

# Framework for capacity credit assessment of electrical energy storage and demand response

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**Abstract:** The use of electrical energy storage (EES) and demand response (DR) to support system capacity is attracting increasing attention. However, little work has been done to investigate the capability of EES/DR to displace generation while providing prescribed levels of system reliability. In this context, this study extends the generation-oriented concept of capacity credit (CC) to EES/DR, with the aim of assessing their contribution to adequacy of supply. A comprehensive framework and relevant numerical algorithms are proposed for the evaluation of EES/DR CC, with different 'traditional' generation-oriented CC metrics being extended and a new CC metric defined to formally quantify the capability of EES/DR to displace conventional generation for different applications (system expansion, reliability increase etc.). In particular, specific technology-agnostic models have been developed to illustrate the implications of energy capacity, power ratings, and efficiency of EES, as well as payback characteristics and customer flexibility (that often also depend on different forms of storage available to customers) of DR. Case studies are performed on the IEEE RTS to demonstrate how the different characteristics of EES/DR can impact on their CC. The framework developed can thus support the important debates on the role of EES/DR for smart grid planning and market development.

## 1 Introduction

Electrical energy storage (EES) and demand response (DR) are now widely accepted as key to the realisation of future low carbon power systems. For instance, in several countries there are general discussions about capacity markets or similar schemes which are also open to EES/DR (e.g. the UK [1]). However, only a few studies (e.g. [2–5]) have investigated the implications of utilising EES/DR for the purposes of providing system adequacy. In contrast, it is essential to undertake such investigations in order to compare on a level playfield the contribution of EES/DR with generation plants that are currently used to maintain system adequacy, and thus indicate to what extent demand side resources can reliably displace generation plant. In fact, EES/DR is qualitatively distinct from conventional generation in terms of contribution to adequacy. For instance, EES/DR needs to go through a 'load recovery' stage, being it to charge the EES or to provide the underlying demand service in the case of DR. In this respect, the load reshaping capability and so on the potential contribution from EES to adequacy may depend in a non-trivial way on different EES parameters, including energy capacity, power ratings, and roundtrip efficiency. Similarly, the capability of demand to be 'responsive' is also significantly affected by several parameters such as building characteristics, occupancy profiles, desired comfort level and so forth. Thus, it is interesting to point out how DR is also in many cases facilitated by different forms of storage [6], the most common of which being thermal storage from building thermal inertia or hot water tanks [7, 8], or more recently (and expected to grow in the future) electric vehicles [9]. Hence, depending on the underlying physical storage, DR can be more or less flexible (in terms of capability to reduce load consumption) and exhibit specific load recovery (or 'payback') characteristics to re-establish the demand service that was curtailed, for example production of heating or electric vehicle charging.

In the context of formally evaluating the contribution of different generation plants to system adequacy, the concept of capacity credit (CC) was developed several decades ago through the effective load carrying capability (ELCC) metric [10]. The integration of different variable renewable technologies such as wind [11–13] has then

driven an increasing interest in the CC topic in the last years. In particular, more CC metrics have been proposed for CC assessment, including the equivalent firm capacity (EFC) [14, 15], equivalent conventional capacity (ECC) [16], and guaranteed capacity [16]. Only very recently was the CC of demand side resources investigated, by applying the ELCC and ECC metrics for EES [17] and ELCC for DR [18, 19]. Nonetheless, neither of these studies has carried out a systematic analysis of the impact on CC of the parameters that characterise EES/DR.

On the basis of the existing literature, so far there has been no comprehensive framework to evaluate different CC metrics for EES/DR. Moreover, no developed methodology has systematically assessed the CC of these resources taking into account and highlighting the role of their parameters. On these premises, this paper develops a novel and comprehensive framework to evaluate the CC of EES/DR, effectively establishing a bridge between generation side and demand side resources and allowing a level playfield comparison in the context of system reliability. This framework includes, as key contributions: the fundamental definitions of CC metrics for EES/DR; the adequacy-oriented models of EES and DR; and a set of algorithms for evaluating these metrics. In terms of CC definitions, the 'classical' generation-oriented CC metrics are extended to value the EES/DR's capacity contribution. Moreover, a new CC metric, namely the equivalent generation capacity substituted (EGCS), is defined to quantify to what extent certain EES/DR can displace generation. The context when each metric should be applied is also critically discussed. Further to that, specific synthetic models are proposed for EES and DR, aiming at highlighting the role of their key parameters for the CC analysis. Detailed algorithms for assessing the CC metrics are then developed using a dual stage optimisation approach (which ensures uniqueness of the solution) for scheduling EES/DR with assumed perfect foresight of the load profile. Finally, by applying this framework to various EES/DR scenarios, several case studies provide general strategic insights into the CC concept for different potential EES/DR applications, which is also part of the contributions of this work.

The rest of this paper is organised as follows: the CC metrics for EES/DR are defined in Section 2; the synthetic models of EES and DR are proposed in Section 3; the detailed evaluation algorithms are developed in Section 4; Section 5 demonstrates the case studies and discussions. The conclusions of this work are summarised in Section 6.

## 2 Concepts, definitions, and conceptual evaluation methodologies

A comprehensive framework for CC evaluation of EES/DR is developed, which can quantify the capacity contribution of these resources by different metrics. According to the existing CC definitions, three classical CC metrics are extended to EES/DR (namely, ELCC for system expansion purposes, and EFC and ECC for portfolio comparison purposes). In addition, in the light of assessing EES/DR's capability to replace generation, a new CC metric, namely, the EGCS is defined.

Ultimately, four CC metrics are thus included in this framework with different contexts of application. The general methodologies of evaluating these metrics and the computational algorithm for the underlying reliability assessment are illustrated below as part of this framework.

### 2.1 Application to EES/DR of classical CC metrics

On the generation side, ELCC, EFC, and ECC are the three classical CC metrics widely applied [18] and are thus extended here to EES/DR too. Their evaluation methodologies are illustrated in Fig. 1 and discussed below.

**2.2.1 Effective load carrying capability:** The ELCC metric was originally presented in [12] and it is applied here as follows. The deployment of EES/DR in a system allows the system to supply an additional ('virtual') load while preserving its reliability level, as illustrated in Fig. 1a. The reliability level here is represented by the expected energy not supplied (EENS). In addition, as the curve in Fig. 1a must have a cross point with the EENS assessed for the original system, the ELCC definitely exists.

**2.2.2 Equivalent firm capacity:** In this case, a 'virtual' generator that is perfectly reliable is applied to the original system to achieve the same reliability level (indicated by the EENS) as with EES/DR. Thus, the EFC of EES/DR is then defined as the capacity of this virtual generator where the curve in Fig. 1b has an intersection point with the EENS assessed for the system with EES/DR. In addition, the EENS decreases to zero when the capacity of this virtual generator is beyond the peak load, and hence this intersection point in Fig. 1b must exist, meaning the EFC must exist.

**2.2.3 Equivalent conventional capacity:** The concept of ECC is based on the same philosophy as the EFC with the difference of using a 'real' conventional generator that has certain reliability characteristics. Thus, the ECC is in principle always greater than the EFC. As an imperfectly reliable benchmark unit is now used, EENS would saturate at a non-zero value as seen in Fig. 1c. Interestingly, in the case of curve (A) the ECC by definition cannot exist because the benchmark unit cannot provide the same EENS as EES/DR. This may be seen as a paradox caused by the selected benchmark unit. On the other hand, in the case of curve (B) the ECC of EES/DR is determined as the capacity of the benchmark unit when curve (B) reaches the EENS assessed for the system with EES/DR.

