Sustainable Energy, Grids and Networks 26 (2021) 100421

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

journal homepage: www.elsevier.com/locate/segan

Insights on the capacity value of photovoltaics, community batteries and electric vehicles☆

Wouter L. Schram [a,*], Hamid Aghaie [b], Ioannis Lampropoulos [a], Wilfried G.J.H.M. van Sark [a]

[a] Copernicus Institute of Sustainable Development, Utrecht University, Princetonlaan 8A, The Netherlands
[b] Austrian Institute of Technology, Giefinggasse 4, 1210 Vienna, Austria

ARTICLE INFO

Article history:
Received 28 April 2020
Received in revised form 20 October 2020
Accepted 13 December 2020
Available online 25 December 2020

Keywords:
Resource adequacy
Capacity Value Ratio
V2G
Smart charging
Distributed resources
Photovoltaics
Community energy storage
Effective Load Carrying Capability
Capacity Credit
Firm capacity

ABSTRACT

The Capacity Value Ratio (CVR), or the part of its capacity that a technology can supply during peak residual load hours, is an important concept in the context of future resource adequacy. Especially for distributed resources, this is still underexplored territory. In this research, we investigate the peak reduction potential on both the distribution and transmission system level for a community battery coupled with photovoltaic (PV) systems as well as for smart charging approaches of electric vehicles (EVs) and vehicle-to-grid (V2G) technology. On the distribution level, it is shown that batteries charged only with PV-generated electricity reduce the peak residual load by 14.6%, whereas grid-charged batteries can reduce peak residual load by 30.0%. It is also found that deploying V2G can result in a decrease of the peak residual load, despite the additional EV charging demand. On the transmission system level, it is found that the CVR of PV is only 0.6%, however, the CVR of a PV-charged community battery is 25.0% whereas a grid-charged battery can have a CVR of 47.0%. The approximation method used in this study generates similar results as reliability-based methods found in literature. Regarding EVs, we approximate the load shifting potential of EV smart charging at 78.5% and the CVR of V2G at 8.9%. This indicates EVs could play an important role in maintaining resource adequacy in the context of a phase-out of conventional power plants, given that this has priority in the optimization of EV charging.

1. Introduction

Resource adequacy encompasses the ability of a power system to provide long-term adequate supply in meeting electricity demand [1]. Resource adequacy policies are designed to address the "missing money" problem: in energy-only markets the revenues from energy and ancillary services alone may be insufficient to recoup the investments on facilities that only run for a few hours per year [2]. The capacity value of a generator is an important metric as this value is considered in the reserve margin of the power system. The capacity value can be defined as the expected possible amount of the energy output of a technology during the peak residual load [1]. A second important concept for this research is the Capacity Value Ratio (CVR). This is the capacity value divided by the rated capacity of the technology. In other words, the proportion of installed capacity of a technology that is used to satisfy the peak residual load. The CVR of conventional generators is mainly above 80%, as the only limiting factor is the forced outages on those generators during peak residual load hours [3]. As the generation from Variable Renewable Energy Resources (VRES) depends largely on the weather conditions, the correlation between VRES generation and peak demand is much weaker than in case of dispatching conventional generation. As a result, VRES contribute less to resource adequacy compared to conventional power generation. Therefore, electricity markets with high share of VRES require additional back-up capacity to meet the target generation reliability criterion.

Recently, this topic has received much attention from the European Union in general, and the European Network of Transmission System Operators for Electricity (ENTSO-E) in particular. The recent legislative package on Clean Energy for all Europeans, specifically Regulation 2019/943 of 5 June 2019 on the internal market for electricity, places resource adequacy at a central position in the European energy policy context [4]. According to the initial ENTSO-E's proposal, each European Transmission System Operator (TSO) shall calculate the capacity value for all generation technologies in order to determine the required dispatching back-up capacity to maintain system reliability in the presence of a defined volume of variable renewable capacity [5,6].

☆ This work is partly funded by a Short Term Scientific Mission grant from the COST Action PEARL-PV (CA16235), which is supported by COST (European Cooperation in Science and Technology, see www.cost.eu) and this work is part of the FLEET project which received funding from the Dutch TKI Urban Energy program.

* Corresponding author.
E-mail address: w.l.schram@uu.nl (W.L. Schram).

https://doi.org/10.1016/j.segan.2020.100421

The CVR is often used in modelling energy systems at the transmission system level. Because of computational limits, simulations at the transmission system level have to make simplifying assumptions about the flexibility on distribution system level. For example, Zappa et al. assume a European-wide load shifting capacity of 82 GW [7], based on a report assessing the theoretical demand response in Europe [8]. Energy storage and Electric Vehicles (EVs) are left outside of this analysis, despite it is known that batteries can have a large impact on reducing the peak residual load on the distribution system level [9]. With increasing EV charging data availability, opportunities arise to make an assessment for these flexibility resources as well. In the context of resource adequacy, these resources may be especially suitable as they can have multiple applications and thus do not have to stand idle for the time they are not requested to supply power to the grid. Hence, unlike conventional generators they do not rely on the remuneration of selling electricity for the few hours they are needed to ensure sufficient resource adequacy. Also, distributed resources are associated with lower rates of greenhouse gas emissions compared to conventional power plants [10].

In literature, capacity value is also addressed in terms of Effective Load Carrying Capability (ELCC), De-rated Capacity and Capacity Credit [5,11–13]. The calculation of capacity value is always interlinked with reliability assessment of national power systems. Several studies have estimated the capacity value of VRES, in various countries or TSO/ISO (Independent System Operator) control areas. Holttinen et al. [14] compare the capacity value of wind in several countries and conclude that the capacity value depends on the penetration of wind energy in the power system, the geographical location, weather conditions, peak load season, and electricity generation profile of each country. For instance, as the peak load in central and northern Europe occurs mainly during the cold winter evenings, the capacity value of PV in this region is nearly zero. However, due to the strong correlation between PV electricity generation and peak load in summer afternoons in southern Europe, the capacity value of PV is relatively high in those regions. The CVR of wind generation in Germany is estimated at 8%, but is expected to drop to 5% with increased penetration of wind energy [15,16]. In general, higher penetration of VRES results in lower capacity value of it [17].

Historically, the contribution of each generation technology to the resource adequacy was evaluated independently from other technologies. However, by increasing penetration of new flexibility resources such as storage technologies, evaluating the capacity value of storage technologies integrated with VRES has been discussed in the literature in the last few years [18]. Sioshansi et al. proposed a dynamic programming approach to estimate the capacity value of storage [19]. Denholm and Margolis [20] show the interaction between PV integrated with battery storage and their integrated capacity value in the Californian electricity system. In an analysis performed for the Singapore power system, Koh et al. [21] found that storage can increase the contribution of PV to decreasing Loss Of Load Expectation (LOLE) of a system, especially at higher penetration rates of PV. However, at low penetration rates of PV, storage does not increase the capacity value as PV coincides with the residual load peak. Konstantelos et al. show the capacity value of batteries and emphasize the importance of outage duration on the capacity value of storage [22]. These findings are in line with findings of the British Transmission System Operator, National Grid, which shows the importance of discharge time of duration-limited storage in determining the capacity value [23].

To the best of our knowledge, this study is the first that addresses capacity value of PV combined with storage in the European context. Furthermore, it is the first that investigates the contribution that EVs can have to the resource adequacy of a system. We investigate the CVR of distributed resources PV, a community battery and EVs on a distribution system level as well as on the transmission system level, to investigate the different contributions flexibility resources can have on each level. In this study, a detailed model at the community level is connected to the residual load peak at power system level, thereby aiming to bridge the gap between the power modelling on distribution system level and transmission system level.

This paper is outlined as follows. First, it is described how to determine capacity value of flexible resources in Section 2. In Section 3, the system architecture is presented, and the algorithms used in this study are explained. In Section 4, the CVRs of the technologies and different algorithms are shown. Subsequently, we reflect on these findings in Section 5. Last, concluding remarks are provided in Section 6.

2. Determination of capacity value ratio

In literature, several methods for the CVR calculation have been introduced and described [24–26]. Castro and Fereira [26] cluster the CVR calculation methods into two main categories, namely chronological and probabilistic, and compare them. Chronological methods, also called approximation methods, revolve around calculating the capacity factor over the peak load hours, which is suitable to help the system operation. Probabilistic methods calculate CVR by considering the probability distribution function of generation and demand and their associated uncertainties, which is suitable for system planners like TSOs [26]. Probabilistic methods revolve around the LOLE. The LOLE represents the sum of all Loss Of Load Probabilities (LOLPs) during a certain period, e.g. a year. The LOLP is defined as the probability of a system load that is larger than the system available generation capacity. Based on historical data, statistical analysis can determine the LOLE of the current generation mix. Subsequently, a specific technology can be added to the generation mix, and new simulations can determine the updated LOLE. As a last step, the studied technology is removed from the generation mix, and a hypothetical fully reliable power generation unit is added. The capacity of this unit is varied over different iterations, until the same LOLE is found as with the added capacity of the studied technology. The equivalent firm capacity is then the ratio between the capacity of the technology added and the fully reliable capacity.

