

Dynamic Equivalent Battery as a Metric to Evaluate the Demand Response Performance of an EV Fleet

Sung Hyun Yoon*, Young Gyu Jin[†] and Yong Tae Yoon*

Abstract – Electric vehicles (EVs) are significant resources for demand response (DR). Thus, it is essential for EV aggregators to quantitatively evaluate their capability for DR. In this paper, a concept of dynamic equivalent battery (DEB) is proposed as a metric for evaluating the DR performance using EVs. The DEB is the available virtual battery for DR. The capacity of DEB is determined from stochastic calculation while satisfying the charging requirements of each EV, and it varies also with time. Further, a new indicator based on the DEB and time-varying electricity prices, named as value of DEB (VoDEB), is introduced to quantify the value of DEB coupled with the electricity prices. The effectiveness of the DEB and the VoDEB as metrics for the DR performance of EVs is verified with the simulations, where the difference of charging cost reduction between direct charging and optimized bidding methods is used to express the DR performance. The simulation results show that the proposed metrics accord well with the DR performance of an EV fleet. Thus, an EV aggregator may utilize the proposed concepts of DEB and VoDEB for designing an incentive scheme to EV users, who participate in a DR program.

Keywords: Electric vehicle, Demand response, Equivalent battery, DR metric, EV aggregator.

1. Introduction

The number of electric vehicles (EVs) has steadily increased due to their environment-friendly characteristics. Additionally, EVs can support the grid operation through demand response (DR) using their batteries [1]. There are two factors why EVs are suitable for DR. One is the internal battery can be charged fast and controllable under some constraint such as the rated power/capacity limits. Thus, the aggregate of EVs can function as an energy storage system (ESS) in the power system operation. The other factor is the usage pattern of EVs. EVs are parked most of the time and only less than 5% of the time is used to drive [2]. Thus, there are plenty of time to perform as DR resources, particularly overnight.

The capacity of an individual EV battery is so small that EVs are aggregated by so-called an EV aggregator to be used as DR resources in an electricity market [3,4]. According to market rules, an EV aggregator schedules its DR resources and submits the bids in the day ahead (DA) and/or real time (RT) markets to maximize its profit. In other words, the EV aggregator mainly focus on how to delicately and practically optimize its bids for the maximum profit.

There are studies on the various aspects of EVs, such as the charging behavior of EV users and the method for

using EVs as the DR resources. In [4], the energy storage system (ESS) is used for developing an energy bidding strategy to mitigate the EV behavioral uncertainty. In [5], EVs are utilized for DA bidding and RT frequency control combined with flexible load control techniques and uninterruptible power supply. A simple implementation using dynamic programming for the frequency regulation is proposed in [6]. The results of field tests for several ancillary services are demonstrated in [7]. In [9], the DA bid and the penalty due to the deviation from the bid are considered using the stochastic programming. In [10], the stochastic programming is utilized considering the EV staying pattern.

Although such methods in the previous studies are useful for the operational strategy of an EV aggregator, it is very difficult to recognize how much benefit can be achieved using EVs as the DR resource, and when the EVs are available to participate a DR program. In addition, the resulting strategies from the literatures can be applied only to a given circumstance, but they do not give any insight about the available DR resource from an EV fleet.

Therefore, in this paper, we propose a new concept for representing a large number of small batteries of an EV fleet as a single equivalent battery, which can be used as a metric to quantitatively evaluate the DR performance of the EVs. The number of EVs arriving/departing and charging/discharging at a certain time changes with time. Each EV has different initial state-of-charge (SOC) when it starts charging, and it has different target SOC and staying time before departure. Thus, the capacity of the equivalent battery is time-varying or dynamic, and it is named as

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dynamic equivalent battery (DEB) in this paper. The capacity of DEB can be determined from the probabilistic calculation assuming that the probability density functions (pdfs) of the parameters related the EVs are known. This method for determining the capacity of DEB is also presented. Using the concept of the DEB, an EV aggregator can easily grasp the available DR resources from EVs over time. Further, the DR performance is dependent on the electricity prices. Therefore, we also introduced the concept of value of DEB (VoDEB) to quantify the value of DEB coupled with the electricity prices. The VoDEB is closely related to the DR performance, that is, the reduction of charging cost of EVs.