### 2.2 Definition of a new CC metric for EES/DR

Since EES/DR is capable to reduce the peak demand, a certain amount of generation resources, in particular the peaking units could be displaced while preserving the level of system adequacy. However, the aforementioned CC metrics are not defined in this respect. Therefore, in order to explicitly quantify the CC of EES/DR in the light of replacing existing generation resources, a new CC metric is defined for the proposed framework, namely, the EGCS. The evaluation methodology for the EGCS metric is illustrated in Fig. 2.

In Fig. 2, it is assumed that the existing generation system has  $U$  units, which are sorted from 1 to  $U$  based on the descending order of their operational costs. It is worth mentioning that sorting the units based on operational cost is a reasonable manner for EES/DR to replace generation resources. However, the concept of EGCS is not limited by this manner. Then in the system with EES/DR, units are iteratively replaced one by one starting from the most expensive unit, and SMSC is run to quantify EENS (representing the reliability level). Once the total replaced capacity leads to an EENS that is equal to or higher than the EENS of the original system, the replacement of generation should stop. Subsequently, the EGCS for EES/DR can be computed through linear interpolation (because of the discreteness of generation capacity). This newly defined EGCS metric thus distinctly indicates the conventional generation capacity that could be displaced by EES/DR without compromising the original level of system adequacy.

### 2.3 Underlying reliability assessment for CC studies

As seen earlier, evaluation of CC metrics is based on evaluating and comparing adequacy levels. These can be quantified by different reliability indices, e.g. loss of load probability, loss of load expectation, EENS, loss of load frequency (LOLF), loss of load duration (LOLD) etc. [20, 21]. In fact, different indices address different aspects of system reliability, and therefore the CC metric

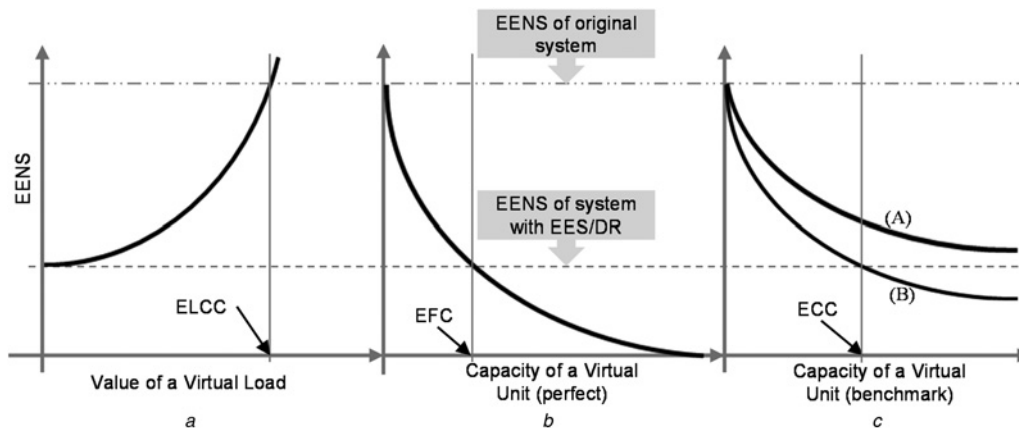


Fig. 1 Conceptual evaluation methodologies for classical CC metrics applied to EES/DR

- a ELCC
- b EFC
- c ECC

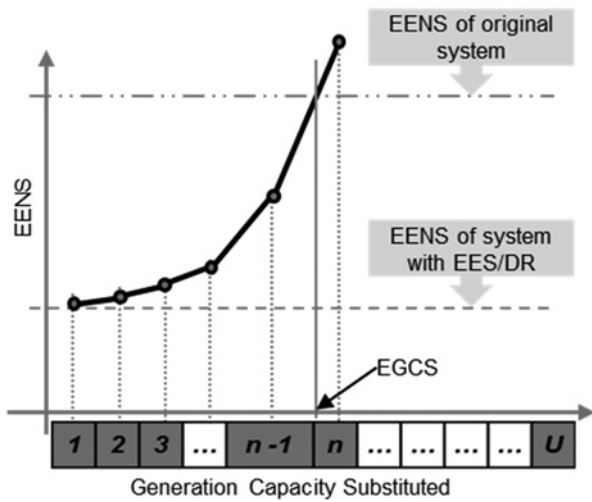


Fig. 2 Conceptual methodology for EGCS evaluation

that uses a specific index indicates the capacity value in terms of the reliability performance that index is measuring. Without loss of generality, in this paper the EENS is applied. In terms of computational method, both analytical and Monte Carlo simulation (MCS) techniques might be used [20]. More specifically, the analytical and state-sampling MCS techniques are generally used for time-collapsed analysis, while the sequential MCS technique is suitable for chronological analysis involving inter-temporal constraints [21]. Though it is not strictly required by the following EES/DR's models and assessment algorithms developed in this paper, sequential MCS is used to assess the EENS in the case study and is suggested to be the computational method for the proposed framework. In fact, on the one hand this is because other indices, particularly frequency and duration indices (e.g. LOLF and LOLD), can be accurately quantified by sequential MCS; on the other hand, the following EES/DR's models, as a general module of the proposed framework, could be replaced by other more complex models that might involve inter-temporal constraints such as post-contingency controls or interactions between EES/DR and generation resources, which do require sequential MCS. Ultimately, as a recommendation for the computational method, sequential MCS makes the proposed framework more general and compatible.

### 3 Adequacy-oriented models of EES/DR

Major research effort has been devoted to the modelling of different operational strategies and economic incentive schemes for operating EES/DR. However, while the actual implementation of EES/DR operational strategies depends on specific economic arrangements, the impact of EES/DR on system adequacy can generally be synthesised by focusing exclusively on their technical characteristics for the purpose of peak reduction, which is eventually how EES/DR can provide capacity support. This is in line with the generation adequacy assessment by using generators' reliability parameters without involving any short-term operational considerations (e.g. unit commitment), thus also abstracting from specific market designs. In this light, the EES/DR's models presented below focus on the operational characteristics that constrain their contribution to peak reduction, regardless of the specific economic arrangements in place [If the ultimate aim is to provide capacity support, the peak reduction would anyway be the objective of properly designed economic schemes.].

#### 3.1 Adequacy-oriented model of EES

In line with the general framework proposed, a technology-agnostic model is presented here for EES, which can represent the EES's key operational characteristics that have major impact on adequacy of

supply independently of specific technologies under analysis (e.g. the model can seamlessly be used to depict pumped hydro-power or bulk/distributed battery, once the parameters of the particular storage technology are plugged in the model). More specifically, for a certain EES type or device  $j$ , let  $E_t^j$  be the energy stored at the end of each time  $t$  during a considered time window  $T$ , and then  $E_t^j$  can be calculated from (1) where  $E_{\max}^j$  is the energy capacity,  $E_{\min}^j$  is the minimum energy that needs to be kept in the storage, and  $E_{\text{ini}}^j$  is the energy stored at the beginning of  $T$ , which can be used as a decision variable in the EES dispatch, or be given a specific value between  $E_{\min}^j$  and  $E_{\max}^j$ . In addition,  $S_{\tau}^j$  in (1) represents the equivalent power consumed by the EES during the time  $\tau$ , impacting directly on the state of charge  $E_t^j$ .  $S_{\tau}^j$  is derived from the actual charging power  $S_{\tau}^{+j}$  and discharging power  $S_{\tau}^{-j}$  in (2), where  $\delta_{\tau}^{+j}$  and  $\delta_{\tau}^{-j}$  are the loss of efficiency [The efficiency for standing losses, such as to account for possible energy leakage during the time window considered could be included too. This efficiency would depend on the specific storage type, e.g., evaporation of water in pumped-hydro storage. However, this is not explicitly modelled here for the sake of simplicity and without affecting the generality of the CC implications of EES/DR.] corresponding to  $S_{\tau}^{+j}$  and  $S_{\tau}^{-j}$ , respectively. The binary variable  $b_{\tau}^j$  in (3) is used as: if  $S_{\tau}^j$  is for charging,  $b_{\tau}^j = 1$ ; otherwise,  $b_{\tau}^j = 0$ . The charging and discharging power ratings are denoted by  $S_{\max}^{+j}$  and  $S_{\max}^{-j}$  in (3), respectively.

