Sustainable Energy, Grids and Networks 34 (2023) 101005

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

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

The effect of short term storage operation on resource adequacy

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ARTICLE INFO

Article history:
Received 18 October 2022
Received in revised form 17 December 2022
Accepted 14 January 2023
Available online 30 January 2023

Dataset link: https://gitlab.kuleuven.be/u0128861/storage-operation-and-lole

Keywords:
Resource adequacy
Electricity storage
Adequacy assessments
Capacity remuneration mechanisms
Capacity credits
Security of supply

ABSTRACT

The potential contribution of short term storage technologies such as batteries to resource adequacy is becoming increasingly important in power systems with high penetrations of Variable Renewable Energy Sources (VRES). However, unlike generators, there are multiple ways in which storage may be operated to contribute to resource adequacy. We investigate storage operational strategies which result in the same amount of Expected Energy Not Served (EENS) but differing Loss of Load Expectation (LOLE) to investigate the range of LOLE possible and what factors affect this range. A case study of a Belgium-like power system using an economic dispatch model, typical of state-of-the-art adequacy assessments, results in a LOLE ranging between 2 and 6 h/yr, with the difference decreasing for greater storage duration and increasing for higher installed capacities of storage. Capacity Credits (CCs), which give the relative contribution of a resource to system adequacy, may also be affected by storage operation and the CC of storage is shown to differ by up to 30% depending on the operation and how the CC is calculated. Given these findings, it is recommended that modellers be explicit and transparent about the storage operation they assume in adequacy assessments and capacity credit calculations.

1. Introduction

Modern power systems across the world should be shaped by three forces: competitiveness, sustainability and security of supply [1]. The concept of security of supply has many dimensions, one of them being resource adequacy which is defined as the ability of the bulk power system to meet load at steady state under many different conditions [1], preferably so that the marginal costs of shedding additional load are equal to the marginal costs of additional resource [2].

In order to enable greater penetrations of VRES and reach sustainability targets, storage technologies, such as grid or residential scale batteries, are gaining increasing attention.[1] This is because storage can 'smoothen' the variable production of renewables in time in much the same way that transmission can smoothen it in space. While the amount of storage in many power systems remains small and how that share will evolve is uncertain [4], storage, and in particular batteries, will undoubtedly play an increasingly important role in power systems with high penetrations of VRES.

The potential contribution of flexible assets such as demand response and storage to resource adequacy is widely recognised [2,5,6]. However, as this paper will extensively discuss, how short term storage is operated impacts the adequacy indicators[2] of the system, *even if the amount of load shed is the same*.[3] This issue is particular to short term storage, which depletes its energy content by the end of a scarcity event, and it is illustrated in Fig. 1. The amount of load shed, otherwise known as the EENS,[4] is constant for each operational strategy but other adequacy indicators are not. In all cases the total cost is the same as well as the storage owners profit.

This issue raises questions as to the impact of the assumed storage operation on the perceived adequacy of the power system, since many systems around the world use LOLE as an indicator, which is the mean number of hours per year that a power system would experience load shedding. Fig. 1 clearly shows that it is possible to get different LOLE while keeping the EENS constant. Put differently, a storage operation which minimises EENS does not uniquely define the adequacy of a power system.

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1 When considering the merits of batteries, as with any technology, their environmental footprint over the entire lifecycle should be considered and not just the greenhouse gas emissions during operation. This footprint can be considerable in the case of batteries [3].

2 An adequacy indicator may also go by the name of 'reliability standard' or 'reliability metric'.

3 A similar argument may be made for demand response, though we only consider storage in this paper.

4 To be precise, the EENS is the expected amount of load shed per year, not per event. In this example and introduction we conflate indicators for a specific scarcity event and their expectation over a whole year since the observations made are valid for both.