The disadvantage of the traditional approach is that it involves the use of complex planning models, which is accompanied with substantial cost regarding data analysis, expertise and computational time [27] and could be hampered by lack of available data [25]. In the context of the energy transition, with VRES having very location-specific output due to variations in weather patterns, the traditional methods may not be adequate. Therefore, various approximation methods have been developed to be able to estimate the CVR of VRES [25,27,28]. Often, one considers the average output of technologies in a certain amount of peak residual load hours that are considered critical. In that sense, the amount of peak hours is an important design option for the determination of the CVR. This can vary from 0.01% of peak hours (i.e. a single peak load hour) to 30% of peak residual load hours [7,25]. VRES may record very different CVRs when different amount of peak hours is studied [7]. This is even more the case for duration-limited flexible resources such as electricity storage. When looking at a few peak hours, these resources may have a high CVR, while the CVR may be low when looking at many peak hours. To date, there are few studies that attempt to determine the CVR of storage and provide insights on these dynamics.

Currently, no consensus exists on the amount of Peak Hours *PH* that should be taken into account when approximating the

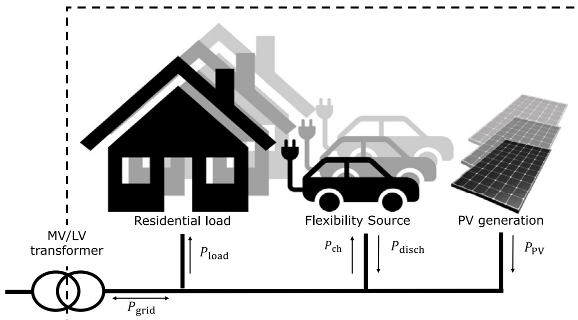

Fig. 1. System architecture.

capacity value. Therefore, in this study the amount of *PH* is varied by looking at the hours associated with the peak residual load of 0.5 GW to 4.0 GW (2.7% to 22% of the Dutch peak residual load in 2018), which is called "Peak Capacity" in the remainder of this paper. At present, 4.0 GW is equivalent to the current coal-fired power generation capacity in the Netherlands (3990 MW) [29]. This is a relevant upper limit given the discussions on the phase-out of coal-fired generation [30], to comply with national emission reduction targets agreed between EU member states. In this study, the residual load hours are sorted and the *PH* are subsequently determined as the hours which fall into the hours of Peak Capacity. For the Netherlands in 2018, which is the focus of this study, the Peak Capacity from 0.5 GW to 4.0 GW relates to five peak hours ($PH = 5$, which is 0.06% of the hours) to $PH = 1017$ (12% of the hours). This approach also provides insights on how the impact of PV, batteries and EVs may change when supplying a larger part of the load.

The capacity value was determined by employing a commonly used approximation method (e.g. in [25,27,28]), as follows:

$$\mathrm{CVR}_j = \frac{\sum_{h\in\mathcal{H}} E_{\mathrm{S},hj}}{PH * C_j}. \tag{1}$$

Here, subscript j depicts the technology, E_S is the electricity supplied to the system during a set of hours $h \in \mathcal{H}\{1, 2, \dots, PH\}$ and C is the capacity of the technology. The CVRs are reported for a peak capacity of 1.5 GW, but we also show how it varies when increasing/decreasing this peak capacity. In case of PV coupled with batteries, the capacity of the battery is taken as C_j.

3. Methods

3.1. System architecture

In Fig. 1 the system architecture of this study is illustrated. The system boundaries of this study contained a single Low-Voltage (LV) grid connected to a Medium-Voltage (MV) grid via a MV/LV transformer. It contained a set of households, PV systems and a flexibility source, which was either a community battery or a set of EV (bidirectional) charging stations. These loads were also connected in a communication network with one central operator, e.g. an aggregator. The residential load can be satisfied by PV electricity generation, and/or by importing electricity from the grid, and/or by discharging the community battery/EV fleet. All loads were aggregated at the community level.

Perfect foresight in residential load, PV generation and EV charging requirements and availability was assumed.

3.2. Modelling EV charging behaviour as a community battery

The EV fleet was modelled as a community battery, in similar fashion to [31] . Whereas a community battery has fixed power and energy constraints, the power and energy constraints of this EV fleet varies. This was determined using the "Latest charging" scenario developed by [32]. This means that the energy capacity of the EV battery should be at a certain level at the plug-out time, but also at a certain minimum in the hours directly before plug-out time, depending on the maximum charging power $P_{\mathrm{ch,max}}$ of a specific EV. The $P_{\mathrm{ch,max}}$ varied from 1 to 22 kW per EV, depending on the charging transaction data. The power and energy limits of all EVs were subsequently aggregated and the EV fleet was treated as a set of 25 community batteries.

3.3. Optimization problem formulation

Fig. 2 illustrates the different steps to perform in the optimization process. The objective function is formulated in Eq. (2):

$$\text{minimize} \sum_{t=1}^{T} (P_{\mathrm{grid},t} * S_t). \tag{2}$$

Here, $P_{\mathrm{grid},t}$ represents the power through the LV/MV transformer and S_t represents the target variable. Note that the analysis was performed at two levels: the distribution system level and the transmission system level. When the focus is on the distribution system level, S_t is the aggregated residual load within the LV-grid (i.e. $P_{\mathrm{grid},t}$) and operation were optimized to minimize the peaks within the LV-grid. Hence, in this case the problem becomes a mixed-integer quadratic optimization problem. When the focus switches to the transmission system level, S_t is a binary variable reflecting whether it is a peak load hour, and the operation was optimized to have the highest possible capacity value. This entails that in the optimization on the transmission system level, S_t is 1 for peak hours and 0 for non-peak hours. Hence, on the transmission system level the problem is a mixed-integer linear problem. The objective function was subject to various constraints, explained below.

The power balance constraint is formulated in Eq. (3):

$$P_{\mathrm{grid},t} = P_{\mathrm{load},t} - P_{\mathrm{PV},t} + \frac{P_{\mathrm{ch},t}}{\eta_{\mathrm{ch}}} - \eta_{\mathrm{disch}} P_{\mathrm{disch},t} \ \forall t, \tag{3}$$

where $P_{\mathrm{load},t}$ and $P_{\mathrm{PV},t}$ represent the aggregated load and PV generation in the studied LV grid at timestep t. $P_{\mathrm{ch},t}$ and $P_{\mathrm{disch},t}$ represent the charging and discharging power of the community battery/EV fleet at timestep t and η_{ch} and η_{disch} represent the battery charging and discharging efficiencies.

To determine the CVR of distributed resources, it is important to comply with local power constraints. The MV/LV transformer power constraint is formulated in Eq. (4):

$$-P_{\mathrm{trafo,max}} \le P_{\mathrm{grid},t} \le P_{\mathrm{trafo,max}} \ \forall t, \tag{4}$$

in which $P_{\mathrm{trafo,max}}$ is the maximum allowed power that can pass through the transformer.

The aggregated charging and discharging power of the community battery/EV fleet were constrained by a maximum charging and discharging power:

$$0 \le P_{\mathrm{ch},t} \le P_{\mathrm{ch,max}} \ \forall t \tag{5a}$$

$$0 \le P_{\mathrm{disch},t} \le P_{\mathrm{disch,max}} \ \forall t. \tag{5b}$$

The energy in the community battery/EV fleet should always be within the energy limits of the batteries:

$$E_{\mathrm{bat,min}} \le E_{\mathrm{bat},t} \le E_{\mathrm{bat,max}} \ \forall t, \tag{6}$$

where $E_{\mathrm{bat},t}$ represents energy charged in the community battery/EV fleet at timestep t and $E_{\mathrm{bat,max}}$ is the battery's (aggregated) energy capacity (only useable capacity was considered). $E_{\mathrm{bat},t}$ is based on the energy in the battery of the previous timestep and the charging and discharging power at timestep t:

$$E_{\mathrm{bat},t} = E_{\mathrm{bat},t-1} + (P_{\mathrm{ch},t} - P_{\mathrm{disch},t}) * \Delta t \quad \forall t. \tag{7}$$

A Big-M constraint was used to ensure that the proposed operation of the community battery is not at the expense of the self-consumption of PV-generated electricity:

$$y_t P_{\mathrm{S},t} - P_{\mathrm{charge,t}} \leq M(1 - x_t)\ \forall t, \tag{8}$$

where x_t is a binary input variable that is 1 when there is surplus PV electricity (P_{S}). On days where the total $P_{\mathrm{S},t}$ exceeds the battery capacity, this constraint cannot be met without the fraction y_t. This is an input variable that represents the fraction of $P_{\mathrm{S},t}\ \delta t$ that fits in the battery without violating the battery's energy constraints on such days. The value of M should be sufficiently large, resulting in that the artificial variable would not be part of any feasible solution. For the optimized algorithm (see Section 3.4), this constraint was also removed to be able to compare a battery that is coupled with PV and thus increases self-consumption of PV, and a standalone battery which is exclusively aimed at maximizing the capacity value.