$$E_t^j = \left( \sum_{\tau=1}^t S_{\tau}^j \cdot \Delta\tau \right) + E_{\text{ini}}^j, \quad E_{\min}^j \leq E_t^j \leq E_{\max}^j \quad (1)$$

$$S_{\tau}^j = S_{\tau}^{+j} \cdot (1 - \delta_{\tau}^{+j}) + S_{\tau}^{-j} \cdot (1 + \delta_{\tau}^{-j}) \quad (2)$$

$$0 \leq S_{\tau}^{+j} \leq b_{\tau}^j \cdot S_{\max}^{+j}, \quad (1 - b_{\tau}^j) \cdot S_{\max}^{-j} \leq S_{\tau}^{-j} \leq 0 \quad (3)$$

As modelled in (1) and (2), the roundtrip efficiency is implicitly set up by certain values of  $\delta_{\tau}^{+j}$  and  $\delta_{\tau}^{-j}$ . On the other hand, in order to be able to explicitly and readily specify the roundtrip efficiency, it is also assumed, as typical in such studies and without the loss of generality, that the energy stored in EES at the end of  $T$ ,  $E_T^j$ , is equal to its initial energy level  $E_{\text{ini}}^j$  resulting in (4). In addition,  $\delta_{\tau}^{+j}$  and  $\delta_{\tau}^{-j}$  are assumed to share the same constant value (referred to as  $\delta$ ). [The loss of efficiency for charging and discharging in reality may vary according to specific charging and discharging rates. However, by assuming  $\delta_{\tau}^{+j} = \delta_{\tau}^{-j} = \delta$ , a simple approach to explicitly set the roundtrip efficiency can be formulated analytically while allowing the use of linear programming.] Then, the roundtrip efficiency  $\eta^j$  is calculated from (5), which is derived based on (4), and in turn  $\delta_{\tau}^{+j}$  and  $\delta_{\tau}^{-j}$  can be computed from (6) with a specified roundtrip efficiency, such as, if  $\eta^j = 75\%$ , then  $\delta_{\tau}^{+j} = \delta_{\tau}^{-j} = \delta = 14.3\%$ ;  $\forall \tau$ .

$$\sum_{\tau=1}^T [S_{\tau}^{+j} \cdot (1 - \delta_{\tau}^{+j}) + S_{\tau}^{-j} \cdot (1 + \delta_{\tau}^{-j})] \cdot \Delta\tau = 0 \quad (4)$$

$$\eta^j = - \left( \sum_{\tau=1}^T S_{\tau}^{-j} \cdot \Delta\tau \right) / \left( \sum_{\tau=1}^T S_{\tau}^{+j} \cdot \Delta\tau \right) = \frac{1 - \delta}{1 + \delta} \quad (5)$$

$$\delta_{\tau}^{+j} = \delta_{\tau}^{-j} = \delta = \frac{1 - \eta^j}{1 + \eta^j}, \quad \forall \tau \quad (6)$$

#### 3.2 Adequacy-oriented model of DR

In terms of peak reduction that DR can bring in the system, this depends on the intrinsic flexibility characteristics of specific appliances. In particular, load restoration is required in most cases as a consequence of load reduction, unless the service that was curtailed is forfeited. In order to abstract from the specific customer and appliance's characteristics and carry out studies of general validity (as for EES), a technology-agnostic model is



proposed for DR, taking explicit account of both load reduction and payback characteristics in general terms.

Let  $O_t^i$  be the *original* load,  $M_t^i$  be the *modified* load by using DR,  $R_t^i$  be the *reduced* load, and  $P_t^i$  be the *payback* load, then

$$M_t^i = O_t^i - R_t^i + P_t^i \quad (7)$$

where, superscript  $i$  denotes a customer group and subscript  $t$  represents a time point in the time series of load. In addition,  $R_t^i$  and  $P_t^i$  can be further expressed respectively as

$$R_t^i = \sum_{d=1}^{D^i} r_t^{d,i}, \quad P_t^i = \sum_{d=1}^{D^i} \sum_{\tau=1}^T \alpha_{t,\tau}^{d,i} \cdot r_\tau^{d,i} \quad (8)$$

where,  $r_t^{d,i}$  is the *load reduction* attributed to a particular type of DR, denoted by  $d$ , and  $D^i$  is the group of available DR types. The factors ( $\alpha_{t,\tau}^{d,i}$ ) are defined here as *payback coefficients*, which represent the percentage of  $r_\tau^{d,i}$  that needs to be restored at the time  $t$ . These payback coefficients can be synthetically organised as a matrix, basically providing a map of the load restorations at different times as the consequences of certain reductions.  $T$  is the considered time window for DR.

The load reduction  $r_t^{d,i}$  is generally limited by the flexible consumption from DR customers in the system. This is called here *customer flexibility* and represents the percentage of the customers' original consumption at a given time  $t$  that could be scheduled for DR. More specifically, if  $f_t^{d,i}$  is the customer flexibility of customer group  $i$  with DR type  $d$  at time  $t$ , then it holds that

$$0 \leq r_t^{d,i} \leq f_t^{d,i} \cdot O_t^i \quad (9)$$

The sum of  $\alpha_{t,\tau}^{d,i}$  with respect to  $\tau$  reflects the 'efficiency' of DR, and as mentioned earlier the 'payback' phenomenon is in many cases associated to the physical form of storage that is allowing demand flexibility in first place. For instance, a sum less than 100% indicates that a part of the original demand is foregone; this may happen to electro-thermal loads relying on storage in building thermal inertia, whereby comfort is traded with electricity consumption reduction, as measured by accepted changes in internal temperature [7]. On the other hand, a sum greater than 100% means that the phenomenon incurs losses, e.g. heat losses associated to load shifting in the presence of thermal energy storage. The sum may be 100% in some cases of lossless shiftable loads, e.g. washing machines or dish-washers. Modelling these payback coefficients and the time of their occurrence (which can both be accounted for in the proposed formulation) is thus key to address the actual characteristics and constraints of DR in terms of contributing to system capacity, since load restoration potentially causing new peaks could effectively limit the possible overall demand reduction.

### 3.3 Dual stage optimisation of peak reduction

On the basis of the developed models, a day-ahead (i.e.  $T=24$ ) and dual stage optimisation is proposed to dispatch the EES/DR resources, in order to demonstrate the implications of their different parameters modelled earlier. The first stage minimises the peak demand taking exclusive account of the constraints imposed by these parameters. Hence, the peak demand  $L$  in (10) is minimised subject to the constraints in (1)–(4), (7)–(9) and (11), so that the optimal peak demand (denoted later by  $L^*$ ) can be determined. Note that  $J$  and  $I$  are the sets of EES types/devices and customer groups, respectively.

$$\text{Min: } L \quad (10)$$

$$\left\{ L > \sum_{j=1}^J (S_t^{+j} + S_t^{-j}) + \sum_{i=1}^I M_t^i \right\}, \quad t = 1, 2, \dots, 24 \quad (11)$$

The total energy that is used to charge the EES and/or the total

demand that is shifted by DR are then minimised in the second stage, while the optimal peak demand  $L^*$  becomes the constraint for the net demand. To this end, the objective function in (12) is minimised subject to the constraints in (1)–(4), (7)–(9), (11) and (13) so as to determine the exact schedule of EES/DR. The factors  $w_t$  at each time  $t$  are defined to be equal to the total original demand at the same time  $t$  and are used to make sure that the EES charges starting from the original off-peak period (corresponding to the lowest original demand).

$$\text{Min: } \sum_{t=1}^T \sum_{j=1}^J (S_t^{+j} \cdot \Delta\tau \cdot w_t) + \sum_{t=1}^T \sum_{i=1}^I (R_t^i \cdot \Delta\tau), \quad w_t = \sum_{i=1}^I O_t^i \quad (12)$$

$$\left\{ \sum_{j=1}^J (S_t^{+j} + S_t^{-j}) + \sum_{i=1}^I M_t^i < L^* \right\}, \quad t = 1, 2, \dots, 24 \quad (13)$$

It is important to note that, although the relevant economic aspects are not being modelled, the above optimisation is consistent with realistic commercial arrangements that might occur, whereby the aggregated EES/DR could provide capacity in response to a request by the system operator to manage the anticipated peak demand. Moreover, besides guaranteeing the uniqueness of the EES/DR dispatch [In fact, without the second stage optimisation, multiple schedules might be found that minimise the peak demand, which is an undesirable feature in the definition of a framework.], the minimisation in the second stage is also in line with the minimisation of the potential system cost for deploying these resources.