https://doi.org/10.1016/j.segan.2023.101005
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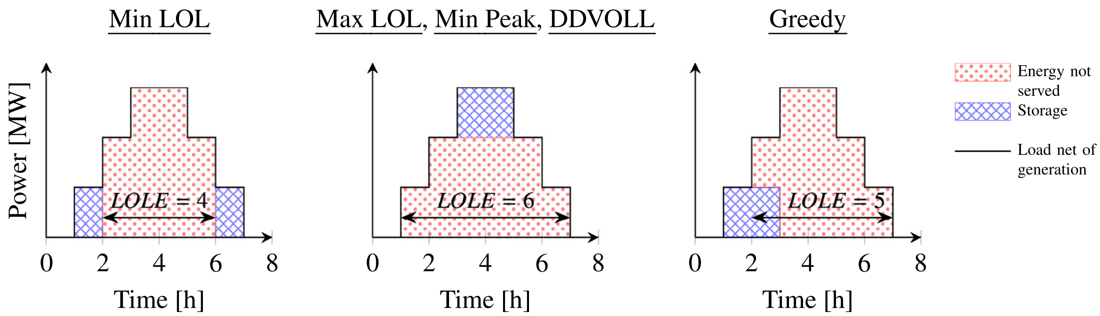


Fig. 1. Three different storage operational strategies which give three different LOLE values* despite the EENS being the same. Titles above plots are the names of the strategies investigated in this paper (see Section 3.2) which coincide with the illustrated behaviour.

Abbreviations

ENS	Energy Not Served
EENS	Expected Energy Not Served
LOL	Loss of Load
LOLE	Loss of Load Expectation
LOLD	Loss of Load Duration
ELOLD	Expected Loss of Load Duration
MPNS	Maximum Power Not Served
EMPNS	Expected Maximum Power Not Served
CC	Capacity Credit
ELCC	Effective Load Carrying Capability
EFC	Effective Firm Capacity
VOLL	Value of Lost Load
CRM	Capacity Remuneration Mechanism
VRES	Variable Renewable Energy Sources

To the best of the authors' knowledge, this impact has not been thoroughly investigated in the literature so far and so it is unclear whether and under which conditions it would be a cause for concern.

This issue of storage operation may also have an impact on CCs[5], and by extension capacity remuneration mechanisms, where the CC of a resource is the amount of firm capacity that must be added to a baseline system such that it has the same adequacy as the baseline system plus an additional MW of that resource [7][6]. Indeed, the methodologies used to determine capacity credits require modelling power system operations just as adequacy assessments do. Depending on how the capacity credit is calculated, storage operation may impact its value.

While several publications hint at the effect of storage operation on adequacy indicators and capacity credits (see for example Zachary et al. [7]), none attempt to thoroughly quantify this effect. Only one report [9], not published in the scientific literature, investigates the effect on capacity credits. The contributions of this article are therefore as follows:

- Quantification of the effect of five different storage operational strategies on adequacy indicators, in particular the LOLE. This includes sensitivity analysis of key parameters including storage duration, storage penetration and the underlying load net of generation time series.
- Quantification of the effect of storage operation on capacity credit.
- Discussion of the consequences of this for adequacy assessments and capacity remuneration mechanisms.

In summary, our objective with these contributions is to investigate whether non-unique but equally cost optimal storage operational strategies may produce adequacy indicators and capacity credits which differ significantly. By significant we mean that the range of values obtained due to storage operation is of a similar order of magnitude to the uncertainty inherent in such calculations.

The rest of this paper is structured as follows. Relevant context and literature is given in Section 2 followed by a description of the methodology used in Section 3. An illustrative example is presented in Section 4 in order to gain insight in a toy setting while Section 5 follows up with a case study inspired by the Belgian power system. Section 6 discusses the drawbacks and implications for stakeholders and finally Section 7 concludes.

2. Literature review

In this section we review the literature on storage and resource adequacy, beginning with the main contributions in this area and then works which specifically mention or investigate how storage operation affects resource adequacy. This review is summarised in Table 1.

There has been a growing amount of literature which investigates the contribution of storage to resource adequacy [10]. A very comprehensive analysis is given by Zhou et al. [5] in which the objective of storage is to minimise peak load. It is concluded that storage can improve adequacy but also changes the duration and severity of scarcity events. In a subsequent paper Zhou et al. [6] developed a technology agnostic framework for determining the CC of storage and demand response based on EFC and Effective Load Carrying Capability (ELCC). This builds on previous works which calculated the ELCC for storage [11] and demand response [12,13] by investigating the effect of the parameters which characterise these technologies on CCs. The non-uniqueness of storage operation is implicitly acknowledged in Zhou et al. [6] since a 'dual' (two) stage optimisation is used, in which first the peak demand is minimised followed by minimisation of the energy used to charge storage or energy shifted by demand response.