The remainder of this paper is organized as follows. In Section 2, the process of modeling the DEB is described. A method for determining the capacity of DEB is presented in Section 3. The concept of the VoDEB is explained also in Section 3. In Section 4, the effectiveness of the DEB and the VoDEB as metrics for the DR performance of EVs is verified with the simulations. In the simulations, 100 scenarios for 369 EVs are generated from the pdfs. Concluding remarks are given in Section 5.

2. Modeling of Dynamic Equivalent Battery

In the model of the DEB, it is assumed that the behavioral information of EVs are available. The parameters of the usage information of EVs considered in this study are listed in Table 1. The initial SOC, target SOC, arrival time, departure time and number of incoming EVs are random variables with its own pdf. In the following expression, the index k for the k -th EV will be added to the parameters in Table 1. Thus, for example, $T_{a,k}$ indicates the arrival time of the k -th EV.

Fig. 1 shows the method for determining the capacity of

Table 1. Usage information of EVs for modeling the DEB

SOC_i	Initial SOC of EV	T_a	Arrival time
SOC_f	Target SOC of EV	T_D	Departure time
N_{EV}	Number of incoming EV	T_s	Staying time
P_r	Rated power	C_n	Rated capacity

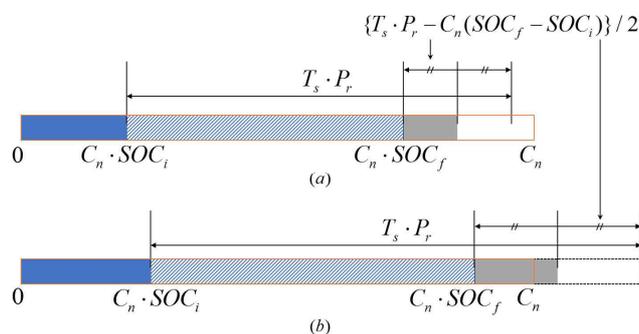


Fig. 1. Capacity of equivalent battery for an EV: (a) basic case; (b) when the staying time is relatively long

equivalent battery of an EV. If the EV has enough time to charge it to the target SOC, the rest of time before departure can be used for DR. In other words, the charging pattern can be changed to implement the DR function once the constraint on the target SOC is met at the departure time.

Basically, as shown in Fig. 1(a), the total available charging quantity is $T_s \cdot P_r$, and the required charging quantity is $C_n(SOC_f - SOC_i)$. The extra charging capacity for DR is the difference of these two quantities. The same amount of the charging (or discharging) quantity is necessary to recover the SOC to the target value on departure. Therefore, the equivalent charging capacity for k 's EV, which is represented with gray region, is defined as half of the extra virtual capacity during the stay:

$$C_{eq,ch,k} = \frac{T_{s,k} \cdot P_r - C_n(SOC_{f,k} - SOC_{i,k})}{2} \cdot d(t) \quad (1)$$

where $d(t)$ is a duration function to indicate the time duration when the EV is connected to grid, given by

$$d(t) = u(t - T_{a,k}) - u(t - (T_{a,k} + T_{s,k})) \quad (2)$$

However, the EV cannot be charged beyond its physical capacity. Thus, when the staying time is so long that the capacity in (1) exceeds the physical capacity, as shown in Fig. 1(b), the upper limit of the equivalent capacity for charging, $C_{eq,ch,k}$, can be expressed as

$$C_{eq,ch,k} = C_n(1 - SOC_{f,k}) \cdot d(t) \quad (3)$$

The equivalent capacity for discharging is defined in a similar manner. In the basic case, the equivalent capacity for discharging is the same as (1). However, the EV cannot discharge beyond the SOC of zero. Thus, when the capacity in (1) exceeds the initial SOC, the equivalent capacity for discharging, $C_{eq,dch,k}$, should be differently calculated as

$$C_{eq,dch,k} = C_n(SOC_{i,k}) \cdot d(t) \quad (4)$$

It should be noted from Eqs. (1), (3), and (4) that the equivalent battery has a symmetric capacity for charging and discharging like a normal battery system in a basic case; but it has the asymmetric capacity in some cases depending on the staying time and the initial/target SOC.