## 4 Algorithms for EES/DR CC evaluation

Specific algorithms for evaluating EES/DR CC metrics are presented here based on the framework proposed in Section 2 and the models presented in Section 3. Fig. 3 shows a general flow chart for the

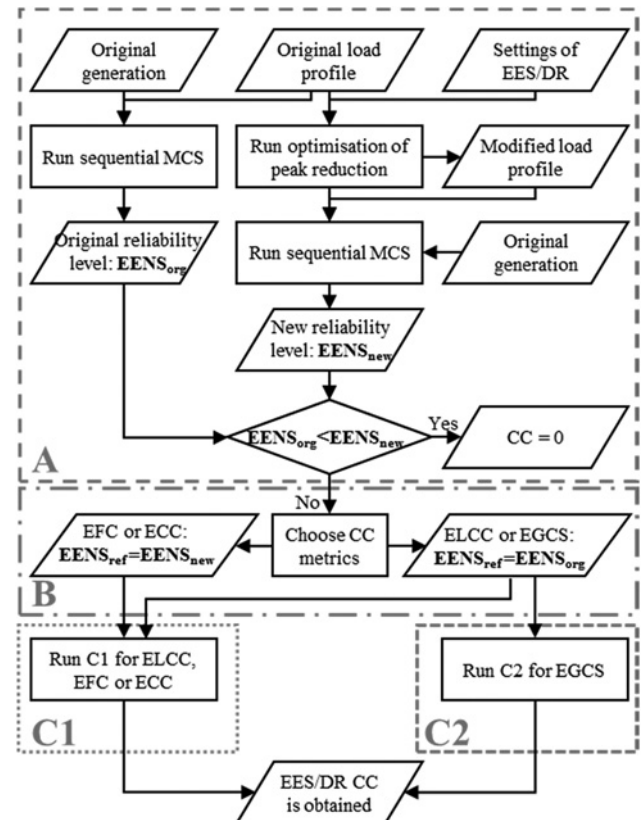
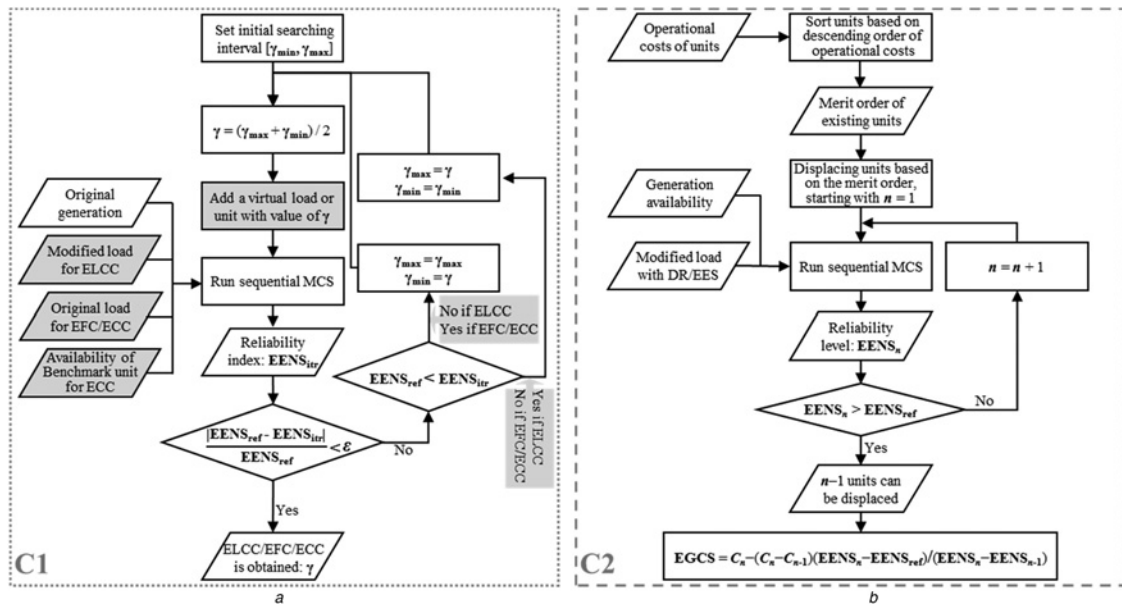


Fig. 3 General algorithm for EES/DR's CC assessment



**Fig. 4** Algorithms for evaluating different CC metrics  
a C1 is the bisection algorithm for evaluating ELCC/EFC/ECC  
b C2 is the algorithm for evaluating newly defined EGCS

overall algorithm, while Fig. 4 gives the specific iterative process conducted to compute traditional CC metrics and the newly defined one.

In Fig. 3, the algorithm starts with *Block A* that applies the models proposed to assess the reliability level (via EENS [The other reliability indices mentioned in Section 2.3 could also be used.]) of both the original system ( $EENS_{org}$ ) and the one with EES/DR ( $EENS_{new}$ ). The subsequent *Block B* selects the ‘reference’ reliability index ( $EENS_{ref}$ ) that will be applied in the iterative procedure depending on the specific CC metric evaluated. Afterwards, *Blocks C1* and *C2* apply the iterative evaluating processes to determine the traditional CC metrics and the newly defined one, respectively.

Fig. 4a adopts a bisection method for searching the numerical value for ELCC, EFC and ECC, respectively. The parts in Fig. 4a with grey shadow are applied differently depending on whether ELCC (with a virtual load) or EFC/ECC (with a virtual generator) is evaluated. In Fig. 4a,  $\gamma$  is the iterative capacity value, while  $\gamma_{max}$  and  $\gamma_{min}$  represent the search interval. In the case of ECC, it needs to be checked *ex ante* whether the benchmark unit is able to measure the ECC so that an initial searching interval could be given accordingly. The searching stops when a specified accuracy  $\epsilon$  (set here to 2%) is satisfied.

The detailed algorithm for evaluating the newly defined EGCS metric is presented in Fig. 4b, which basically illustrates the procedure discussed in Section 2.2. In particular, the EGCS is calculated by adopting linear interpolation between the points  $(C_{n-1}, EENS_{n-1})$  and  $(C_n, EENS_n)$ , where  $C_n$  refers to the total generation capacity that has been substituted and  $EENS_n$  is the reliability level when the  $n$ th unit is replaced.

