaf, Smart ED, Mitsubishi i MiEV, and Renault Kangoo Z.E., etc. are used for this study.

The initial SOC ($SOC_{initial,\ i}$) for the i^{th} EV is calculated based on distance travelled by personal vehicles in Singapore [27] and is given by,

$$SOC_{initial,\ i} = SOC_{final\ \ previous\ \ day,\ i} - \frac{\left(random\ \ (\mu_i,\ \sigma_i^2)\ \ *energy\ \ required/km\right)/2}{battery\ \ capacity_i} \quad (4)$$

where μ_i is the mean and σ_i^2 is the variance of distance travelled by the i^{th} EV respectively on a given day. A normal distribution is considered for the distance travelled by EVs based on the analysis provided in Refs. [13,28]. $SOC_{final\ \ previous\ \ day,\ i}$ is the final SOC required for the i^{th} EV on the previous day. The final SOC on any day is considered to be 100%. This is to account for the plausible preference of EV users to charge using low price off-peak power. In this study, typical energy required (per km) of different types of EVs is also used with the other factors for calculating the initial SOC and final SOC. The factor '2' in (4) is to account for the fact that the EVs would have travelled only half of their daily travel distance when they reach the commercial/office buildings. The arrival time is assumed to be distributed over 08:30 h and the departure time of EVs is assumed to be distributed over 17:30 h (normal distribution and 30 min is considered as standard deviation [13,28]). The initial SOC is calculated using the final SOC of previous day (as obtained from the simulations), the distance travelled by the EVs on the corresponding day (obtained from stochastic samples), and energy required/km. The final desired SOC ($SOC_{final,\ i}$) when vehicles depart from the commercial/office buildings is applicable only in cases where the EVs are used as Smart Energy Storage (SES). The $SOC_{final,\ i}$ is considered to be same as $SOC_{initial,\ i}$, which means the EVs has to be charged at least to $SOC_{initial,\ i}$ before leaving (even though some energy has been used in its function as SES). This is to avoid possible range anxiety of EV users.

The total load demand of Singapore during the years 2005–2009 is collected from Ref. [29]. The data collected is modified (scaled down) to the level that can represent a commercial/office building. The Stochastic samples are generated based on the above information.

$$p_n = (p_1,\ p_2,\ p_3,\ \ldots,\ p_{48}) \quad (5)$$

where p_n represents the load demand of all intervals and p_j is the load demand of j^{th} interval ($j = 1, 2, 3, \ldots, 48$). The information is categorized into monthly, week days and weekends for generating independent and identically distributed (iid) random samples that represents the probability density function (PDF) of load demand used [30].

$$\overline{p_j} \approx \frac{1}{N}\sum_{k=1}^{N} p_j^k \quad (6)$$

$$\overline{\sigma_j^2} \approx \sigma_j^2 \quad (7)$$

For $j = 1, 2, 3, \ldots, 48$, $\overline{p_j}$ is the mean obtained from the data and $\overline{\sigma_j^2}$ is the variance obtained from the data, N is the number of samples generated, p_j^k is the k^{th} iid and σ_j^2 is the variance of generated samples.

Maximum power that can be supplied during each interval is taken as constraint in this paper. Though various parameters [26] can be used as constraints, all the parameters are directly linked to the maximum power that can be supplied.

$$p_{\mathrm{n}}^{\mathrm{limit}} = \left(p_1^{\mathrm{limit}},\ p_2^{\mathrm{limit}},\ p_3^{\mathrm{limit}},\ \ldots,\ p_{48}^{\mathrm{limit}}\right) \quad (8)$$

where $p_{\mathrm{n}}^{\mathrm{limit}}$ is the power limits representing all intervals and $p_{\mathrm{j}}^{\mathrm{limit}}$ corresponds to power limit of j^{th} interval ($j = 1, 2, 3, \ldots, 48$). The utility imposed demand limit/contracted capacity [31] is one such power limit and it is used in this paper. In this paper, a contracted capacity of 300 kW is considered for the building and the average power over the charging period is taken as power limit. Such a power limit is chosen to avoid any possible surge in the total load demand [7,32].

The simulations are carried out for a case where 20% SOC reduction has occurred for all EVs at 12:00 h. The scale of SOC reduction (20%) has an impact on the probability of EVs charging to their desired SOC. However, the scale of SOC reduction has no impact on the proportion at which the EVs fail to charge to their desired SOC. In Table 1, the following three scenarios are compared for different priority criteria.