3. Characteristics of Dynamic Equivalent Battery

3.1 Calculation of dynamic equivalent battery

Eqs. (3) and (4) in Section 2 are given to describe the concept of the equivalent capacity for charging and

Table 2. Probability density functions for calculating the capacity of DEB

SOC_i	SOC_f	$N_{EV}(t)$	T_s
$N(\mu_i, \sigma_i^2)$	$N(\mu_f, \sigma_f^2)$	Poisson($\lambda(t)$)	$N(\mu_s, \sigma_s^2)$
$f_i(x; \mu_i, \sigma_i, a, b)$	$f_f(x; \mu_f, \sigma_f, c, d)$	$f_N(x; \lambda(t))$	$f_s(x; \mu_s, \sigma_s, e, f)$

discharging, respectively. Thus, the stochastic properties, such as probability distribution of the initial SOC, target SOC, staying time, and the number of incoming EVs, should be considered to calculate the specific capacity of DEB. Taking from the parameters in [9-11], the truncated Gaussian distribution (TGD) is used to model initial SOC, target SOC and staying time. The number of incoming EV is modeled as the Poisson distribution. Table 2 lists a set of pdfs used in the calculation of the capacity.

Given the pdfs, the capacity of DEB for an EV is calculated by jointly integrating the pdfs considering the conditions described in Section 2. Then, the capacity of DEB for charging ($C_{eq,ch,k}$) and for discharging ($C_{eq,dch,k}$) for an EV are expressed as

$$C_{eq,ch} = \begin{cases} d(t) \cdot \iiint \frac{T_s \cdot P_r - C_n(SOC_f - SOC_i)}{2} \cdot f_f \cdot f_i \cdot f_s dSOC_f dSOC_i dT_s, & \text{if } 0 \leq \frac{T_s \cdot P_r - C_n(SOC_f - SOC_i)}{2} < C_n(1 - SOC_f) \\ d(t) \cdot \iiint C_n(1 - SOC_f) \cdot f_f \cdot f_i \cdot f_s dSOC_f dSOC_i dT_s, & \text{if } \frac{T_s \cdot P_r - C_n(SOC_f - SOC_i)}{2} > C_n(1 - SOC_f) \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

$$C_{eq,dch} = \begin{cases} d(t) \cdot \iiint \frac{T_s \cdot P_r - C_n(SOC_f - SOC_i)}{2} \cdot f_f \cdot f_i \cdot f_s dSOC_f dSOC_i dT_s, & \text{if } 0 \leq \frac{T_s \cdot P_r - C_n(SOC_f - SOC_i)}{2} < C_n(1 - SOC_f) \\ d(t) \cdot \iiint C_n(SOC_i) \cdot f_f \cdot f_i \cdot f_s dSOC_f dSOC_i dT_s, & \text{if } \frac{T_s \cdot P_r - C_n(SOC_f - SOC_i)}{2} > C_n(SOC_i) \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

Finally, the capacity of DEB of the whole EVs ($C_{eq,ch}$, $C_{eq,dch}$, and C_{eq}) can be determined by summing the capacity for each EV as

$$C_{eq,ch} = \sum_k C_{eq,ch,k}, \quad C_{eq,dch} = \sum_k C_{eq,dch,k} \quad (7)$$