## 5 Case study applications

### 5.1 Overview

Different scenarios based on the Reliability Test System [21] with the peak demand of 2850 MW are performed to illustrate the proposed framework, as presented in the following sections. The benchmark unit used for assessing ECC has a mean time to failure (MTTF) of 1200-hour and a mean time to repair (MTTR) of 50-hour. For the sake of simplicity, the cases focus on the capacity contribution from EES/DR to the annual peak day (as seen in Fig. 6a), which essentially dominates the impact on the capacity value of these

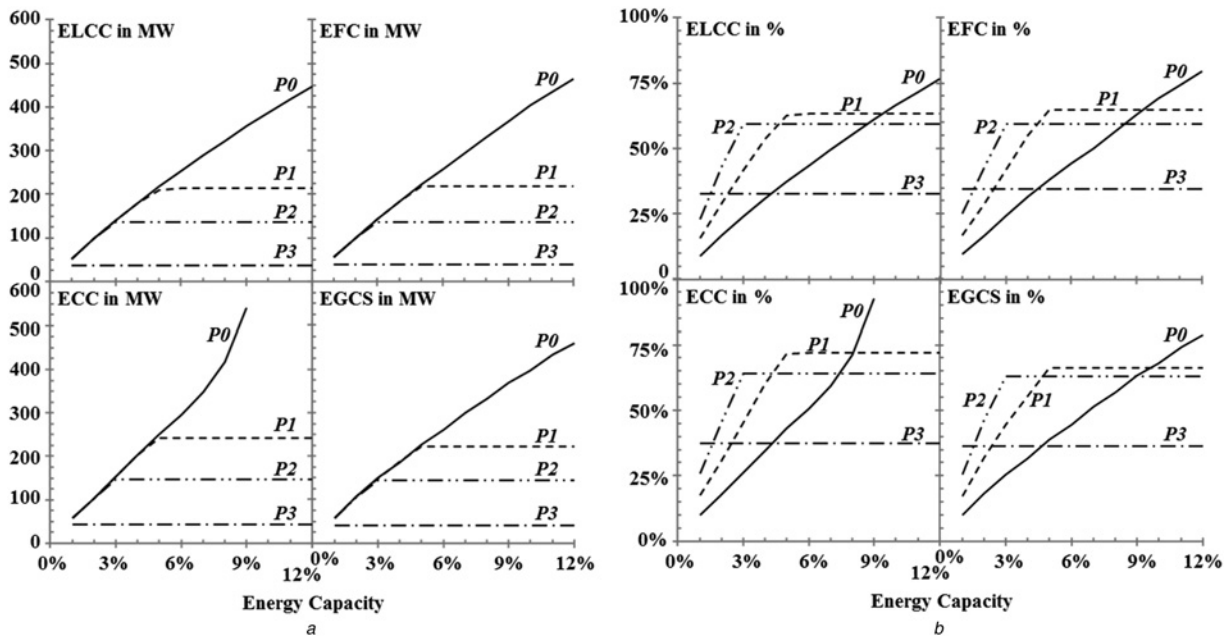
resources. To this end, the hourly load profile of the annual peak day is repeated to form a *virtual* annual profile, while the time series of available generation capacity is also created for a year considering that the MTTFs and MTTRs of the units are from 450 to 2940 h and from 20 to 150 h, respectively. In terms of the accuracy for the evaluation of EENS, the coefficient of variation is kept below 5% in all cases by applying the sampling size of 10,000 *virtual* years.

### 5.2 EES scenarios

The CC of EES (aggregated at the system level) is analysed through the following scenarios that highlight the role of the energy capacity, power ratings, and daily roundtrip efficiency, as demonstrated in Table 1.

### 5.3 EES CC applications

**5.3.1 Energy capacity and power ratings cases:** According to Fig. 5, the four CC metrics increase linearly with the increase of energy capacity when the power ratings are unconstrained in  $P_0$ . This implies that without the constraint on power ratings the CC of EES is directly proportional to its energy capacity. However, the EES’s power ratings in reality are finite so that the CC of EES would saturate when its energy capacity increases continuously, as the cases of  $P_1$ ,  $P_2$  and  $P_3$  in Fig. 5. This practically means that for providing capacity support the required EES’s energy capacity in a system should not exceed a specific amount when certain power ratings are given. In addition, higher power ratings can significantly improve the EES’s CC and postpone the saturation. In fact, the EES contributes to capacity through the peak reduction attained by shifting energy consumption from on-peak to off-peak times, as seen in Fig. 6b. It can be found in Table 2 that the peak reduction also saturates with the increase of the energy capacity when giving certain power ratings. This is because the maximum peak reduction that the EES can contribute is equal to the level of its power ratings, as seen in Table 2 that the peak reduction saturates to the corresponding level of power ratings in the cases of  $P_2$  and  $P_3$ . An exception is found for the case of  $P_1$ , due to the constraint on the EES efficiency that will be further discussed later. Moreover, Fig. 5b shows that higher power ratings lead to a higher saturation value for the CC metrics in percentage of the power ratings. Nonetheless, the increase in the saturation value (in %) for the EGCS comparing  $P_1$  and  $P_2$  is insubstantial. It is also worth noting that the EES is



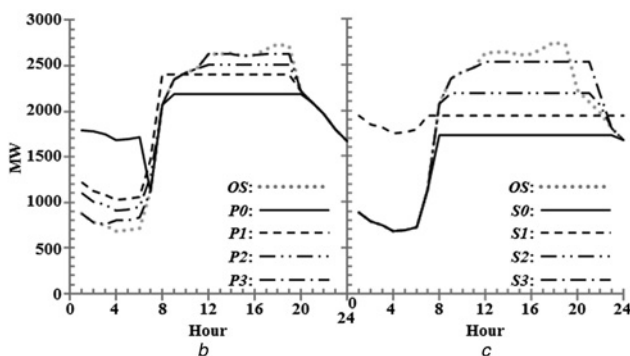
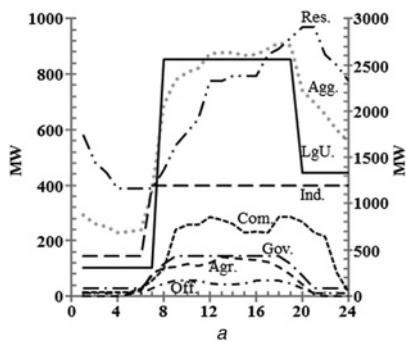
**Fig. 5** CC metrics (ELCC, EFC, ECC and EGCS) as function of energy capacity for different levels of power rating

a the metrics are expressed in MW

b the metrics are expressed as relative values to the relevant power rating (with respect to P1, P2 and P3, the base values are equal to 342 MW, 228MW and 114 MW, respectively, as given in Table 2; in the case of P0 and assuming infinite power rating, the peak reduction obtained at 12% energy capacity (namely, 584.2 MW) is considered as a virtual power rating for the sake of calculating the relative value for the CC metrics)

considered to be 100% reliable, meaning that in practice the unavailability of the EES would de-rate the following values assessed for the CC metrics.

In terms of different CC metrics, *ceteris paribus*, it is found that the ELCC and the newly defined EGCS are less than the peak reduction. This implies that in a system, both the amount of demand growth that could be afforded and the amount of generation resources that could be replaced, are less than the attained peak reduction. Similarly, the assessed EFC values also



**Fig. 6** Load curves for

a Original consumption of the seven customer groups considered in the case study  
b Different EES (Table 2) scenarios, whereby the energy capacity is 12%, four levels of power rating are considered and a fixed daily roundtrip efficiency of 75% is applied; and, c Different DR scenarios (Table 3), whereby the DR customer flexibility is 40% and four types of payback are considered. As a further remark, the load curve represented by grey dots (referred to as 'Agg.' in (a) and 'OS' in (b) and (c)) corresponds to the aggregated consumption of the original system. In addition, the scale of the curve 'Agg.' in (a) is shown by the right-hand vertical axis, while the scale of the rest curves in (a) is shown by the left-hand vertical axis

**Table 1** EES scenarios

Scenario	Energy capacity ( $E_{max}^1$ ) <sup>a</sup>	Power ratings ( $S_{max}^{+1}, S_{max}^{-1}$ ) <sup>b</sup>	Daily roundtrip efficiency ( $\eta^1$ )
energy capacity <sup>c</sup> and power ratings cases	varied from 1% to 12% with steps of 1%	• P0: infinite <sup>d</sup> (unconstrained) • P1: 12% • P2: 8% • P3: 4%	fixed at 75%
daily roundtrip efficiency cases	fixed at 12%	fixed at P1	varied from 70% to 100% with steps of 5%