The PRAS model from NREL [14] employs a 'greedy' operational strategy, in which storage charges when there is excess

[5] In Europe CCs are more commonly referred to as 'de-rating factors', especially in the context of Capacity Remuneration Mechanisms (CRMs).

[6] The definition given here for a CC is that of the incremental EFC, though other, similar, definitions exist such as that of equivalent load carrying capability [8]. Typically CCs are normalising by the amount of additional resource added to obtain a value between 0 and 1.

generation and discharges when there would otherwise be load shedding. This strategy, which is foresight agnostic, has been shown to be Energy Not Served (ENS) minimising by both Edwards et al. [15] and Evans et al. [16] and both generalise this operation to heterogeneous storage units.

There are numerous other publications which investigate the effect of storage operation on adequacy indicators or at least touch upon the subject. Zachary et al. discuss the issue of non-unique storage operation within the context of capacity markets and choose a 'greedy' strategy for their analysis [7]. Božič and Pantoš investigate three different charging strategies for electric vehicles and their impact on the EENS and the LOLE [17]. Shariatkhah et al. compare 'economic' and 'reliability' based operation of storage [18]. Fraunholz et al. compare price versus load based smoothing operation of storage on long term adequacy in a simplified investment setting using an agent based model [19]. Shrestha and Karki consider the effect of storage participation in operating reserve markets on adequacy and shows that this participation actually decreases the loss of load probability [20]. None of these papers compare storage strategies which result in the same EENS, as done in this paper.

In a report from 2017, Great Britain's National Grid looked at the effect of different storage operational strategies on capacity credits [9]. They show that EFC based on LOLE is much more sensitive to the storage strategy used than EENS and that this effect decreases with storage duration. They do not however illustrate the effect on adequacy indicators and only the capacity credit of storage is investigated. To the best of our knowledge, it is the work that most closely resembles this paper, but the scope is limited to CCs of storage.

Table 1 compares the studies cited above and others in terms of storage operation and investigated results. To the best of our knowledge, this list includes the most relevant literature on this topic. Of the 18 works listed, only 9 used a uniquely defined storage strategy. Only five compared different storage strategies, of which only two considered uniquely defined storage strategies and compared adequacy indicators or capacity credits based on EENS as well as other indicators such as the LOLE. These last two, Božič and Pantoš [17] and National Grid [9], limited their investigation to electric vehicle charging profiles impact on adequacy indicators and storage operation on CCs respectively. Neither attempted to quantify the range in LOLE for a given EENS that is possible in the systems with storage.

As such, we believe that there is a gap in the literature for a comprehensive analysis of the effect of storage operation on adequacy indicators and capacity credits, in particular of storage strategies which result in the same EENS. This paper attempts to fill that research gap as well as discuss the policy and regulatory implications of this issue.

3. Methodology

While there exist numerous methods in the literature to assess the adequacy of a power system, in the present paper this is done using an economic dispatch model to mimic operation of the power system and sampling of load, renewable generation and generator outages to generate statistically meaningful adequacy indicators. This is in line with state of the art methods used in industry, see e.g. Stephen et al. [14],Elia [26],ENTSO-E [27].

The following sections elaborate on this framework as well as the investigated storage operational strategies, adequacy indicator definitions and capacity credit calculation methodologies. To begin with, the economic dispatch problem used here is presented in Section 3.1 followed by the five storage operational strategies investigated in Section 3.2. The Monte Carlo framework and adequacy indicators used are described in Section 3.3 and finally the three capacity credit calculation methodologies compared in this paper are described in Section 3.4.

All code and datacan be found at https://gitlab.kuleuven.be/u0128861/storage-operation-and-lole.

3.1. Rolling horizon economic dispatch model

Economic dispatch models are linear optimisation models which minimise the operational cost of operating a power system. Their linear nature limits the technical detail that can be included, since constraints such as minimum stable operating point require binary variables. However, it is typical to neglect such constraints in adequacy assessments [26,27] since they have a limited impact on results [28] and allow for greatly reduced calculation times.