1 The probability of a particular EV not charging to the desired SOC with one interruption from DRM at 14:30 h,

Table 1
Impact of DRM on probability of not charging to desired SOC while using different priority criteria.

	Alt + Slt + SOC			Alt			Alt + Slt			Slt			SOC			Slt + SOC		
	PN1	PN2	PN3	PN1	PN2	PN3	PN1	PN2	PN3	PN1	PN2	PN3	PN1	PN2	PN3	PN1	PN2	PN3
EV1	0.004	0.006	0.010	0.007	0.010	0.014	0.005	0.007	0.010	0.008	0.011	0.014	0.003	0.005	0.007	0.007	0.009	0.013
EV2	0.004	0.006	0.009	0.006	0.009	0.011	0.005	0.007	0.010	0.008	0.011	0.014	0.003	0.005	0.007	0.007	0.009	0.013
EV3	0.004	0.006	0.009	0.004	0.006	0.008	0.005	0.007	0.010	0.008	0.010	0.014	0.003	0.005	0.007	0.007	0.009	0.013
EV4	0.004	0.008	0.013	0.005	0.008	0.011	0.004	0.008	0.012	0.002	0.004	0.008	0.009	0.011	0.016	0.003	0.006	0.010
EV5	0.003	0.006	0.011	0.002	0.004	0.007	0.003	0.005	0.010	0.002	0.004	0.007	0.004	0.006	0.010	0.002	0.005	0.008
EV6	0.003	0.004	0.008	0.000	0.000	0.004	0.003	0.005	0.008	0.002	0.004	0.008	0.010	0.014	0.019	0.003	0.005	0.008
EV7	0.003	0.005	0.008	0.000	0.000	0.003	0.003	0.004	0.008	0.002	0.004	0.008	0.009	0.014	0.018	0.002	0.005	0.008
EV8	0.003	0.005	0.008	0.000	0.000	0.003	0.003	0.005	0.008	0.003	0.005	0.008	0.009	0.013	0.018	0.002	0.004	0.008
EV9	0.003	0.005	0.009	0.000	0.002	0.004	0.003	0.005	0.009	0.002	0.004	0.007	0.005	0.007	0.010	0.002	0.005	0.009
EV10	0.003	0.006	0.010	0.002	0.003	0.007	0.003	0.005	0.009	0.002	0.004	0.007	0.005	0.007	0.011	0.002	0.005	0.008
EV11	0.003	0.006	0.010	0.009	0.011	0.016	0.003	0.006	0.010	0.002	0.004	0.007	0.005	0.007	0.011	0.003	0.004	0.009
EV12	0.003	0.006	0.009	0.012	0.016	0.020	0.003	0.005	0.010	0.002	0.004	0.007	0.005	0.007	0.011	0.002	0.005	0.008
EV13	0.017	0.022	0.029	0.020	0.024	0.029	0.014	0.019	0.027	0.002	0.004	0.008	0.007	0.010	0.015	0.006	0.009	0.015
EV14	0.017	0.022	0.028	0.023	0.029	0.035	0.015	0.020	0.028	0.002	0.005	0.009	0.019	0.025	0.031	0.006	0.009	0.014
EV15	0.017	0.022	0.029	0.024	0.029	0.036	0.015	0.021	0.028	0.002	0.005	0.009	0.019	0.025	0.030	0.006	0.009	0.015
MDM	**0.011**	**0.013**	**0.016**	**0.016**	**0.018**	**0.022**	**0.009**	**0.012**	**0.015**	**0.005**	**0.005**	**0.005**	**0.011**	**0.014**	**0.016**	**0.003**	**0.003**	**0.004**

Notes:
1. Slt − Slack time.
2. Alt − Allotted time.
3. PN1 − Probability of an EV not charging to its desired SOC (interruption at 14:30 h).
4. PN2 − Probability of an EV not charging to its desired SOC (interruptions at 14:30 h and 15:30 h).
5. PN3 − Probability of an EV not charged to its desired SOC (interruptions at 14:30 h, 15:30 h and 16:30 h).