In one of the developed battery algorithms (see Section 3.4), it was assumed that the battery is only charged by PV-generated electricity. This was forced by the following constraint:

$$P_{\mathrm{grid},t} \leq P_{\mathrm{load},t}\ \forall t \tag{9}$$

To determine the CVR of smart charging, the possibility to discharge was disabled using the following constraint:

$$P_{\mathrm{disch},t} = 0 \quad \forall t \tag{10}$$

The model was programmed in MATLAB by using the Yalmip toolbox [33] and solved with the Gurobi optimizer.

3.4. Battery and EV algorithms

Four algorithms were deployed. All algorithms and accompanying constraints are shown in Fig. 2. For the community battery, a "Delayed Discharging" algorithm was developed to only use PV-generated electricity. This way, we determined to what extent batteries affect the CVR of PV. Also, an "Optimized" algorithm was developed. Here, the CVR of a battery was determined in the case of allowing charging from the grid. Note that both algorithms use optimization, but only the "Optimized" algorithm maximizes the battery's CVR. For the EV algorithms, a distinction was made between smart charging and Vehicle-to-Grid (V2G). In both algorithms the charging was flexible, but only in the V2G algorithm discharging from the EVs was also possible.

3.5. Data inputs

The data input is summarized in Table 1. Data represent a single LV-Grid in the neighbourhood Lombok in Utrecht, the Netherlands. Residual system load profiles were taken from the ENTSO-E Transparency platform [34], residential load profiles were taken from [35]. The PV installed capacity was multiplied by a performance ratio of 80% to realistically calculate maximum PV power in relation to the current transformer capacity of 400 kVA. This translates to 1.5 kWp per household (HH), which is well within the rooftop PV potential of this area [36]. The power capacity of the battery was fixed at the peak PV output, corrected by the performance ratio and a direct self-consumption of 30%. This was done to represent the main rationale to install batteries on community level, which is to increase self-consumption. The discharge time of the battery, or the energy capacity, was set at 1.5 h, but was also varied from 0.5 to 4 h in a sensitivity analysis. Two years of logged EV charging data from the studied grid were used to generate future sets of EV charging transactions, using the methods described in [37]. The analyses in this study were performed for an EV adoption rate of 100%, considering the current car possession rate of 0.4 car/household in the Lombok district. The focus was on EVs owned by local residents; visiting EVs were left outside of the analysis. In the transmission system level optimization, it was assumed that energy already stored in the EV batteries at arrival could be used to some extent; if an EV arrived with an SOC above 50%, all energy above this 50% could be used for V2G. The value for this minimum SOC of V2G was altered to 20% and 80% in the sensitivity analysis of Section 4.3.4. As no measured data on V2G power capacity were available, $P_{\mathrm{disch,max},t}$ was set at 11 kW per EV, which reflects the power capacity of one charging point. A technical availability of 96.1% was assumed based on [23], which is used to scale the results of the final CVR of the battery.

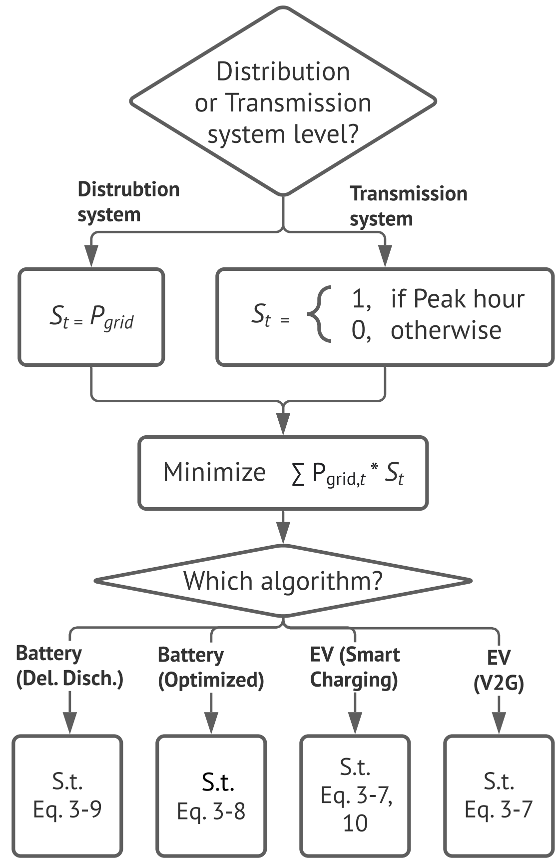

Fig. 2. Flowchart illustrating the logic of the different employed optimization algorithms in this study.

4. Results

4.1. Contribution of PV, storage and EV to peak reduction at distribution level

Fig. 3 illustrates the Load Duration Curves (LDCs) of the residential loads with PV only and the residential load when batteries under various algorithms are connected to PV. The load duration curves including EVs are illustrated in Fig. 4. These results are addressed in more detail in the following sections.

Table 1
Important data inputs.

Parameter	Value	Unit
Electricity consumption	2678	kWh/HH/y
Number of households	340	–
EV adoption rate	0.4	EV/HH
Installed PV capacity	1.5	kWp/HH
Battery power capacity	0.56	kW/kWp
Discharge time	1.5	h
Transformer capacity	400	kVA
V2G capacity	11	kW
V2G min. SOC	50 (±30)	%
Technical availability battery	96.1	%

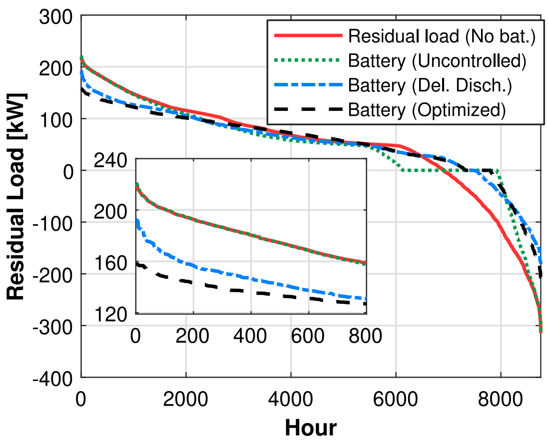

Fig. 3. Load duration curves of residual load without battery (i.e. PV only) and with battery without optimization (Uncontrolled), with optimization and PV-charged (Del. Disch.) and with optimization and grid-charged (Optimized) algorithms.

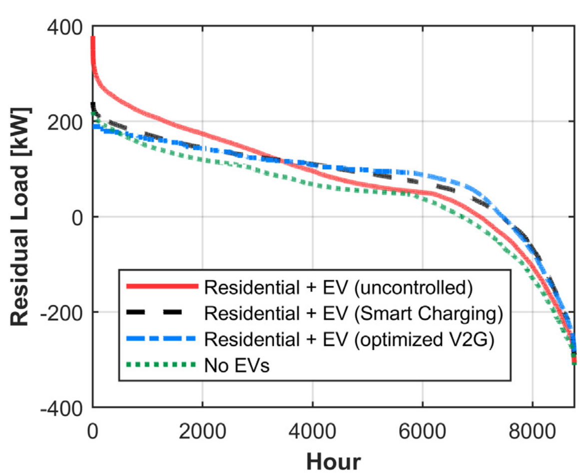

Fig. 4. Load duration curves of residual load without EVs and with EVs under various charging procedures.

4.1.1. PV only and PV with uncontrolled battery

For the cases of PV only and PV combined with an uncontrolled battery, the same peak load was found as the case of the community level without PV: 220 kW. PV does not contribute to satisfy the peak community load; it only has some contribution in the intermediate load hours. Adding an uncontrolled battery to PV does not increase the contribution to the peak load; the LDC with the uncontrolled battery is lower than the original LDC from approximately hour 1200 to hour 6800 (see Fig. 3). This is due to peak residual load hours being in winter, when there is limited PV electricity generation. When not controlling the battery, the

Table 2
Approximation of capacity value ratio of the different distributed resources and algorithms at peak capacity of 1.5 GW.

Configuration	Capacity value ratio
PV only	0.6%
PV + Battery (Uncontrolled)	2.6%
PV + Battery (Delayed Discharging)	25.0%
PV + Battery (Optimized)	47.0%
EV (Smart charging)	78.5%
EV (V2G)	8.9%

PV electricity is in most cases used directly, or immediately when $P_L > P_{PV}$. Generally, this does not coincide with the peak residual load.