Typically in adequacy assessments an economic dispatch model is solved for many Monte Carlo years $y \in \mathcal{Y}$ to obtain a load net of power injection[7] profile ϕ_{yt} where $t \in \mathcal{T}$ is the set of timesteps (here hours) of operation. A Monte Carlo year is a combination of a weather profile and forced outage draw (see Section 3.3) which determines the availability AF_{ryt} of resources $r \in \mathcal{R}$ and load profile D_{yt}. An economic dispatch problem for year y can be written as:

$$
\begin{aligned}
\min & \sum_{g\in\mathcal{G},t\in\mathcal{T}} C_g \cdot q_{gyt} + \sum_{t\in\mathcal{T}} ls_{yt} \cdot VOLL \\
& \text{s.t.} \\
& \sum_{g\in\mathcal{G}} q_{gyt} + \sum_{h\in\mathcal{H}} (d_{hyt} - c_{hyt}) = D_{yt} + ls_{yt} \quad t \in \mathcal{T} \\
& e_{hyt+1} = e_{hyt} + 1/\sqrt{\eta_h} \cdot c_{hyt} - \sqrt{\eta_h} \cdot d_{hyt} \quad h \in \mathcal{H},\ t \in \mathcal{T} \\
& 0 \le q_{gyt} \le AF_{gyt} \cdot K_g \quad g \in \mathcal{G},\ t \in \mathcal{T} \\
& 0 \le c_{hyt} \le AF_{hyt} \cdot K_h \quad h \in \mathcal{H},\ t \in \mathcal{T} \\
& 0 \le d_{hyt} \le AF_{hyt} \cdot K_h \quad h \in \mathcal{H},\ t \in \mathcal{T} \\
& 0 \le e_{hyt} \le AF_{hyt} \cdot K_h / E2P_h \quad h \in \mathcal{H},\ t \in \mathcal{T}
\end{aligned}
\tag{1}
$$

where the variables ls, q, c, d and e are load shedding, generation, storage charge, discharge and energy content. $VOLL$, C_g, K, $E2P$ are the Value of Lost Load, cost of generation, capacity (in MW) and energy to power ratio (in hours).

The load net of power injection is defined as[8]:

$$
\phi_{yt} = D_{yt} - \sum_{g\in\mathcal{G}} (AF_{gyt} \cdot K_{gyt}) - \sum_{h\in\mathcal{H}} (d_{hyt} + c_{hyt}) \tag{2}
$$

Clearly negative values of ϕ_{yt} indicate surplus available generation and positive values indicate scarcity and $ls_{yt} > 0$.

In this paper the set of resources contains both generation $\mathcal{G}$ and storage $\mathcal{H}$. The case where storage is not present, i.e. $\mathcal{R} = \mathcal{G}$, is denoted by $^{-\mathcal{H}}$. The load net of power injection, ϕ_{yt}, then becomes the load net of generation, $\phi_{yt}^{-\mathcal{H}}$. In the rest of this paper, the index y is sometimes omitted for brevity and indicates applicability to all Monte Carlo years. Load shedding refers to the case where ϕ_{yt} exceeds a (small) threshold ϵ (see Section 3.3).

When modelling power system operations it is typical to employ a rolling horizon based approach as is done in this paper. In a rolling horizon approach the economic dispatch problem is solved for a limited time horizon, in this paper $\mathcal{T} = 1, \dots 48$ hours, the results stored, the optimisation horizon 'rolled forward', in this paper by 24 h, and then the process is repeated. This serves the dual purpose of reducing computational effort by breaking up a large optimisation problem into smaller ones as well as better mimicking the actual operation of the power system

[7] The load minus the generation and storage charge and discharge.

[8] To be precise, this is the load net of *possible* power injection, as it ignores how much generators actually produce. During scarcity all generators would be dispatched to their full capacity and this distinction is unnecessary.

Table 1
Overview of selected works which investigate storage operation and adequacy. Works were said to investigate a uniquely defined storage strategy if a *Greedy* or *DDVOLL* strategy was employed (see Section 3.2). 'Other' means any adequacy indicator CC which is not based on EENS e.g. LOLE or EFC based on LOLE. Half of the works listed did not use a uniquely defined storage strategy. Only two works, Božič and Pantoš [17] and National Grid [9], investigate different storage strategies (including at least one strategy which is uniquely defined in terms of LOLE) and their effect on adequacy indicators or capacity credits based on EENS as well as other indicators, as was done in this paper. However, National Grid [9] limit their investigation to the impacts of storage operation on CCs and Božič and Pantoš [17] to electric vehicle charging profiles on adequacy indicators (Also see Refs. [21–25]).