<sup>a</sup>Energy capacity is set based on the original daily energy consumption (45.9 GWh)

<sup>b</sup>Power ratings are set based on the original annual peak demand (2850 MW)

<sup>c</sup>In all the cases for EES, the initial energy level  $E_{ini}^1$  is considered to be equal to the minimum energy level  $E_{min}^1$ , which is assumed to be 20% of the corresponding energy capacity  $E_{max}^1$ , i.e.,  $E_{ini}^1 = E_{min}^1 = 0.2E_{max}^1$ . Note that this consideration for the initial and minimum energy levels practically leads to a net reduction of the energy capacity by 20%

<sup>d</sup>In the simulation, the infinite power rating (P0) is implemented by assuming a relatively large power rating equal to 35% of the original peak demand (2850 MW): this is to ensure that the peak reduction and the CC metrics do not saturate following the increase in the energy capacity

**Table 2** Peak reduction (MW) for P0 to P3

Power rating	Energy capacity					
	1%	2%	3%	4%	5%	12%
P0: infinite	134.9	185.2	235.5	284.8	328.6	584.2
P1: 342 MW	134.9	185.2	235.5	284.8	328.6	336.4
P2: 228 MW	134.9	185.2	228.0	228.0	228.0	228.0
P3: 114 MW	114.0	114.0	114.0	114.0	114.0	114.0



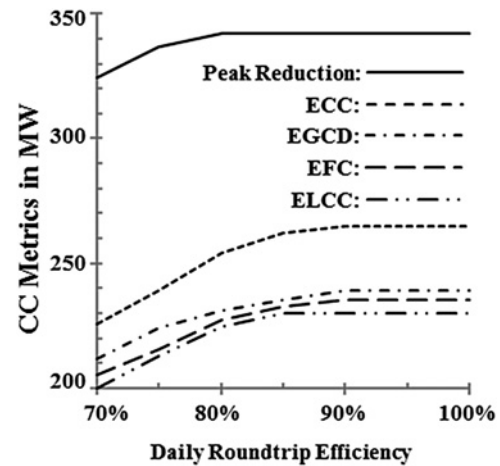
**Table 3** EES case study scenarios

Scenario	Payback characteristics ( $\alpha_{r,t}^{d,i}$ ) <sup>a</sup>	Customer flexibility ( $f_t^{d,i}$ )	Example of the form of storage in DR
<b>S0</b>	'No payback'. The load reduced through DR is not restored. This is an 'ideal' scenario of DR.	for the four scenarios, all customers share the same value of $f_t^{d,i}$ , which is parametrically varied from 5% to 45% with steps of 5%	not applicable
<b>S1</b>	'Unconstrained payback with 100% load recovery'. The demand that is curtailed at peak times can be freely shifted and recovered in its entirety at off-peak times.		lossless hot water tanks; dishwashers with clean dishes stored in cupboard; washing machine with clean clothes stored in closet
<b>S2</b>	'Constrained payback with 50% load recovery'. Here, the curtailed demand is restored immediately after the load reduction, i.e., a 50% power recovery with one-hour lag.		building thermal inertia storage (e.g. heat pumps or air conditioning units with partial loss of thermal comfort)
<b>S3</b>	'Constrained payback with 100% load recovery'. Similar to S2, but with 100% power recovery with one-hour lag.		ventilation system with 'air quality storage' in a building to deal with no ventilation for one hour only

<sup>a</sup>In reality the seven customer groups have different payback characteristics. However, in order to be as transparent as possible about the payback settings and their impact, all the customer groups are assumed to have the same payback characteristics. On-peak and off-peak periods in different customer groups are taken into proper account when assigning values to the payback coefficients ( $\alpha_{r,t}^{d,i}$ ). The detailed information regarding the load profiles of the seven customer groups and settings of payback coefficients can be found in Tables 5 and 6 in the Appendix

indicate that the EES's CC in the form of a perfectly reliable generation capacity is less than the attained peak reduction, too. This is due to the prolonged peak duration that is attributed to EES, as seen in Fig. 6b. In terms of the ECC metric, it is always greater than the EFC according to their definitions. It is worth mentioning that the ECC might be higher than the attained peak reduction in the case that a low-reliability benchmark unit is used. Finally, the EGCS provides the results that are consistent with the other CC metrics but with the advantage of being clear and straightforward to be used in terms of replacing generation resources.

**5.3.2 Daily roundtrip efficiency cases:** The CC metrics when varying daily roundtrip efficiencies are illustrated in Fig. 7, along with the relevant peak reductions. When the daily roundtrip efficiency increases, at first both the peak reduction and CC metrics increase linearly. Once the peak reduction is equal to the relevant level of power ratings, the CC metrics also saturate. A daily roundtrip efficiency below 80% (e.g. 75% as in the previous section) does not allow the peak reduction being equal to the level of power ratings ( $P1$ ). Moreover, the lines in Fig. 7 representing the CC metrics are parallel to the one for the peak reduction. This means that increasing efficiency does not improve the CC of EES by getting closer to the relevant peak reduction. Furthermore, increasing the efficiency by 10% leads to an increase of 10 MW in the CC metrics (1 MW per 1%-increase of roundtrip efficiency). According to Fig. 5a, the average slope of the lines representing the relationship between the CC metrics and energy capacity in the case of  $P0$  is 30 MW per 1%-increase in energy capacity, which corresponds to the maximum increase in the CC metrics that can be



**Fig. 7** CC metrics for different roundtrip efficiencies and the relevant peak reductions. Note that the energy capacity is 12% and the power rating is  $P1$

provided by increasing energy capacity. On the other hand, at the energy capacity of 12%, increasing power rating can increase the CC metrics on average by 22 MW per 1%-increase of power rating. Hence, in terms of improving the EES's CC, it emerges that increasing efficiency is not as effective as increasing energy capacity and power rating, thus implying that EES's energy capacity and power rating should be viewed with more interest than efficiency within the context of contribution to adequacy of supply.