4.1.2. PV+battery (Delayed Discharging)

In self-consuming PV electricity, one can prioritize charging the battery over satisfying the load. In that case, the grid is used to satisfy the load, while the PV-generated electricity is used to charge the battery. When the discharging of the battery is optimized to minimize the peak residual load, this peak decreases from 220 kW to 188 kW (−14.6%). Fig. 3 illustrates the LDCs of the community with and without batteries. The residual load when deploying batteries with the Delayed Discharging algorithm lies lower in the peak hours of the year, and higher in the hours with the lowest residual load, compared to the LDCs without a battery and with an uncontrolled battery. When the battery is not controlled, the interaction is zero for many hours; in these hours, the community operates fully on the battery. A demonstration of the battery operation of the Delayed Discharging algorithm can be found in Appendix, Fig. A.2.

4.1.3. PV+battery (Optimized)

When charging the battery from the grid is allowed, the maximum power extracted from the grid can be minimized. Executing this, the peak load decreases from 220 kW without PV and batteries, to 154 kW with PV and batteries: a peak reduction of 66 kW or 30.0%. Looking at the load duration curves in Fig. 3, once can see that the Optimized algorithm results in much lower peak grid demand than the situation without a battery and with a uncontrolled battery. This effect is similar with the Delayed Discharging algorithm, but rather amplified. A demonstration of the battery operation of the Optimized algorithm can be found in Appendix, Fig. A.3.

4.1.4. Electric vehicles

Fig. 4 illustrates the load duration curve of the community without EVs, with uncontrolled EVs, with smart charging EVs and with V2G. Uncontrolled charging increasing the peak on the LV-grid from 220 kW to 379 kW. However, when these EVs are charged in such manner to minimize peaks, the community peak increases to 240 kW. In case of V2G, despite adding a large load to the system, EVs can even decrease the peak load to 189 kW (−14%), without limiting the charging requirements of individual EVs. This is partly due to smart charging, i.e. charging in off-peak hours, and partly due to V2G. A demonstration of the V2G operation can be found in Appendix, Fig. A.1.

4.2. Capacity value ratio of PV, storage and EV on transmission system level

In Table 2, our approximations for the CVR of the various distributed resources are reported. Each configuration is discussed in Sections 4.2.1 and 4.2.2.

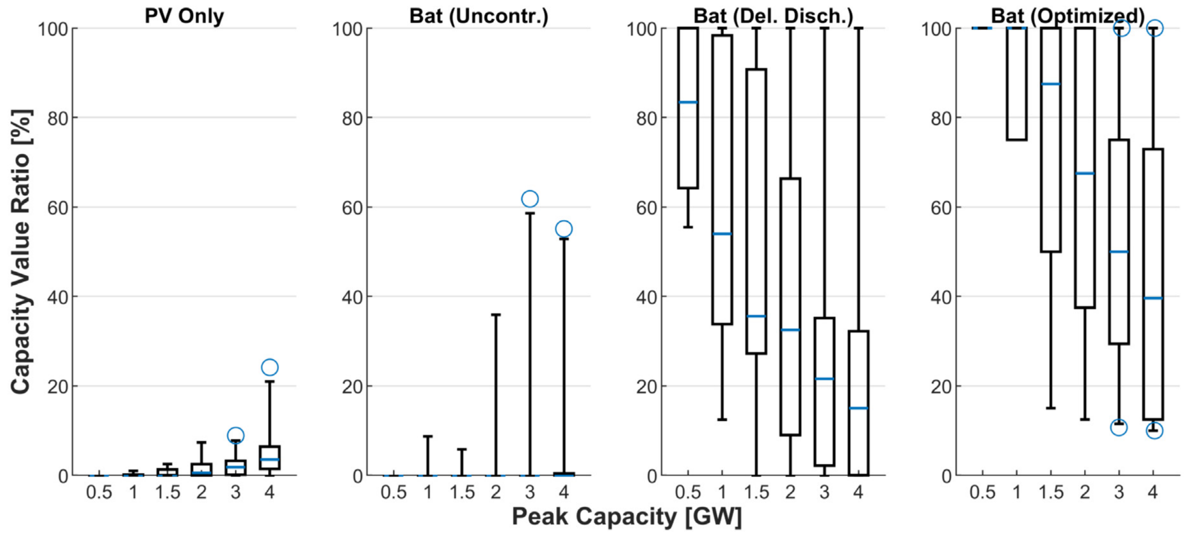

Fig. 5. Boxplots of average Capacity Value Ratio per day of PV only and batteries with various algorithms: no optimization (Uncontr.), PV-charged optimized battery (Del. Disch.) and grid-charged optimized battery (Optimized). Peak capacity relates to the upper 0.5 to 4 GW of residual load, which is equivalent to the upper 2.7% to 22% of residual load.

4.2.1. Capacity value ratio of PV and storage in the Netherlands, 2018

Fig. 5 illustrates the average CVR per day of PV and batteries for different levels of peak capacity. Note that for visual purposes one day is one data point in this figure, also when there are multiple peak hours on that day. This figure shows the trend with increasing amount of peak capacity or peak hours, whereas Table 2 gives a better approximation of the CVR because all peak hours are equally weighted. In general, the PV only scenario and the uncontrolled battery have relatively low CVRs; 0.6% for PV only and 2.6% for PV with uncontrolled battery. The optimization algorithms on the other hand result in substantially higher CVRs, with 25.0%[1] for the Delayed Discharging algorithm and 47.0% for the Optimized algorithm. The uncontrolled battery can increase the CVR of PV in some hours. The CVR of PV and the uncontrolled battery increase when looking at a larger range of the peak capacity, because in those cases more hours with solar irradiation are included; the CVR is zero when focusing on the peak 500 MW only.

The Delayed Discharging and Optimized algorithm reverse this trend. They show very high CVRs when focusing on 0.5 GW to 1 GW. The CVRs decrease when the peak capacity range is enlarged; when there are more consecutive peak hours, batteries need to distribute the stored energy over these hours. This can be seen in the battery operation illustrated in Fig. 6; if only PV-generated electricity is used, the battery can only supply electricity for one hour. Given that there are five peak hours on this day, the battery with the Delayed Discharging algorithm has a CVR of ∼10% on this day. The Optimized algorithm can have a CVR of almost 100%, because on this specific day there was a morning and an evening peak and the battery could recharge in between. However, also days exist with more consecutive peak hours, resulting in lower CVRs of the Optimized algorithm on those days.

The results of the Optimized algorithm were also compared with a battery that is not coupled with PV but instead exclusively operates to maximize the CVR. The difference between these batteries is that the PV-coupled battery is forced to accommodate surplus PV-generated electricity (see Eq. (8)), because of the prioritization of self-consumption, whereas the stand-alone battery can still feed into the grid in these hours. The results for the categories of 0.5 GW to 3 GW are identical. Only in the category 4 GW, the PV-coupled battery has a slightly lower average CVR. This means it seldom occurs that there is a PV surplus and a peak in residual load simultaneously. This is in line with the results found for the CVR of PV. This provides strong support for the attractiveness of using a battery both for self-consumption and for providing capacity in peak hours.

[1] The capacity of the battery is used. Using the capacity of PV, the CVR would be 14.0%.

4.2.2. Capacity value ratio of EVs in the Netherlands, 2018

In Fig. 7, the CVRs of smart charging and V2G are illustrated. Note that the "capacity" of smart charging is its load in case of uncontrolled charging. The CVR for smart charging is thus not capacity value in a strict sense, but rather reflects the part of the demand that can be shifted from peak load hours. As per ENTSO-E definition, explicit demand-response can be considered in the supply curve [6]. For V2G, the CVR reflects the part of the entire EV fleet's (i.e. also non-connected EVs) discharging power that can be exported to the grid in peak residual load hours.