$$C_{eq} = C_{eq,ch} + C_{eq,dch} \quad (8)$$

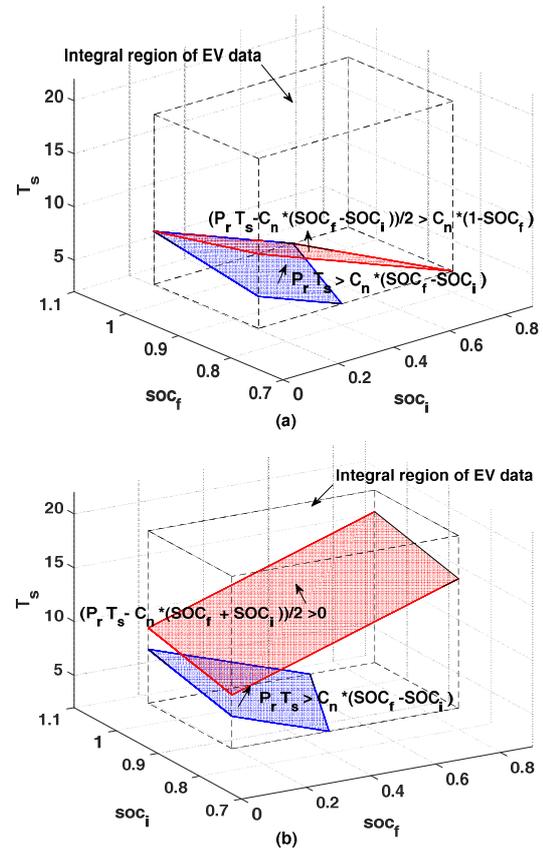


Fig. 2. Integral area of equivalent capacity: (a) charging case; (b) discharging case

Fig. 2(a) and Fig. 2(b) shows the integration area for the capacity of DEB for charging and discharging in (5) and (6), respectively. Since the values of the variable are limited, the whole integration area is given as a cuboid. In the case of charging, the first value of Eq. (5) corresponds to the region between the blue and the red planes. Specifically, if there is enough time for DR while fulfilling the charging requirements and not exceeding the physical capacity of 100% SOC, all the remaining time can be utilized as the DR capacity in this intermediate region. However, the initial SOC is high and/or the staying time is long, there is much capacity for DR and the physical capacity of 100% SOC limits the equivalent capacity for charging. Then, the second value of Eq. (5) is aggregated as the capacity of DEB. The third value of zero in (5) indicates the case where it is short of time for meeting the target SOC due to the, e.g., short staying time. The same reasoning is applied to the capacity of DEB for discharging in (6) and Fig. 2(b).

3.2 Value of DEB coupled with electricity prices

A price-based DR program is conducted by buying electricity at a low price and selling it at a high price. The EV aggregator performs the same operation. Consequently, the DR performance depends on the time-varying

electricity prices. In other words, even the ESSs with the same capacity result in the different values of cost reduction for different electricity prices.

The value of the DEB in terms of DR is coupled with the electricity prices. It is obvious that the DEB at the time of high price is more valuable than that at the time low price. Thus, we further introduce the concept of value of DEB (VoDEB) based on both the capacity of DEB and the time-varying prices. The VoDEB is calculated by summing the DEB multiplied by the relative magnitude of the price, which is expressed as

$$\text{Value of DEB(VoDEB)} = \sum_t C_{eq} \cdot (\rho_t - \min(\rho_t)) / \rho_s \quad (9)$$

$$\rho_s = \sum_t \rho_t \quad (10)$$

where ρ_t is the electricity price, and ρ_s is the sum of ρ_t for normalizing the price. Since the benefit from DR is closely related the relative price difference, the VoDEB can be used as a metric to evaluate the DR performance of EVs together with the DEB.

4. Simulation results

To verify the effectiveness of the DEB and VoDEB as metrics for DR performance, simulations are performed for an EV fleet with an average 369 EVs. The DR performance is measured by the difference of the charging cost of direct charging and optimized charging methods for 100 randomly generated scenarios. For the direct charging method, charging operation starts at arrival and ends as soon as the target SOC is satisfied. For the optimized charging, the charging schedule of individual EV is adjusted to minimize the charging cost. This optimization problem is explained in detail in the appendix. Then, the DR performance is calculated as

$$\text{DR performance} = \frac{\text{Direct charging cost} - \text{optimized charging cost}}{\text{Direct charging cost}} \quad (11)$$

The specific parameters of the probability distributions are given in Table 3, and the numbers of incoming EVs for 24 hours from noon today (12h) to noon of the next day (35h) are listed in Table 4. In Table 3, the pdf of the initial SOC is taken from in [11], of which the average is modified to magnify the amount of DR resource; the pdf of the staying time, T_s , is calculated as the difference between the departure and arrival times as in Eq. (12), whose pdfs are taken from Mobilität in [10].