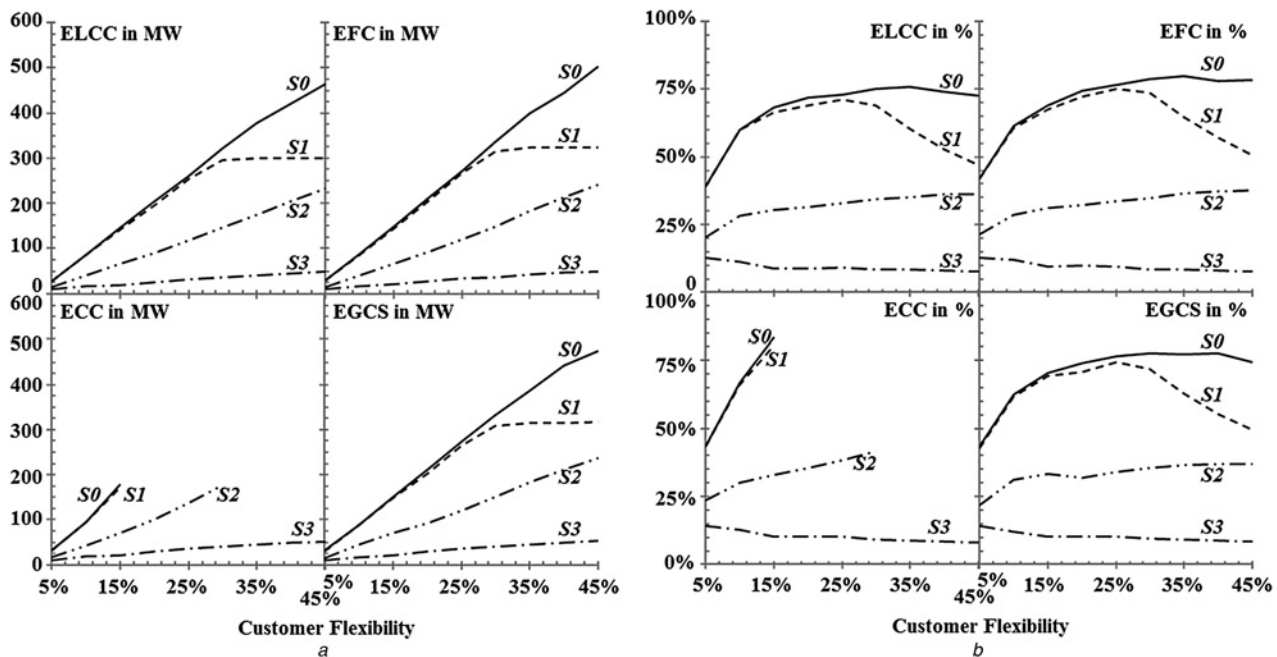
#### 5.4 DR scenarios

The customer groups considered here are: residential, commercial, industry, government, office building, large-user and agriculture. The load data can be found in [3, 4]. In order to demonstrate the impact of the DR payback on its CC, four scenarios and their respective paybacks will be studied, as presented in Table 3.

#### 5.5 DR CC applications

Fig. 8 shows the ELCCs, EFCs, ECCs and EGCSs that are assessed for  $S0$  to  $S3$ . It can be observed that all the CC metrics increase linearly with the customer flexibility. More specifically,  $S0$  and  $S1$  result in similar values of the CC metrics until they saturate in  $S1$ . This is because the net on-peak load profiles in  $S0$  and  $S1$  are the same at the beginning of the increase in customer flexibility (e.g. the same peak reduction can be found for  $S0$  and  $S1$  in Table 4). However, eventually in  $S1$ , due to load restoration requirements, the DR cannot continuously reduce the peak demand (as does the 'zero-payback' DR in  $S0$ ) following the increase in customer flexibility, which is shown in Fig. 6c. On the contrary, in  $S2$  and  $S3$ , the reduced load needs to be restored in the next hour without the shifting flexibility to off-peak times; in addition, the payback in  $S3$  also requires a greater volume of load to be restored. Thus, the DR in  $S2$  and  $S3$  can only reduce the peak load by a certain amount as presented in Table 4. Meanwhile, the immediate payback extends the duration of peak load as seen in Fig. 6c. The relative values for the CC metrics in Fig. 8b exhibit distinct trend, compared with the values in MW. This inconsistency is because the base value, which is defined as the maximum available DR capacity, used for computing the CC metrics in percentage varies with the customer flexibility and is the same for different DR scenarios. For instance, 10% customer flexibility corresponds to the base value of 285 MW. Moreover, it also needs to be noted that the DR customers are considered to be always available whenever they are dispatched to reduce the load consumption. Therefore, in practice the DR's CC might not reach the values that are evaluated using the illustrative models considered for DR, as DR resources might not be perfectly reliable.

Similar to Section 5.3, in terms of different CC metrics, it is also found that ELCC and EFC are less than the relevant peak reduction



**Fig. 8** CC metrics (ELCC, EFC, ECC and EGCS) as function of customer flexibility for different DR scenarios: (a) the metrics are expressed in MW; (b) the metrics are expressed as relative values to the relevant maximum available DR capacity (which varies with the customer flexibility)

a ELCC, EFC, ECC and EGCS in MW

b ELCC, EFC, ECC and EGCS in % of maximum available DR capacity at each level of customer flexibility

achieved by DR, and it is the same phenomenon in case of EGCS. As discussed in Section 5.3, this is again due to the fact that load profile is flattened by DR (lower peak but longer peak duration as shown in Fig. 6b). Unlike the cases in Section 5.3, as from Fig. 8c, ECC does not exist for very flexible DR cases, corresponding to the paradox mentioned in Section 2.2.3. This implies that it is possible that with a certain level of customer flexibility and payback setting the reliability characteristics of DR (with other forms of storage) can be better than a certain type of generation plant. Thus, the adequacy level that is provided by the DR could not be provided by a chosen type of generation resources.

## 6 Conclusion

This paper has presented a systematic framework to extend the concept of CC to EES and DR, thus enabling setting up a level playground for comparison of generation-side and demand-side resources in adequacy of supply assessment. Within this framework, classical CC metrics including ELCC, EFC and ECC have been considered and the respective evaluation algorithms presented. In the light of replacing conventional generation, a new CC metric, namely, the EGCS has then been defined. In addition, specific EES/DR models have been proposed and applied, which explicitly

consider the constraints arising from energy capacity, power ratings and roundtrip efficiency of EES, as well as customer flexibility and payback effect (which may depend on different forms of storage available to customers, as discussed and exemplified) of DR. SMCS has been deployed to assess these CC metrics, accounting for full representation of the EES/DR constraints.

With regards to the application of different EES/DR CC metrics, the ELCC metric should be used for system expansion in the presence of load growth. On the other hand, for the purposes of comparing reliability characteristics of EES/DR with supply-side resources, either the EFC metric can be used – to value EES/DR’s capacity contribution in an amount equal to a perfect (100% reliable) generation plant; or the ECC metric – to compare EES/DR with a ‘real’ generation plant. In addition, in the light of replacing existing generation, the newly defined EGCS metric can be used in a clear and straightforward manner to indicate to what extent certain EES/DR resources can allow substitution of generation capacity.

Case studies indicate that for ELCC, EFC and EGCS the CC of EES/DR is less than the relevant peak reduction. On the other hand, depending on the reliability characteristics of the benchmark unit, ECC might be lower but also higher (i.e. DR flexibility can provide better performance than an ‘unreliable’ generator) than the load reduction, or even not measurable in some cases. However, it can be generally said that when EES/DR is used to contribute to system adequacy, neither the additional load that could be supplied by the system nor the amount of conventional generation that could be replaced are equal to the corresponding peak reduction provided by certain EES/DR resources.

In terms of the impact of EES/DR constraints, the CC of EES is constrained by the interplay between energy capacity and power ratings. This indicates that there is a limit to the EES contribution to adequacy of supply, and therefore to the amount of EES that the system may need in this respect. In addition, a percentage increase in roundtrip efficiency leads to a lower increase in the EES’s CC than that attributed to the same percentage increase in energy capacity or power rating. As for DR, the CC decreases with level of payback constraints. Hence, more flexible customers, for instance adopting water heaters or shiftable devices such as electric vehicles, should be targeted at first to contribute to system capacity.

**Table 4** Peak Reduction (MW) for S0 to S3

DR scenario	Customer flexibility <sup>a</sup>					
	5%:	15%:	25%:	35%:	40%:	45%:
	MW	MW	MW	MW	MW	MW
S0	136.9	410.8	666.5	915.3	1006.4	1097.4
S1	136.9	410.8	666.5	768.1	792.7	792.7
S2	98.2	229.3	357.0	484.4	548.1	611.9
S3	72.2	132.5	164.3	196.2	205.3	214.4

<sup>a</sup>The MW value under the customer flexibility refers to the maximum available DR capacity, which is computed by multiplying the customer flexibility by the annual peak load



In general, a key message of this work is that it is not straightforward to compare generation capacity and EES/DR's peak reduction in terms of adequacy of supply. In this light, depending on the context of practical applications the developed CC framework can comprehensively support policy and decision making by informing the current debates about the role of EES/DR to provide system capacity and participate in capacity markets or similar schemes on a like-for-like basis with generation.

Work in progress aims at establishing a full techno-economic comparison of generation and EES/DR for system planning purposes.