Most EV charging in the studied area that occurred in peak hours can be postponed to off-peak hours. The average CVR of smart charging in the peak 1.5 GW system capacity is 78.7%. This indicates that charging of EVs requires some, but not much additional capacity to retain the same system reliability, if this is taken as an objective in charging optimization. For larger amounts of peak hours, the CVR of smart charging becomes somewhat lower; when there are many consecutive peak load hours it is more often inevitable to charge the EV in peak hours. The contribution of V2G is moderate with on average 8.9% in the 1.5 GW peak capacity. If all vehicles in the Netherlands would be EVs, this relates to a capacity value of 8.3 GW. In the context of a phase-out of coal-fired power plants, it is worthwhile to study the CVR of V2G in the peak 4.0 GW instead of peak 1.5 GW as done in the previous paragraph, as 4.0 GW relates to the current coal-fired generation capacity. On average, EVs can provide a CVR of 5.2% in the peak 4.0 GW of residual load. This CVR relates a capacity value of 4.8 GW if all 8.5 million passenger vehicles in the Netherlands would be EVs. Hence, these results indicate that all current coal-fired power plants could be phased-out without losing system reliability, if all EVs were used for this purpose. Evidently, there are some considerations with this notion: e.g. perfect foresight of EV charging needs is needed, as well as acceptance of EV owners that their EV battery is used for this purpose. However, it does

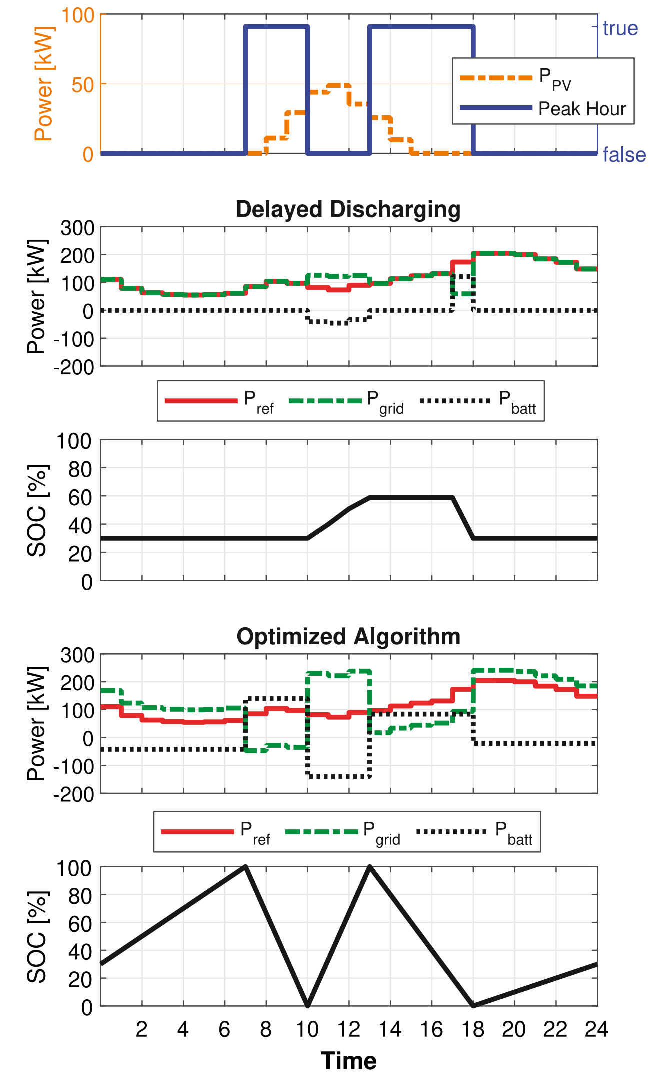

Fig. 6. Demonstration of battery operation of the Delayed Discharging algorithm and Optimized Algorithm. Binary variable S_t is illustrated in the upper graph in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

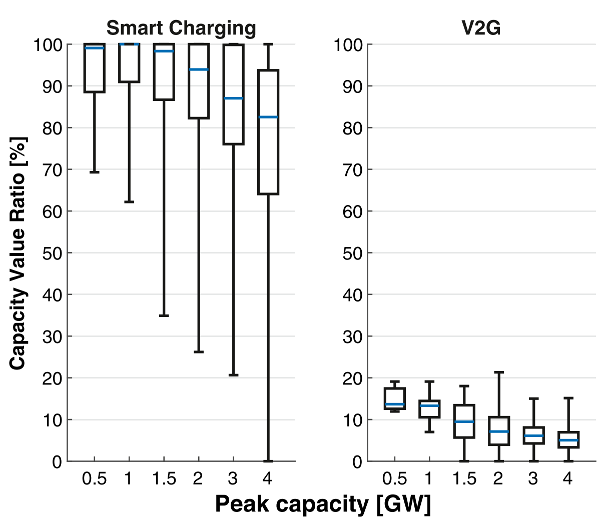

Fig. 7. Contribution of smart charging and V2G for various amounts of peak load hours associated with the peak capacity displayed on the *x*-axis. Peak capacity relates to the upper 0.5 to 4 GW of residual load, which is equivalent to the upper 2.7% to 22% of residual load.

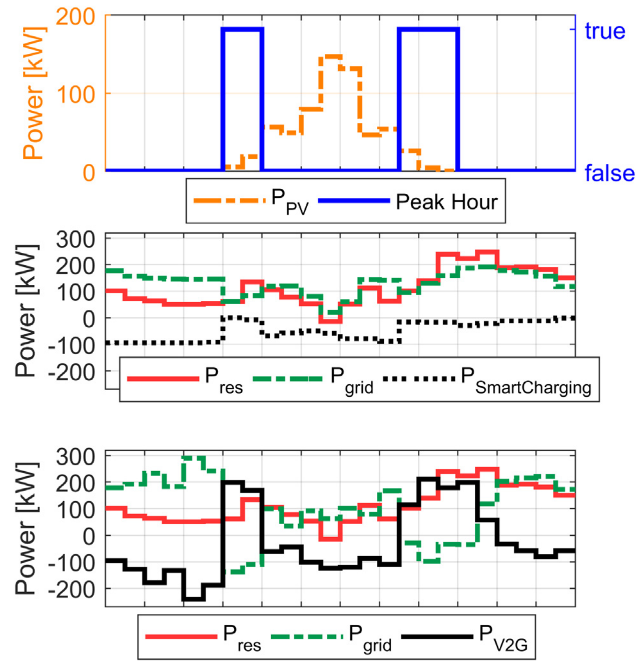

Fig. 8. Demonstration of EV smart charging and V2G operation. Binary variable S_t is illustrated in the upper graph in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

illustrate the large potential EVs have to contribute to system reliability in the context of a phase-out of conventional power plants.

Fig. 8 illustrates the operation of smart charging of EVs and of V2G. It shows charging in peak hours can be postponed; the charging power of EVs in the peak hours is approximately zero. When V2G is applied, EVs charge more before the peak load, and part of this charged energy can be fed back into the grid during peak hours. The community becomes even a net contributor in these hours as the graph of P_{grid} becomes negative in these hours.

4.3. Uncertainty analyses

4.3.1. Future loads: CVRs in case of electrification heat and transport sector

In accordance with the ENTSO-E's proposal for determining CVRs [6], future load profiles have been constructed to study the CVRs in scenarios of electrification of heat and transport. Values for additional demand due to electrification of heat and transport in the Netherlands, 18 and 25 TWh/year, respectively, were taken from Zappa et al. [7]. In order to obtain a rough future EV load profile, arrival time data of public charging were taken from open source data [38]; in line with the charging data of this study, it was assumed that EVs charge in two hours. The heat profile G1A, which is a typical heat profile for residential sector, for 2018 from NEDU [35] was used as a base profile. Ambient temperature data from [39] were used to scale the temperature-dependent (i.e. space heating) profile, using a base temperature of 15 degrees Celsius [40]. The natural gas profile was translated to a heat pump profile based on heat pump coefficient of performance values taken from [41] and ratio temperature-dependent and temperature independent (i.e. hot water use) heat from [42]. Evidently, this uncertainty analysis should be treated rather indicative, as scenario building was not the main purpose of this study.

Table 3 provides the CVRs for three future load scenarios: electrification of (a) heat, (b) transport and (c) heat and transport.

Table 3
Approximation of capacity value ratio for three future load scenarios: electrification of (a) heat, (b) transport and (c) heat and transport. For comparison with current load, see Table 2.

Configuration	CVR. Scenario: electrification of		
	Heat	Transport	Heat and transport
PV only	2.6%	0.3%	0.9%
PV + Battery (Uncontrolled)	0.4%	1.0%	0.6%
PV + Battery (Delayed Discharging)	43.9%	45.1%	59.6%
PV + Battery (Optimized)	67.0%	70.8%	80.2%
EV (Smart charging)	93.1%	94.1%	84.3%
EV (V2G)	12.6%	15.3%	18.8%

The target capacity was set equivalent to 1.5 GW, which was 8.2% of peak residual load in 2018 (but more when additional load is added). In general, electrification of heat and transport lead to higher CVRs for duration-limited storage, including V2G. Somewhat surprisingly, the electrification of transport leads to higher values of CVR for V2G: an increase from 8.9% to 15.3%. This is in contrast to what is known from the penetration of renewables, where the CVR decreases with increasing penetration. An explanation can be found in a change of the shape of the residual LDC of the Netherlands. Without the electrification of heat and transport, this profile is relatively flat, because of a large share of electricity demand by industry. This results in days of high load in which many consecutive peak load hours occur, which is not ideal for the CVR of duration-limited storage. The large additional load of 25 TWh for transport (an increase in electricity demand of 18.8%) occurs for a large part in the evening hours, whereas the electrification of 18 TWh of heat occurs in winter morning and evening hours. This results in a less flat LDC, and in fewer days with many consecutive peak hours. Also notable is the higher CVR of PV in case of electrification of heat, which increases to 2.6%. This is due to more peak hours occurring in the morning, when PV is generating electricity.