2 The probability of a particular EV not charging to the desired SOC with two interruptions via one at 14:30 h and the second at 15:30 h, and
3 The probability of a particular EV not charging to the desired SOC with three interruptions one at 14:30 h, the second at 15:30 h and third at 16:30 h.

The probability of an EV not charging to its desired SOC is given by,

$$PN(EV_i) = \frac{N(EV_i)}{N(S)} \tag{9}$$

where $PN(EV_i)$ is the overall probability that i^{th} EV is not charged to its desired SOC, $N(EV_i)$ is the number of events during which the i^{th} EV did not reach its desired SOC and $N(S)$ is the total number of charging events/days. Time coordinated charging is used as dynamic charging algorithm. It is to be noted that the authors used coordinated charging algorithms from their earlier work [20]. However, the analysis can be applied to any type of DRM and coordinated charging algorithm. The difference between the analysis presented in Ref. [20] and this work is the considered interruptions at different time in the charging events (14:30 h, 15:30 h and 16:30 h).

It can be observed from Table 1 that when SOC is used as one of the priority criteria (3 out of 6 cases), the probability of not charging to desired SOC with interruptions from DRM is lower for EVs with lower battery capacity and energy requirement (i.e., EV1, EV2 and EV3). This is because, an equal priority value for α_i will be obtained from (1) for all the EVs having same SOC even if their battery capacities are different. E.g., a 7 kWh and a 24 kWh will have equal priority value for α_i as given by (1). Hence, both the EVs will be treated in same manner. However, the EV with 7 kWh battery capacity will be charged faster compared to the EV with 24 kWh battery capacity and results in lower probability of not charging to desired SOC. When allotted time is used as one of the priority criteria (3 out of 6 cases) a phenomenon similar to SOC is observed. From (3) it is evident that EVs with higher allotted time will have lesser value for δ_i. The increase in SOC of a 24 kWh battery with the same amount of allotted time will be lower than the increase in SOC of a 7 kWh battery. However, it is to be noted that the results are similar but not same; the degree of preference given to different EVs is different. When slack time (total 3 out of 6 cases) is used as the priority criterion, an opposite effect compared to SOC/allotted time is observed. The probability of an EV not charged to the desired SOC reduces with increase in battery capacity (i.e., EV13, EV14 and EV15). Since higher battery capacity results in lower slack time and hence higher priority value from β_i.

It is to be noted that the combination of SOC and allotted time is not examined due to the obvious fact that both of them have a similar effect and hence using them together will not provide results that are fair to all EVs. It can also be observed that, the probability that an EV is not charged to the desired SOC increases with the number of interruptions. From the values of maximum deviation from mean (MDM), it is obvious that using slack time as priority criteria results in minimum variations in the probability of not charging to desired SOC for all EVs (while using single criterion). This is because the SOC of all EVs have to be increased by same amount i.e., 20%. The best performance is obtained when SOC and slack time are used together and can be seen from MDM values (0.003). It can also be observed that using allotted time results in higher scale of preference to vehicles with lower battery capacity.

The percentage of interruptions for different EVs while using different combination of priority criteria is illustrated in Table 2. The percentage of interruptions for an EV is given by,

$$\% \text{ of interruptions } for\ i^{th}\ EV = \frac{I(EV_i)}{I(S)} * 100 \tag{10}$$

where $I(EV_i)$ is the number of events during which the charging of i^{th} EV will be stopped (if DRM is invoked). $I(S)$ is the total number of interruptions.

It can be observed from Table 2 that, when allotted time is used as priority criterion, charging of EV3, EV4, EV5 and EV6 encounter more than 70% of interruptions (when DRM is invoked at 14:30 h). This is due to the fact that incase of allotted time the EVs are charged sequentially based on their IDs as all the EVs have equal priority to start with. Hence, there is very high probability that EV1 and EV2 are already charged by 14:30 h and the other vehicles have not yet started charging. This can also be verified with increase in

Table 2
Percentage of interruptions while using different priority criteria.