Paper	Year	Different storage strategies investigated?	At least one uniquely defined storage strategy?	Investigated adequacy indicator or capacity credit
Bagen and Billinton	2005	✗	✓	Other
Sioshansi et al.	2014	✗	✗	Other
Zhou et al.	2015	✗	✗	EENS based + Other
Božič and Pantoš	2015	✓	✓	EENS based + Other
Zhou et al.	2016	✗	✗	EENS based
Shariatkhah et al.	2016	✓	✗	EENS based + Other
Edwards et al.	2017	✗	✓	EENS based
Fraunholz et al.	2017	✓	✗	Other
National Grid	2017	✓	✓	EENS based + Other
Evans et al.	2019	✗	✓	EENS based
Stephen et al.	2019	✗	✓	EENS based + Other
Parks	2019	✗	✗	Other
Denholm et al.	2020	✗	✓	Other
Shrestha and Karki	2020	✗	✗	Other
Xcel Energy Services	2021	✗	✗	Other
Zachary et al.	2022	✗	✓	EENS based
Wang et al.	2022	✗	✗	EENS based
This paper	2022	✓	✓	EENS based + Other

while capturing inter-day arbitrage opportunities for short-term storage.

Perfect foresight is assumed over the optimisation horizon, in this paper 48 h, meaning that load and renewable output is assumed to be known exactly. This assumption is typical of adequacy assessments [26] though it is unrealistic. A brief discussion on how imperfect foresight would affect the results is given in Section 6.1 though a full treatment of this issue is beyond the scope of this work.

3.2. Storage operational strategies

The economic dispatch problem may have multiple solutions in the case of storage and a single VOLL. This is because in the face of a scarcity situation, there are an infinite number of ways a storage unit may distribute its energy content in time *while incurring the same system cost*. In turn this means that there are an infinite number of ways that energy not served or load shed may be distributed in time, leading to different values for adequacy indicators other than EENS. This implies that minimising system costs, as is frequently done in adequacy assessments [26,27], does not uniquely define the adequacy of a power system which contains storage.[9]

The sections that follow describe the different storage operation strategies investigated in this paper. Of particular interest is the consecutive optimisation approach used for some of these strategies which is inspired by Zhou et al. [6]. In this approach two or more optimisation problems are solved consecutively with the following optimisation problem including the objective of the previous optimisation problem as a constraint. This allows investigating storage strategies which lead to the same total cost (which is the objective value of the first optimisation problem) and by extension the same EENS but different values for other indicators such as the LOLE. These combinations are described in the following sections and summarised in Table 2 along with expected impacts.

3.2.1. Cost minimisation with a uniform Value of Lost Load (Min Cost)

This storage strategy is the result of solving the economic dispatch problem described by Problem (1) which minimises generation and load shedding costs. If the effect of limited foresight is negligible, then this approach also minimises EENS.[10]

Minimising total costs does not uniquely define the adequacy of a system, as illustrated by Fig. 1. As explained in the previous section, this is because there is a single cost per unit of load shed and hence it does not matter how storage distributes the shed load in time.

3.2.2. Cost minimisation with a depth dependent Value of Lost Load (DDVOLL)

While a uniform VOLL is typical of many power system models, it is widely recognised that this value is different for different consumers [29]. A more accurate method would be to have the VOLL increase with the amount of load shedding, such that the first unit of load shedding costs less than the second and so on.[11] Indeed, load shedding is typically done in 'tranches' (see [30]) so as to minimise the socio-economic cost of shedding load.

This is done by defining a minimum VOLL, $\mathrm{VOLL}^{\mathrm{min}}$, a maximum VOLL, $\mathrm{VOLL}^{\mathrm{max}}$ and a VOLL depth dependency *VDD*. The first MWh of load shedding incurs a cost of $\mathrm{VOLL}^{\mathrm{min}}$after which the cost increases linearly for *VDD* MW until $\mathrm{VOLL}^{\mathrm{max}}$, as illustrated in Fig. 2. After *VDD* MWh of load shedding, the same cost $\mathrm{VOLL}^{\mathrm{max}}$ is incurred. Unless otherwise specified, $\mathrm{VOLL}^{\mathrm{min}}$= 9,000 e/MWh , $\mathrm{VOLL}^{\mathrm{max}}$= 10,000 e/MWh and VDD = 15 GW,[12].