4.3.2. Historical loads: CVRs of batteries in different years

In accordance with ENTSO-E's proposal [6], this study covered multiple years to determine the robustness of the found CVRs. Fig. 9 illustrates the analysis of the batteries performed with the residual load and solar irradiation of 2016 and 2017. From these graphs, and also by comparing with Fig. 5, one can see that the CVR of PV has decreased somewhat over the years. This is due to the recent rapid increase in installed capacity of PV in the Netherlands, which has an impact on the residual load; with lower amounts of installed capacity of PV, chances are higher on a peak residual load hour with high solar irradiation and vice versa. This is in line with general findings that capacity values of VRES decrease with a deeper penetration of VRES [14–17]. For the optimization algorithms, results are quite robust over the years; batteries are less sensitive for a deeper penetration of batteries, because their charging/discharging power is to a very large extent controllable. In this case, they are more sensitive to the steepness of the load duration curve. A very steep peak in the load duration curve leads to fewer peak hours; batteries perform better when there or not many consecutive peak hours.

4.3.3. Impact of discharge time on CVRs batteries

Fig. 10 illustrates the impact of discharge time on the CVR of the community battery. It is evident that discharge time has a large impact on the CVR. The CVR increases in a non-linear fashion with increasing discharge time. In other words, larger batteries can have a higher contribution to supply the peak residual load, but the incremental benefits of increasing storage size diminish with increasing discharge time. For example for the delayed discharged algorithm, it is notable that increasing the battery above 2.5 h of discharge time does not make sense from a capacity value perspective with the assumed PV sizes; PV-generated electricity is the limiting factor.

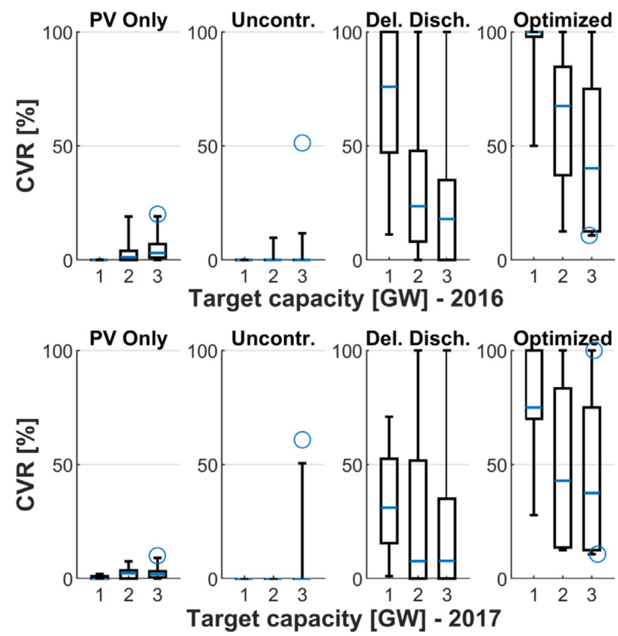

Fig. 9. Capacity Value Ratio for PV only, for uncontrolled batteries and for batteries with the Delayed Discharging algorithm and the Optimized algorithm. Assumed discharge time of batteries is 1.5 h.

Table 4
Impact of discharge time — comparison with previous studies.

Discharge time	Sioshansi et al. [19]	National grid [23]	This study
0.5 h	–	17.9%	21.1%
1.0 h	36.3%	36.4%	36.1%
1.5 h	–	52.3%	47.0%
2.0 h	49.8%	64.8%	55.1%
2.5 h	–	75.5%	63.3%
3.0 h	–	82.0%	69.4%
3.5 h	–	85.7%	75.1%
4.0 h	66.8%	–	80.7%

These results can be compared with previous studies, i.e. [19, 23]; this is shown in Table 4. Our results correspond well with a study performed for the United Kingdom [23], although our study finds a lower CVR for higher discharge times. For California, Sioshansi et al. [19] report somewhat lower values for the CVR than the results of our study; hence, our results are between the other studies on this topic. As has been stressed before, the CVR of technologies are strongly influenced by the geographical locations. This comparison indicates that this is less the case for batteries than for VRES technologies.

4.3.4. Impact access to energy at arrival on CVR EVs

In this study, it was assumed that energy from an EV battery at arrival above an SOC of 50% could be used for V2G. Fig. 11 illustrates the impact of changing this assumption to 20% or 80%.

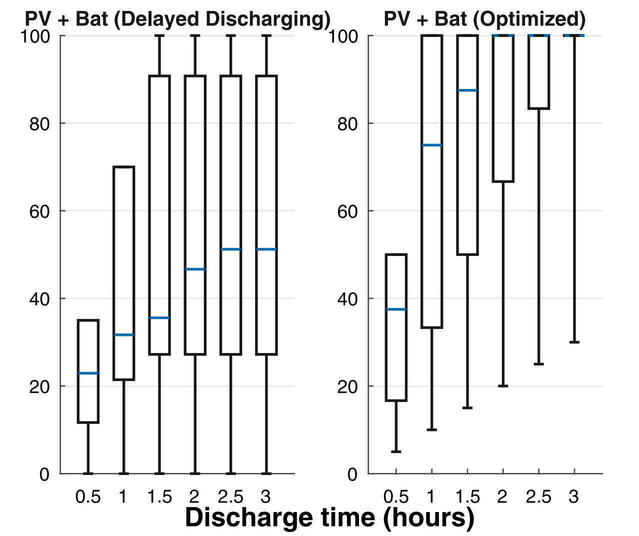

Fig. 10. Impact of discharge time on CVR of community battery. Assumed peak load is 1.5 GW, which relates to the upper 8.2% of absolute residual load.

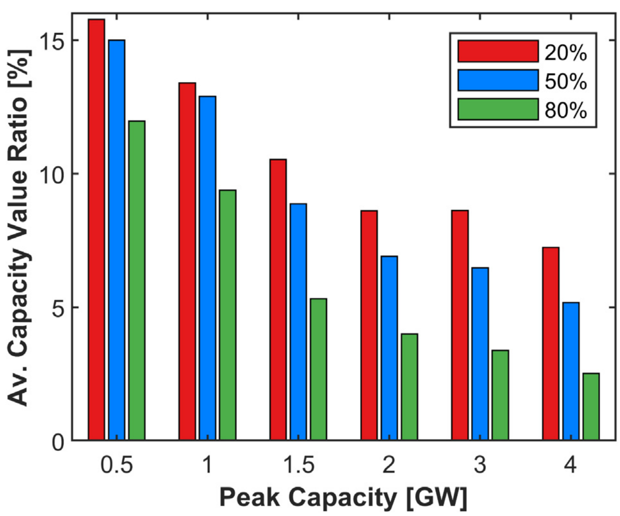

Fig. 11. Impact of Assumed V2G SOC limit on Capacity Value Ratio of V2G. Energy in EV batteries could be used for V2G until a minimum SOC of 20%, 50% and 80%, respectively. Peak capacity relates to the upper 0.5 to 4 GW of residual load, which is equivalent to the upper 2.7% to 22% of residual load.

It is apparent that this impact is large. In general, the higher the minimum SOC the lower the CVR, while absolute values of CVR decrease with higher target capacity. For example, when EV owners would accept their EV would be used for providing capacity to the grid until an SOC of 20%, the CVR in case of a target capacity of 1.5 GW increases from 8.9% to 10.5%, while still satisfying the eventual charging requirements. However, when only energy in excess of an SOC of 80% can be used, the CVR decreases to 5.3%. The impact is more pronounced when studying higher target capacities, because in case of multiple consecutive peak hours, directly using EVs when they connect, which often occurs during peak hours, has substantial impact.

5. Discussion

In this section, we reflect on the presented results and provide various considerations and recommendations on determining the CVR for distributed resources.

5.1. Large range of CVRs

The results indicate a substantial impact of batteries and V2G to deliver electricity at peak residual load hours, and also a high potential of load shifting of EV charging to off-peak hours. However, it is also evident that a large variation between days exist. Days with multiple consecutive hours of peak load are accompanied with lower CVRs of batteries. It is thus important to stress that (a) the reserve margin should consist of multiple technologies, spreading the risk in case of stress events, and (b) PV coupled with batteries and EVs can have a substantial contribution in the first stage of the phase-out of conventional power plants, but other solutions should be present in a deeper phase-out of conventional power plants.