	Alt + Slt + SOC			Alt			Alt + Slt			Slt			SOC			Slt + SOC		
	I1	I2	I3	I1	I2	I3	I1	I2	I3	I1	I2	I3	I1	I2	I3	I1	I2	I3
EV1	0.0	1.5	3.3	1.2	0.7	0.6	0.0	1.3	2.8	0.0	0.0	0.0	3.1	5.0	6.4	0.0	0.1	1.0
EV2	0.0	1.6	3.2	4.8	2.4	2.0	0.0	1.3	2.7	0.0	0.0	0.0	2.8	4.9	6.4	0.0	0.1	1.1
EV3	0.0	1.6	3.2	9.6	4.8	3.7	0.0	1.4	2.8	0.0	0.0	0.0	2.8	4.9	6.3	0.0	0.1	1.0
EV4	10.6	10.0	8.9	26.0	16.7	11.8	11.3	10.3	9.3	9.9	10.5	10.5	2.4	4.5	6.0	11.4	11.0	9.8
EV5	10.0	9.8	9.2	26.8	20.2	15.7	9.7	9.8	9.3	8.5	8.1	8.1	9.8	9.1	9.0	8.6	9.3	9.2
EV6	9.9	9.7	9.5	10.9	13.7	12.9	9.1	9.6	9.4	7.6	7.1	5.5	5.9	5.2	3.9	6.9	8.4	8.7
EV7	10.0	9.8	9.6	3.2	9.9	10.1	9.2	9.3	9.4	7.4	6.6	6.2	6.4	5.6	4.6	7.2	8.4	8.9
EV8	9.9	9.7	9.6	1.6	6.9	10.3	9.3	9.4	9.4	7.5	6.7	5.1	6.9	6.2	4.9	7.2	8.6	8.7
EV9	10.0	9.8	9.3	4.5	7.7	9.8	10.2	9.9	9.4	8.3	8.4	7.6	9.6	8.9	9.0	9.8	9.5	9.3
EV10	9.9	9.8	9.2	5.4	5.9	7.6	10.3	9.8	9.4	8.4	8.5	7.1	9.2	8.7	8.7	8.8	9.1	9.3
EV11	10.0	9.9	9.4	4.1	4.8	5.8	9.8	9.8	9.4	8.8	8.5	7.7	8.9	8.3	8.5	9.0	9.4	9.2
EV12	10.0	9.8	9.5	1.5	2.2	3.5	10.2	9.8	9.5	8.4	8.5	7.9	8.5	8.2	8.4	8.5	9.3	9.4
EV13	2.8	1.9	1.9	0.3	1.4	2.0	3.0	2.3	2.0	7.8	9.3	11.9	11.3	10.4	9.8	7.1	5.3	4.6
EV14	3.4	2.6	2.0	0.0	1.3	2.1	3.8	2.8	2.5	7.8	8.7	11.0	6.1	5.2	4.0	7.8	5.7	4.9
EV15	3.3	2.6	2.1	0.0	1.4	2.0	4.1	3.3	2.6	7.7	9.0	11.5	6.5	5.2	4.0	7.6	5.8	4.9
MDM	**6.7**	**5.2**	**4.8**	**20.1**	**13.5**	**9.0**	**6.7**	**5.4**	**4.7**	**6.5**	**6.7**	**6.7**	**4.6**	**3.7**	**3.1**	**6.7**	**6.6**	**5.7**

Notes:
1. Slt – Slack time.
2. Alt – Allotted time.
3. I1 – Percentage of interruption for each EV (interruption at 14:30 h).
4. I2 – Percentage of interruption for each EV (interruptions at 14:30 h and 15:30 h).
5. I3 – Percentage of interruption for each EV (interruptions at 14:30 h, 15:30 h and 16:30 h).
6. MDM – maximum deviation from mean
7. 0.0 – Represents very low value

percentage of interruptions for EV7-EV15 and decrease in percentage of interruptions for EV1-EV6 with two more interruptions at 15:30 h and 16:30 h. Even though EV13-EV15 have low percentage of interruptions, the probability of them charging to the desired SOC is significantly affected and can be observed from Table 1. This also due to the sequential charging based on the EV IDs. From MDM values, it is obvious that allotted time results in worst performance in terms of percentage interruptions.

Although using SOC as the priority criteria results in a lower percentage of interruptions for EV1-EV4, it provides the fairest percentage of interruptions for all EVs with increase in number of interruptions. This can also be observed from the MDM values. When slack time is used as priority criterion, a fair distribution in percentage of interruptions is observed for EV4-EV15 and EV1-EV3 seems to be least affected. However, if the results are correlated with Table 1, it can be inferred that increase in probability of failure for EV1-EV3 is due to the fact that, the charging of EV1-EV3 will be pushed to end of charging period with more number of interruptions.