## 7 Acknowledgment

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I, Yutian Zhou, on behalf of the authors of the aforementioned publication hereby make the following statement regarding the access to the relevant research data.

All research data supporting this publication are directly available within this publication [DOI: 10.1049/iet-gtd.2015.0458].

Additional research data supporting this publication are available as supplementary information accompanying this publication at [DOI: 10.1049/iet-gtd.2015.0458].

Multiple datasets openly available at various data repositories were used to support these research findings. All the data used are referred to in the 'References' section of this publication.

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## 9 Appendix

See Tables 5 and 6.

**Table 5** Original data for the load profiles of the different customer groups

Hour	Load profile in per-unit for the customer group of:						
	Residential ( $i=1$ )	Commercial ( $i=2$ )	Industry ( $i=3$ )	Government ( $i=4$ )	Office Building ( $i=5$ )	Large-user ( $i=6$ )	Agriculture ( $i=7$ )
1	0.6	0.05	0.36	0.2	0.2	0.12	0
2	0.5	0.05	0.36	0.2	0.2	0.12	0
3	0.46	0.05	0.36	0.2	0.2	0.12	0
4	0.4	0.05	0.36	0.2	0.2	0.12	0
5	0.4	0.05	0.36	0.2	0.2	0.12	0.05
6	0.4	0.1	0.36	0.2	0.2	0.12	0.15
7	0.4	0.2	1	0.5	0.5	0.12	0.58
8	0.47	0.35	1	0.8	0.8	1	0.72
9	0.56	0.84	1	1	1	1	0.75
10	0.61	0.9	1	1	1	1	0.82
11	0.66	0.9	1	1	1	1	0.78
12	0.8	1	1	1	0.8	1	0.86
13	0.8	0.96	1	1	0.75	1	1
14	0.82	0.92	1	1	0.75	1	0.98
15	0.82	0.8	1	1	0.8	1	0.96
16	0.82	0.82	1	1	1	1	0.92
17	0.9	0.8	1	1	1	1	0.88
18	0.92	1	1	1	1	1	0.76
19	0.96	1	1	0.8	0.8	1	0.56
20	1	0.94	1	0.5	0.5	0.52	0.3
21	1	0.8	1	0.2	0.2	0.52	0.06
22	0.9	0.75	1	0.2	0.2	0.52	0
23	0.86	0.3	1	0.2	0.2	0.52	0
24	0.8	0.05	1	0.2	0.2	0.52	0
Annual Peak (MW)	969	285	399	145.35	57	855	139.65

**Table 6** Payback settings for different DR scenarios in different customer groups

Customer group	Payback coefficients ( $\alpha_{t,\tau}^{d,i}$ , where $t$ and $\tau$ refer to curtailing time and recovering time, respectively) for the DR scenario of:			
$(i, T_{\text{on-peak}}, T_{\text{off-peak}})^a$	S0	S1	S2	S3
Residential ( $i=1$ , $T_{\text{on-peak}} = [12, 24]$ , $T_{\text{off-peak}} = [1, 8]$ )	$\forall t, \tau: \alpha_{t,\tau}^{1,1} = 0$	$t \in T_{\text{on-peak}}, \tau \in T_{\text{off-peak}}: \alpha_{t,\tau}^{1,1} = 0.125$ ; Otherwise: $\alpha_{t,\tau}^{1,1} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,1} = 0.5$ ; Otherwise: $\alpha_{t,\tau}^{1,1} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,1} = 1.0$ ; Otherwise: $\alpha_{t,\tau}^{1,1} = 0$ ;
Commercial ( $i=2$ , $T_{\text{on-peak}} = [9, 22]$ , $T_{\text{off-peak}} = [1, 8] \cup [23, 24]$ )	$\forall t, \tau: \alpha_{t,\tau}^{1,2} = 0$	$t \in T_{\text{on-peak}}, \tau \in T_{\text{off-peak}}: \alpha_{t,\tau}^{1,2} = 0.1$ ; Otherwise: $\alpha_{t,\tau}^{1,2} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,2} = 0.5$ ; Otherwise: $\alpha_{t,\tau}^{1,2} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,2} = 1.0$ ; Otherwise: $\alpha_{t,\tau}^{1,2} = 0$ ;
Industry ( $i=3$ , $T_{\text{on-peak}} = [7, 24]$ , $T_{\text{off-peak}} = [1, 6]$ )	$\forall t, \tau: \alpha_{t,\tau}^{1,3} = 0$	$t \in T_{\text{on-peak}}, \tau \in T_{\text{off-peak}}: \alpha_{t,\tau}^{1,3} = 0.167$ ; Otherwise: $\alpha_{t,\tau}^{1,3} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,3} = 0.5$ ; Otherwise: $\alpha_{t,\tau}^{1,3} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,3} = 1.0$ ; Otherwise: $\alpha_{t,\tau}^{1,3} = 0$ ;
Government ( $i=4$ , $T_{\text{on-peak}} = [9, 18]$ , $T_{\text{off-peak}} = [1, 6] \cup [21, 24]$ )	$\forall t, \tau: \alpha_{t,\tau}^{1,4} = 0$	$t \in T_{\text{on-peak}}, \tau \in T_{\text{off-peak}}: \alpha_{t,\tau}^{1,4} = 0.1$ ; Otherwise: $\alpha_{t,\tau}^{1,4} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,4} = 0.5$ ; Otherwise: $\alpha_{t,\tau}^{1,4} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,4} = 1.0$ ; Otherwise: $\alpha_{t,\tau}^{1,4} = 0$ ;
Office building ( $i=5$ , $T_{\text{on-peak}} = [9, 18]$ , $T_{\text{off-peak}} = [1, 6] \cup [21, 24]$ )	$\forall t, \tau: \alpha_{t,\tau}^{1,5} = 0$	$t \in T_{\text{on-peak}}, \tau \in T_{\text{off-peak}}: \alpha_{t,\tau}^{1,5} = 0.1$ ; Otherwise: $\alpha_{t,\tau}^{1,5} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,5} = 0.5$ ; Otherwise: $\alpha_{t,\tau}^{1,5} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,5} = 1.0$ ; Otherwise: $\alpha_{t,\tau}^{1,5} = 0$ ;
Large-user ( $i=6$ , $T_{\text{on-peak}} = [8, 19]$ , $T_{\text{off-peak}} = [1, 7] \cup [20, 24]$ )	$\forall t, \tau: \alpha_{t,\tau}^{1,6} = 0$	$t \in T_{\text{on-peak}}, \tau \in [1, 7]: \alpha_{t,\tau}^{1,6} = 0.1$ ; $t \in T_{\text{on-peak}}, \tau \in [20, 24]: \alpha_{t,\tau}^{1,6} = 0.06$ ; Otherwise: $\alpha_{t,\tau}^{1,6} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,6} = 0.5$ ; Otherwise: $\alpha_{t,\tau}^{1,6} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,6} = 1.0$ ; Otherwise: $\alpha_{t,\tau}^{1,6} = 0$ ;
Agriculture ( $i=7$ , $T_{\text{on-peak}} = [7, 19]$ , $T_{\text{off-peak}} = [1, 6] \cup [21, 24]$ )	$\forall t, \tau: \alpha_{t,\tau}^{1,7} = 0$	$t \in T_{\text{on-peak}}, \tau \in T_{\text{off-peak}}: \alpha_{t,\tau}^{1,7} = 0.1$ ; Otherwise: $\alpha_{t,\tau}^{1,7} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,7} = 0.5$ ; Otherwise: $\alpha_{t,\tau}^{1,7} = 0$ ;	$t \in T_{\text{on-peak}}, \tau = t+1: \alpha_{t,\tau}^{1,7} = 1.0$ ; Otherwise: $\alpha_{t,\tau}^{1,7} = 0$ ;

<sup>a</sup>The hours in a day start with 1 and end with 24



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