5.2. Approximation method versus reliability-based methods

In this study, it was found that the CVRs of the approximation method are in line with previously reported CVRs by the reliability-based methods of [19,23]. If this finding is robust, this dramatically decreases the computational time and data requirements when performing analyses on CVRs. However, it is important to consider that three different power systems are compared; we recommend more comparative research on this topic. Furthermore, our estimates should evidently not be used as a full replacement of the reliability-based methods. The specific residual load profile differs per country as it is based on e.g. the load profile, installed capacity of VRES, weather fluctuations and common outages. TSOs will still use reliability-based methods; ENTSO-E has already provided guidelines on this [6]. This ensures reliable results for determining resource adequacy. However, some of the requirements make analysis on factors influencing the CVR of technologies and algorithms troublesome: Monte Carlo analyses require many unit commitment and economic dispatch model runs to ensure statistical reliability, the models are required to run 10 years into the future, the models are required to include, among others, uncertainty in random outages and various weather conditions. This makes it a very reliable method to determine the full system's resource adequacy, but less adequate to determine the capacity value of individual technologies let alone algorithms within technologies. Here, the approximation method has value in several aspects. It provides the possibility to make fast comparisons and indications of a wide range of technologies and algorithms, for different (future) load profiles. Furthermore, it can show which parameters are important in determining the CVR of a technology and algorithms. Results of the approximation methods could be used as input for reliability-based methods.

5.3. Future residual load

This study demonstrated the potential impact electrification of heat and transport on the CVR of the various distributed resources. Our results give an indication, but will differ when different future residual load scenarios are used. As stressed before, the future load scenarios implemented here were rather simplistic. For example, future profiles may be very different as a result of different market incentives that are present. Also, it should be noted that while the CVR of EVs might increase with the electrification of heat and transport, this should be weighed against a potential additional capacity needed to accommodate charging of EVs. The results of the distribution level optimization give some indication here, showing the electrification of EVs can lead to a decrease in the peak residual load, if this is an objective and V2G is applied.

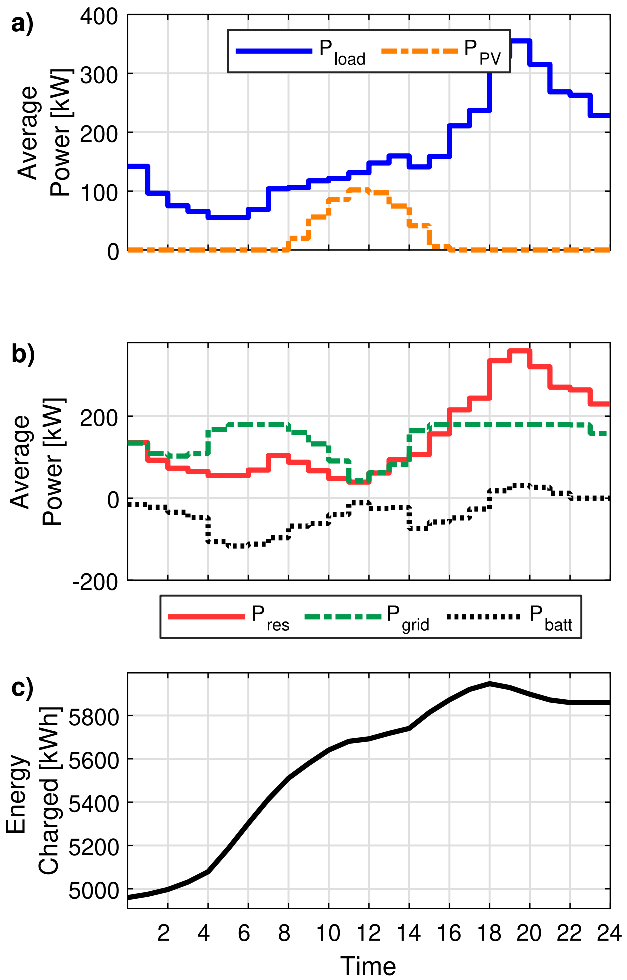

Fig. A.1. Battery operation with V2G. Graph (a) reflects the load (including uncontrolled charging load) and PV generation, (b) illustrates the residual load in red and the optimized residual load in green when power of the EV battery (in black) is used and (c) illustrates the accumulated energy charged in the EV battery fleet. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The increased deployment of VRES will also change the residual load, as could already be seen to some extent in Section 4.3.2. CVRs of renewable electricity generation technologies are not constant. In general, the more VRES technology is deployed, the lower its CVR will be, if the technology is not combined with a storage technology. For storage, the relation between deployment of VRES and the CVR of the flexibility storage is not straightforward. Higher deployment of VRES could lead to shorter peak residual load periods (i.e. a steeper LDC), which is beneficial for the CVR of duration-limited storage. Hence, an important recommendation is to perform more scenario analyses with changing residual loads, to periodically update calculations on CVRs and study different weather scenarios. This will lead to a better understanding of the described dynamics.

5.4. Impact specific algorithms

The algorithms that are developed have a large impact on the CVR of flexibility resources. These technologies will probably not be focused on maximizing CVR, as flexibility resources can have a variety of purposes. In this study, this was addressed by combining storage with PV systems while ensuring that providing capacity with the community battery does not hamper self-consumption of PV-generated electricity. Therefore, our results can be interpreted as the potential of providing capacity, on top of a default operation of a community battery. Or the other way around: when batteries are used for capacity value, e.g. by TSOs, they can also be used for other purposes like supporting self-consumption.

At the same time, there could also be other, competing objectives when using the flexibility of these technologies. For example, the technologies might be used for market optimizations or minimizing emissions [43]. In that case, CVRs of these technologies can be substantially lower than reported here. From a policy perspective, we recommend to determine the value of contributing to the resource adequacy for flexible resources. Incentive programmes can be designed accordingly, which could help steering flexible resource operators to allocate their resources to contribute to the resource adequacy.

5.5. Impact of discharge time and energy EV at arrival

By convention, the CVR is determined by dividing the average capacity in peak hours by the power capacity of a technology. This metric may not be the most suitable one in case of storage technologies. In this context, the discharge of a battery is key (or its inverse, the C-rate). Intrinsically, the CVR approaches 1 when the C-rate approaches zero: a very high energy-to-power-ratio ensures a high probability the full power capacity of a battery can be used during the peak hours. Thus, the metric CVR has a bias towards batteries with low C-rates/high discharge times. We addressed this in this study by varying the discharge time. An important recommendation therefore is to always take both the energy and the power capacity of a storage technology into account when determining and using its CVR. Alternatively, storage technologies could be assessed by a different metric, e.g. with the unit h^{-1}, or the CVR could be corrected using the discharge time. More analysis on the impact of the discharge time can be found in [23].

An important assumption for determining the CVR of V2G, is whether the energy that is stored in the EV at arrival can be used for V2G. In this study, it was assumed that if an EV would arrive with an SOC above 50%, the EV could be discharged until 50% to contribute to the peak hours. In Section 4.3.4 it was demonstrated the large impact of changing this assumption to 20% or 80%. Given the importance of this metric, we recommend to perform survey analysis under EV owners to determine whether, and under which circumstances, they are open to grant some of their EV battery capacity to maintain the overall system reliability. Ideally, future models will not assume one value for this parameter, but use a distribution reflecting the individual preferences of EV drivers. Still, there are also some practical considerations. From the historical data, it is relatively straightforward to determine the energy capacity of the battery, e.g. by taking the maximum charged energy in one transaction. However, in reality it is complicated to determine the SOC of a battery in general, and an EV battery specifically. One approach is to measure the open circuit voltage of the battery. However, this is influenced by many factors and is also highly specific for the type of EV. The most realistic approach is to have communication between the EV and the charging point operator, as reliable information about the battery SOC is present in the battery or battery management system. This information exchange then could also include the minimum SOC an EV owner requires for future trips and the expected departure time.