It can also be observed from Table 2 that the percentage of interruptions increased for EV1-EV3 with number of interruptions and vice versa for EV13-EV15 (while using different combination of priority criteria). However, it can be seen from the MDM values that with increase in number of interruptions the percentage of interruptions is fairly distributed (while using multiple priority criteria). Furthermore, using multiple priority criteria provides a higher flexibility for dynamic charging algorithms [20].

4. Determining the chargeability of EVs

From the analysis on the probability of an EV not charging to desired SOC and percentage of interruptions with different combination of priority criteria it is evident that,

1 the priority criteria used,
2 time at which DRM is invoked, and
3 the number of times DRM is invoked

Pseudo-code

1. Initialize the SOC of all EVs to be interrupted with the current value for the starting of next interval.
2. Run the scheduling simulation using stochastic load samples (Section 3)
 a) **If** $j < 48$,
  Calculate the priority values using different priority parameters
  Else Goto Step (e)
 b) **Substitute** $x_{i,j} = 1, \forall i$
 c) **If** $\sum_{i=1}^{n} x_{i,j} * p_j^{b,i} \leq p_j^{limit} - p_j$ **update** the priority values and other values, $j = j + 1$, **Goto** Step (a)
 d) Else $x_{i,j} = 0$ for EV having next minimum value in the priority values
  Repeat until $\sum_{i=1}^{n} x_{i,j} * p_j^{b,i} \leq p_j^{limit} - p_j$, **update** priority values and other values, $j = j + 1$, **Goto** Step (a)
 e) End
3. Estimate the final SOC at departure intervals of each EV
4. Compare the estimated final SOC of i^{th} EV with the desired final SOC
5. If the estimated final SOC is less than the desired final SOC then $cd_i = 0$
6. Else if the estimated final SOC is less than the desired final SOC then $cd_i = 1$

Note: The i^{th} EV will charge during j^{th} interval if $x_{i,j} = 1$ and vice versa and the maximum power at which the i^{th} EV can be charged during the j^{th} is given by $p_j^{b,i}$.

Table 3
Chargeability matrix for a typical day.

	SOC + Slt + Alt			Alt			Slt + Alt			Slt			SOC			SOC + Slt		
	14:30	15:30	16:30	14:30	15:30	16:30	14:30	15:30	16:30	14:30	15:30	16:30	14:30	15:30	16:30	14:30	15:30	16:30
EV1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	0
EV2	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	0	0
EV3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
EV4	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
EV5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EV6	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
EV7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
EV8	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1
EV9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EV10	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0
EV11	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EV12	0	0	0	1	1	1	1	1	0	1	1	0	1	1	1	1	1	0
EV13	1	1	0	0	0	0	1	1	0	1	1	1	1	1	0	1	1	1
EV14	1	1	0	1	1	0	1	1	1	1	0	0	1	0	0	1	1	1
EV15	1	1	1	1	0	0	1	1	1	1	1	1	1	0	0	1	1	1

Notes:
1. Slt – Slack time.
2. Alt – Allotted time.

have an impact on the EV charging. Hence, it is obvious that determining chargeability of the EVs before interruption from DRM is inevitable. A novel scheduling driven algorithm is proposed for estimating the chargeability of the EVs before considering them as an interruptible load. The scheduling driven approach eliminates the dependency of accuracy on the time of interruption. Hence, the probability of not charging to the desired SOC depends only on the accuracy of scheduling algorithm used. However, the preference given by different priority criteria to different types of EVs will not be affected. The algorithm used in Ref. [20] is subset of the algorithm proposed in this study. The estimated SOC at the time of departure is determined using algorithm in Ref. [20] to determine the chargeability of the EVs in the event of interruption. The pseudo-code of the proposed algorithm is given below.