[9] By adequacy of the power system we mean the nature (duration, severity, frequency...) of scarcity events the system would face, not just its EENS.

[10] In theory the limited foresight could lead to storage units having a lower than optimal state of charge when facing a scarcity situation and so the EENS would be greater than optimal. In practice this was not the case here.

[11] To be precise, it is the marginal cost of load shedding that is increasing — the VOLL of individual consumers is a fixed value.

[12] 15 GW was chosen to ensure that the cost of load shedding never reached $\mathrm{VOLL}^{\mathrm{max}}$. It is unlikely that load shedding could be differentiated to this extent for the Belgium-like system that we use in Section 5 which has a peak demand of 15.3 GW. Here we abstract from the 'real' costs which could be associated with this depth dependent VOLL and use it as way of defining a storage operational strategy.

Table 2
Overview of storage operational strategies compared in this paper, whether they are uniquely defined and their suspected impact on the LOLE.

Name	Description	Solution suspected to be uniquely defined?	Suspected impact on LOLE?
Min Cost	Cost minimisation	✗	Undefined
DDVOLL	Cost minimisation with a depth dependent Value of Lost Load	✓	Maximising
Min Peak	Cost minimisation followed by peak residual load minimisation	✗	Maximising
Min LOL	Cost minimisation followed by Loss of Load minimisation	✗	Minimising
Max LOL	Cost minimisation followed by Loss of Load maximisation	✗	Maximising
Greedy	Discharge only when scarcity	✓	Undefined

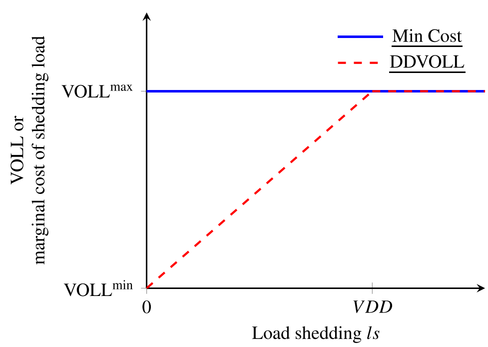


Fig. 2. VOLL or the marginal cost of load shedding as a function of load shed, *ls*, in the economic dispatch model for the *Min Cost* and *DDVOLL* strategies.

Differentiating the VOLL in this way uniquely defines the storage operational strategy as demonstrated in Section 5.2.2. It may be that in general a more detailed VOLL, which differs by time of day, duration of interruption or location [31], may similarly 'fix' storage operation.

3.2.3. *Minimising peak residual load (*Min Peak*)*

The peak residual load is defined as so:

$$\phi^{net} \geq D_t - \sum_{g \in \mathcal{G}} q_{gt} - \sum_{h \in \mathcal{H}} (d_{ht} - c_{ht}) \quad t \in \mathcal{T} \tag{3}$$

The *Min Peak* storage operational strategy then results from minimising ϕ^{net}.

Minimising peak residual load has a similar effect to a depth dependent VOLL: load shedding is spread over a longer time frame to reduce its' magnitude. Unlike using a depth dependent VOLL it does not uniquely define storage operation during scarcity, even when applied after *Min Cost*. This could happen, for example, if two scarcity events occur one after the other and storage is able to charge in between them, as illustrated in Fig. 3.

3.2.4. *Minimising or maximising Loss of Load (*Min LOL, Max LOL*)*

The Loss of Load (LOL) is the number of hours in which load shedding occurs, and to minimise or maximise it a binary load shedding indicator variable γ_t must be defined:

$$\gamma_t \cdot D^{max} \geq ls_t - \epsilon \cdot D^{max} \quad t \in \mathcal{T} \tag{4}$$

$$\gamma_t \cdot D^{max} \leq (1 - \epsilon) \cdot D^{max} - ls_t \quad t \in \mathcal{T} \tag{5}$$

The interpretation of the above equations is that load shedding needs to be above a threshold ϵ before it is considered to be loss of load timestep (i.e. $\gamma_t = 1$) by the solver. This threshold, which was set to 1 MW, is similarly used when computing adequacy indicators (see Section 3.3). Once defined, the sum of the binary variable $\sum_{t \in \mathcal{T}} \gamma_t$ over the optimisation horizon can be minimised or maximised to enforce different storage strategies.