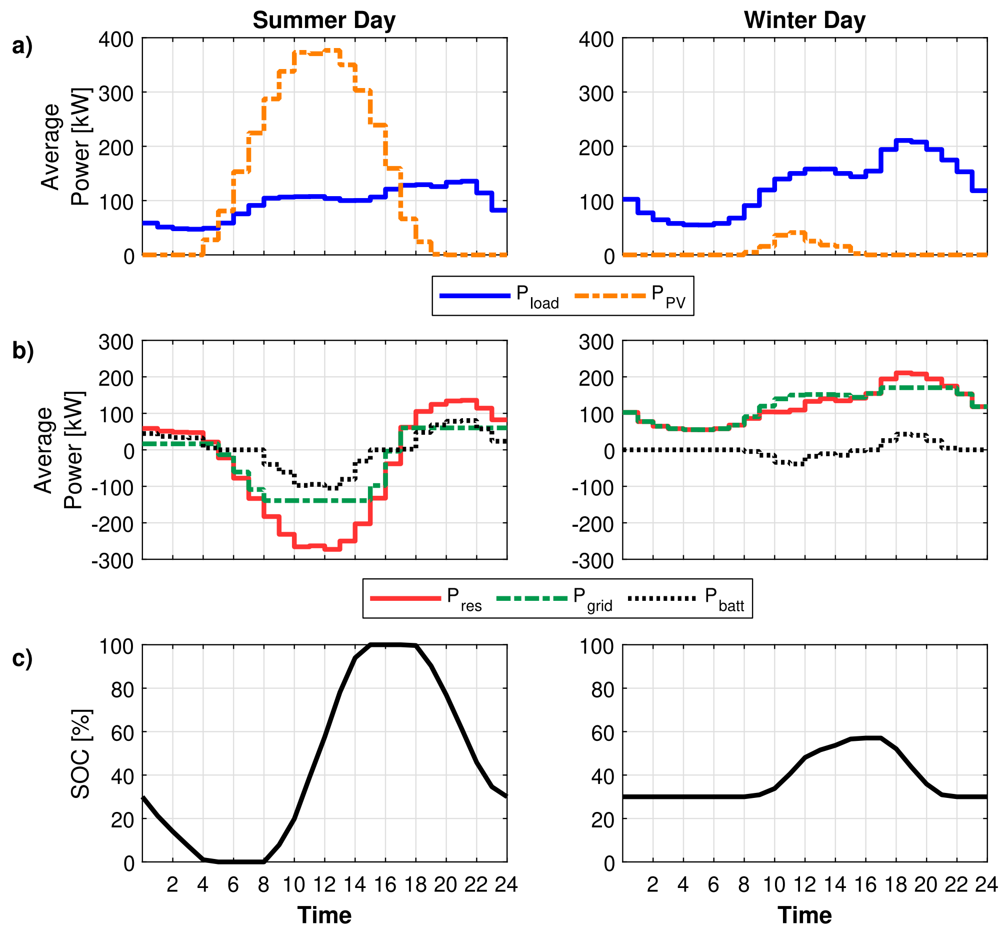

Fig. A.2. Operation of community battery with Delayed Discharging algorithm on summer and winter day. Graph (a) reflects the load and PV generation, (b) illustrates the residual load in red and the optimized residual load in green when power of the battery (in black) is used and (c) illustrates the accompanying SOC of the battery. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

6. Concluding remarks

This study addressed the contribution of distributed resources (PV, community batteries and EVs) to the system resource adequacy and resulted in recommendations regarding critical parameters. As flexible resources are currently being considered in the reserve margin of power system, we have provided handhelds of important factors that should be considered in this analysis. Compared to conventional power plants, the flexible resources of batteries and EVs have the advantage that they can be used for various purposes, thereby being less prone to the "missing money" problem, and moreover have lower greenhouse gas emissions. We have shown that the capacity value of PV can be substantially increased when coupled with storage, without hampering self-consumption of PV. This suggests that PV, coupled with batteries, can play a significant role in contributing to resource adequacy in the context of the phase-out of fossil-fuelled power plants, in particular in the first stages of this phase-out. However, it should be noted that batteries have limitations when they are required to supply larger parts of the load. Regarding EV charging, this study has demonstrated that EV charging load can be shifted away from peak periods to a very large extent. V2G can play an important role in providing capacity at peak hours, especially when a large part of the passenger vehicles are EVs.

Given the central role of resource adequacy in the EU's Clean Energy package, we recommend to determine the economic value of the CVRs of distributed resources. Future research could aim to determine what incentives are required to ensure distributed resources are used to contribute to the resource adequacy (e.g. via capacity mechanisms). However, currently distributed resources cannot be used for system balancing and be considered for the resource adequacy at the same time as per ENTSO-E's methodology proposal. An open question is the trade-off between these two, and whether it is possible to also find synergies.

CRediT authorship contribution statement

Wouter L. Schram: Conceptualization, Methodology, Writing - original draft, Visualization, Funding acquisition. **Hamid Aghaie:** Conceptualization, Writing - review & editing. **Ioannis Lampropoulos:** Writing - review & editing. **Wilfried G.J.H.M. van Sark:** Writing - review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Community battery and EV operation in peak reduction at the distribution level

Fig. A.1 illustrates the V2G operation in peak reduction at the distribution level. The fleet is generally charged at a moderate pace. The charging rate is decreased compared to uncontrolled charging from 16:00, and the fleet starts to feed electricity back into the in the absolute peak (from 18:00 to 21:00). The difference

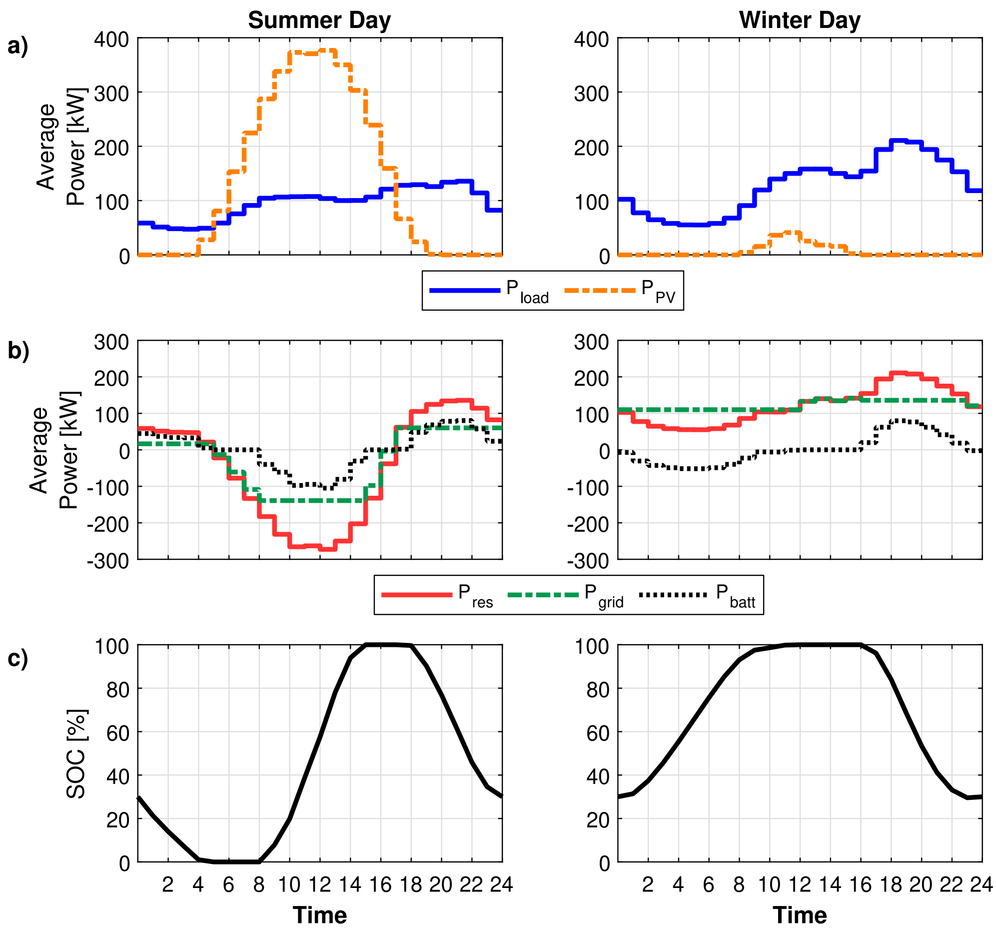

Fig. A.3. Operation of community battery with Optimized algorithm on summer day and winter day. Graph (a) reflects the load and PV generation, (b) illustrates the residual load in red and the optimized residual load in green when power of the battery (in black) is used and (c) illustrates the accompanying SOC of the battery. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

between the peak residual load and the optimized P_{grid} is larger than the amount of power the fleet discharges; hence, this reflects power that is requested from the grid in case of uncontrolled charging, but that can be postponed to off-peak hours.

The battery operation of a summer and a winter day is illustrated in Fig. A.2. We can see that on a summer day, a substantial part of the load is satisfied by the battery. During the day, the battery is charged using PV-generated electricity — also the maximum feed-in is minimized. On a winter day, the battery also satisfies a part of the load, but to a less extent, whereas this load is higher than the load on a summer day. The new peak load occurs on a day with both exceptionally low PV electricity generation and high load. On these days, pre-charging the battery with electricity from the grid can further increase the peak reduction of the combined PV-battery system.

Fig. A.3 illustrates how charging the battery from the grid can increase the peak reduction when compared to Fig. A.2; in winter, the average residual load demand is constant for most of the day.

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