$$\sigma_s = \sqrt{2^2 + 2^2} = 2\sqrt{2} \quad (12)$$

Table 3. Probability density functions and the parameters for simulations

SOC_i	SOC_f	T_s
$N(0.45, 0.25^2)$	$N(0.9, 0.1^2)$	$N(12, 4^2)$
$f_I(x; 0.45, 0.25, 0.1, 0.8)$	$f_f(x; 0.9, 0.1, 0.8, 1)$	$f_s(x; 12, 4, 4, 20)$
$N_{EV}(t)$	P_r	C_n
Poisson($\lambda(t)$)	5kW	50kWh
$f_N(x; \lambda(t))$		

Table 4. Average number of incoming EVs

t	12	13	14	15	16	17	18	19	20	21	22	23
$\lambda(t)$	0	0	0	0	34	46	55	59	55	46	34	22
t	24	25	26	27	28	29	30	31	32	33	34	35
$\lambda(t)$	12	6	0	0	0	0	0	0	0	0	0	0

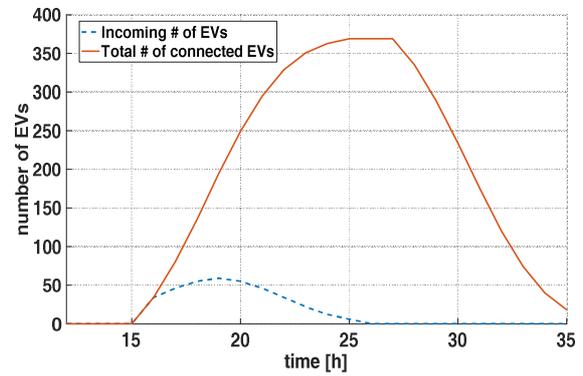


Fig. 3. Total connected EVs and average number of incoming EVs

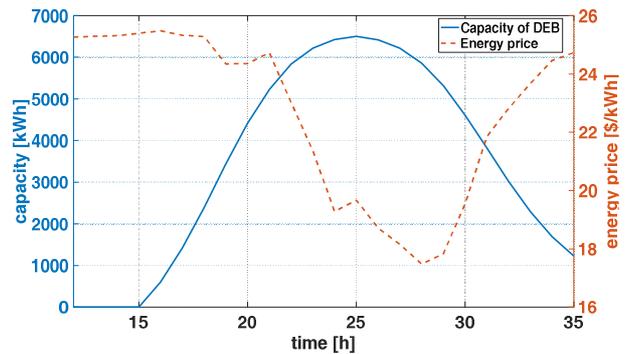


Fig. 4. Capacity of DEB and electricity prices

However, after approximating the value in (12) to $\sigma_s = 4$, the simulations are performed with various values of $\sigma_s = 1, 2, 3, 4$, and 5 to investigate its effect on the values of DEB and VoDEB. For the pdf of the target SOC, its average and standard deviation are arbitrarily selected as 0.9 and 0.1, respectively.

Fig. 3 shows total connected EVs with the average number of incoming EVs. Electricity prices are taken from the PJM's locational marginal prices of a typical day in

2017. The capacity of DEB for this base configuration is calculated and shown in Fig. 4.

To identify the relationship between the DR performance and the DEB, the capacity of DEB is calculated for different values of standard deviation of (σ_s) of the staying time T_s . Fig. 5 shows the capacity of DEB with respect to σ_s . As σ_s becomes larger, the graph spreads out and the peak becomes lower. It means that the capacity of DEB for the small σ_s has more capacity than the capacity of DEB for the large σ_s especially at midnight. Therefore, an EV aggregator can expect that the EV fleet with the small variation of staying time leads to more DR benefit, that is, greater reduction of the charging cost.

The VoDEB for the different values of σ_s are listed in Table 5. It shows that the VoDEB is also inversely

Table 5. DR performance and VoDEB for different distributions of staying time

σ_s	1	2	3	4	5
Direct charging cost (\$)	200.4	197.8	198.0	195.7	193.2
Optimized charging cost (\$)	166.3	165.4	167.5	167.0	165.9
DR performance (%)	17.03	16.37	15.38	14.63	14.14
VoDEB	573	552	525	504	490