The chargeability matrix is given by,

$$Cd_n = \begin{bmatrix} cd_1 \\ cd_2 \\ \vdots \\ cd_n \end{bmatrix} \quad (11)$$

where $cd_i = 1$ if the i^{th} EV can be charged to the desired SOC before the departure interval (even if its charging is interrupted in the current interval) and $cd_i = 0$ if the EV cannot be charged to the desired SOC. When DRM is invoked as in Refs. [3], the interruption signals can be sent to the charging stations after passing them through an AND gate along with chargeability signal. The chargeability matrix is shown in Table 3 for a typical day for at 14:30 h, 15:30 h and 16:30 h respectively (same simulation parameters as in Section 3). It can be observed that, the chargeability of the EVs depends largely on the priority criteria used, the time of interruption and number of interruptions. Notably, the samples (as it is stochastic) differ from one case to other although the simulation setup for all the cases is same. Hence, the chargeability matrix cannot be correlated with each other.

In Table 4, the probability of an EV not charged to the desired SOC and percentage of interruptions are presented for the case when chargeability algorithm is included with DRM (for the case when all three criteria are used). It can be inferred from Table 4 that, even though the chargeability algorithm has the capability to reduce the probability of an EV not charging to the desired SOC, the percentage of interruptions remained the same (but the number of interruptions reduced). This is because the reduction in number of interruptions is proportional to preference given to different types of EV (by a particular set of priority criteria). It is to be noted that after using the chargeability algorithm for DRM, the probability of an EV not charging to the desired SOC is negligible and depends only the accuracy of dynamic charging algorithm and load models.

Table 4
Impact of DRM on probability of not charging to desired SOC and percentage of interruptions and while using all priority criteria together.

	Probability of not charging to desired SOC with chargeability algorithm			Percentage of interruptions with chargeability algorithm		
	PN1	PN2	PN3	I1	I2	I3
EV1	0.002	0.002	0.002	0.0	1.5	2.6
EV2	0.002	0.002	0.002	0.0	1.5	2.6
EV3	0.002	0.003	0.003	0.0	1.5	2.5
EV4	0.002	0.002	0.002	10.5	10.3	9.6
EV5	0.002	0.002	0.002	10.4	10.1	9.6
EV6	0.001	0.002	0.002	10.7	9.9	9.6
EV7	0.001	0.002	0.002	10.4	10.0	9.6
EV8	0.001	0.001	0.002	10.4	9.8	9.6
EV9	0.001	0.001	0.003	10.4	10.0	9.7
EV10	0.002	0.003	0.003	10.7	10.0	9.4
EV11	0.001	0.002	0.002	10.5	10.1	9.4
EV12	0.002	0.002	0.002	10.5	10.0	9.6
EV13	0.009	0.011	0.011	1.8	1.8	2.1
EV14	0.009	0.010	0.012	1.8	1.7	2.0
EV15	0.009	0.011	0.011	1.8	1.7	1.9
MDM	**0.006**	**0.007**	**0.008**	**6.7**	**5.2**	**4.8**

Notes:
1. PN1 – Probability of an EV not charging to its desired SOC (interruption at 14:30 h).
2. PN2 – Probability of an EV not charging to its desired SOC (interruptions at 14:30 h and 15:30 h).
3. PN3 – Probability of an EV not charging to its desired SOC (interruptions at 14:30 h, 15:30 h and 16:30 h).
4. I1 – Percentage of interruption for each EV (interruption at 14:30 h).
5. I2 – Percentage of interruption for each EV (interruptions at 14:30 h and 15:30 h).
6. I3 – Percentage of interruption for each EV (interruptions at 14:30 h, 15:30 h and 16:30 h).
7. MDM – Maximum deviation from mean.
8. 0.0 – Represents very low value.

5. Conclusion

In this paper, an analysis on the impact of DRM on the chargeability of EVs was carried out using stochastic simulations. The chargeability was analyzed for cases with different priority criteria and for different number of interruptions from DRM. It was observed that each priority criterion had a unique impact on the probability of not charging to the desired SOC as well as the percentage of interruptions. It was also observed that the time of interruption and number of interruptions also had a significant impact. Hence, it was inferred that a scheduling based chargeability algorithm is required for overcoming these disadvantages. A scheduling driven algorithm for determining the chargeability was proposed. The proposed algorithm was employed with DRM and the chargeability was examined. It was observed that the proposed algorithm reduced the probability of not charging to the desired SOC to negligible values and had little influence on the percentage of interruptions. Hence, the impact of priority criteria was not changed with the implementation of the algorithm. However, the chargeability was improved and hence the algorithm can result in increased customer satisfaction/comfort. The proposed chargeability algorithm is versatile and could be used along with any DRM program to improve its performance and robustness.

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