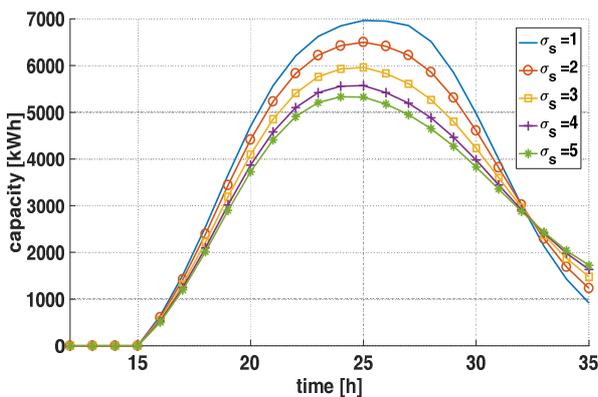


Fig. 5. Capacity of DEB according to standard deviation of staying time (T_s)

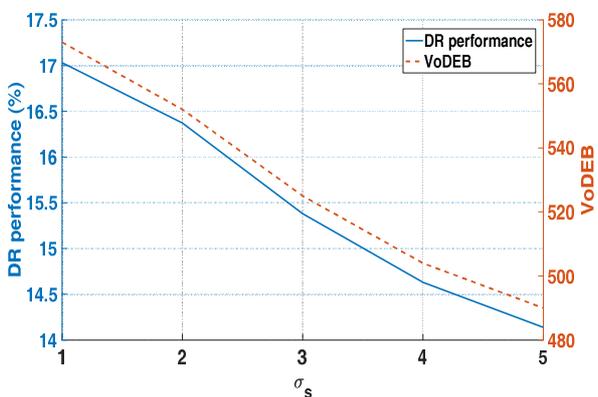


Fig. 6. Relationship between VoDEB and DR performance

proportional to σ_s like the DEB. It can be expected from the results that the DR benefit increases as the variation of staying time of EV is small. Moreover, the results for the DR performance and the VoDEB are depicted in Fig. 6 to clarify their relationship. It can be clearly seen from Fig. 6 that the VoDEB accords very well with the DR performance, which verifies the usefulness of the VoDEB as a quantitative metric for EVs as DR resources.

To further verify the effectiveness of the VoDEB as a metric, the same capacity of DEB is applied to the simulations with the five cases of different prices. Case 1 is the base case with the same electricity price as Fig. 4; in Case 2 and Case 3, the price is increased and decreased from the base case by 5% for all the time instants, respectively; in Case 4 and Case 5, the price is gradually increased to 10% and decreased to -10% from the base case, respectively. The five cases of the price are shown in Fig. 7.

The simulation results are listed in Table 6. In Case 2 and Case 3, the DR performance and the VoDEB are equal to the results of Case 1. This is because the charging schedule from the optimal bidding method selected is determined based on the relative difference of the prices in different time, such that the increase or decrease of the price by the same amount does not change the optimal charging schedule. This result is another evidence of the usefulness of VoDEB because it does not change in Cases 1, 2, and 3.

On the contrary, the DR performance and the VoDEB are different in Case 4 and Case 5 compared with Case 1. To

Table 6. DR performance and VoDEB for five case of different electricity prices

Case	1	2	3	4	5
Direct charging cost (\$)	199.5	209.4	189.5	214.6	184.4
Optimized charging cost (\$)	167.0	175.4	158.7	179.1	154.5
DR performance (%)	16.27	16.27	16.27	16.51	16.20
VoDEB	552	552	552	576	526

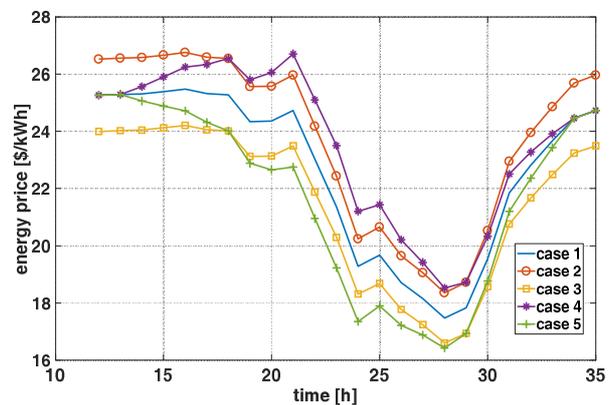


Fig. 7. Five cases of electricity prices

Table 7. Relative values of VoDEB and DR performance compared with the base case (Case 1)

Case	1	2	3	4	5
V_oDEB / V_oDEB (Case 1)	100	100	100	101.43	99.58
DR performance/ DR performance (Case 1)	100	100	100	104.29	95.32

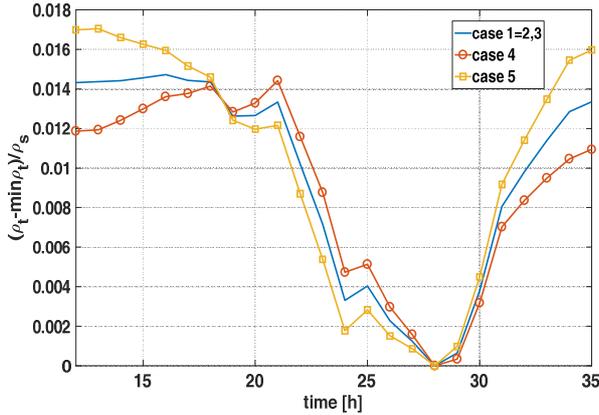


Fig. 8. $\rho_t - \min(\rho_t) / \rho_s$ of five cases of different electricity prices

investigate the correlation between the VoDEB and the DR performance more closely, the relative prices to the base case are depicted in Fig. 8, and the relative values of DR performance and VoDEB and listed in Table 7. The increase in Case 4 and decrease in Case 5 of the DR performance can be reflected as the increase and decrease of the VoDEB. Thus, it can be clearly seen that the VoDEB follows the tendency of the DR performance. In other words, although the change of VoDEB is not exactly equal to the change of the DR performance in the view of absolute value, the VoDEB approximately reflects the DR performance.

Based on these results, it can be concluded that the DEB and VoDEB are useful metrics to evaluate the DR performance of an EV fleet because the capacity of DEB is large when many EVs are available for DR and the VoDEB is high when the DR benefit from EVs is high given the electricity prices. Therefore, an EV aggregator can evaluate its DR resources without complex optimization process but with simple calculation. Moreover, the information from DEB and VoDEB is easy to understand. Thus, an EV aggregator may utilize the proposed concepts of DEB and VoDEB for maximizing its profit and for designing an incentive scheme to EV users, who participate in a DR program.

5. Conclusion

In this paper, the concepts of dynamic equivalent battery

(DEB) and the value of DEB (VoDEB) are proposed as metrics to quantitatively represent the DR performance of EVs. The capacity of DEB is calculated using the probability distributions of the behavioral information of EVs. The simulation results verified the effectiveness of DEB and VoDEB as metrics related to DR.

The proposed concepts of DEB and VoDEB are easy to recognize the aggregate DR resource from EV, and very useful for an EV aggregator to develop its own DR program for EVs. Thus, further researches are necessary to develop a method for designing a DR program maximizing its profit and/or minimizing the charging cost based on these concepts. It may also be interesting to design a campaign for EV users to shape the desirable charging pattern in the view of DEB and VoDEB.

Appendix

The optimized charging is derived by solving the following mixed integer optimization problem.

$$\min \sum_t \sum_k (x(t,k) - y(t,k)) * P_r * \rho_t \quad (A-1)$$

s.t.

$$SOC(t,k) = SOC(t-1,k) + \frac{P_r}{C_n} (x(t-1,k) - y(t-1,k)) \quad (A-2)$$

$$0 \leq SOC(t,k) \leq 1 \quad (A-3)$$

$$x(t,k) + y(t,k) \leq 1 \quad (A-4)$$

$$\sum_{t=departure}^{t=arrival} P_r * (x(t,k) - y(t,k)) \geq C_n * (SOC_f(k) - SOC_i(k)) \quad (A-5)$$

where

$$\begin{aligned} x(t,k) &= \text{binary variable for } k\text{'th EV charging status} \\ y(t,k) &= \text{binary variable for } k\text{'th EV discharging status} \end{aligned}$$

Eq. (A-2) expresses the change of SOC due to the charging and discharging operations; Eq. (A-3) is the constraint on the upper and lower limits of SOC; Eq. (A-4) describes the condition that an EV cannot be charged and discharged at the same time; Eq. (A-5) requires that the target SOC of the EV should be satisfied at the time of departure.

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