Considering this storage operation serves a dual purpose. First and foremost it provides bounds on the magnitude of the impact of the storage strategy on the LOLE. Furthermore, it can cautiously be used to indicate that a storage operation strategy is uniquely defined, or at least that no operation could lead to further difference in LOLE at the same cost. Indeed, if applying *Min LOL* or *Max LOL* leads to the same solution as the previous optimisation then one could speculate that the previous optimisation(s) fully constrained storage operation.

3.2.5. *Greedy (*Greedy*)*

Unlike the previous storage operations, the *Greedy* strategy is described algorithmically rather than by solving an optimisation problem. In this strategy, storage is charged when there is excess generation and discharged when there is a shortage ($\phi_t > 0$). Edwards et al. [15] and Evans et al. [16] both prove that this strategy is EENS minimising while being foresight agnostic. It is also the algorithm used by NREL's PRAS tool [14].

This storage operation differs from the previous in that the cost of operating a system in this way is greater than that of a cost minimisation, since storage is no longer operated so as to minimise costs. However, in this paper the EENS resulting from this strategy was the same as that of the optimisation based problems, allowing for a fair comparison between them. Its popularity in the literature motivated its investigation while this latter fact justified it.

3.3. *Adequacy indicators and Monte Carlo analysis*

Solving an economic dispatch problem for a particular Monte Carlo year, that is a weather year combined with a random forced outage draw, provides one instance of an adequacy indicator. Doing this for many Monte Carlo years produces a distribution of these adequacy indicators for which expected (mean) values can be calculated. A similar methodology may be applied to capacity credit calculations.

The indicators used in this paper are summarised in Table 3. The EENS and LOLE are widely used throughout industry and academia [2,32] and are the expected amount of energy not served and the expected number of hours in which load shedding occurs respectively, both per year. The Loss of Load Duration (LOLD) is the number of consecutive hours for which load shedding occurs, i.e. the duration of a scarcity event. Its expectation is the ELOLD or the mean duration of a scarcity event. Not so common is the EMPNS which is the maximum depth of load shedding during a scarcity event in expectation. These last two are used to characterise the duration and severity of scarcity events.

While we focus on the LOLE in this paper, it is an indicator that is often criticised in the literature due to the little information

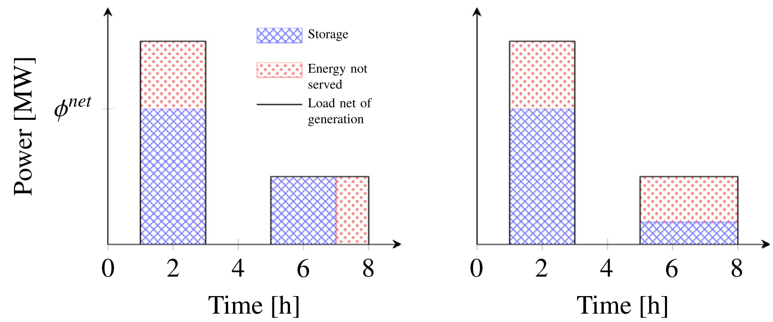


Fig. 3. Two different yet optimal *Min Peak* storage strategies illustrate how *Min Peak* does not uniquely define storage operation during scarcity. Note that this non-uniqueness arises from the possibility of charging in between scarcity events over the optimisation horizon, i.e. the storage recharges during hours 3 and 4.

Table 3
Adequacy indicators employed in this paper. The set T_y is composed of sets of consecutive timesteps in which there is load shedding in year y i.e. the set of scarcity events.

Indicator	Name	Units	Definition
EENS	Expected Energy Not Served	GW h/yr	$\mathbb{E}_{y\in\mathcal{Y}}\left[\sum_{t\in\mathcal{T}} ls_{yt}\right]$
LOLE	Loss of Load Expectation	h/yr	$\mathbb{E}_{y\in\mathcal{Y}}\left[\sum_{\mathcal{T}_{yi}\in T_y} \lvert\mathcal{T}_{yi}\rvert\right]$
ELOLD	Expected Loss of Load Duration	h/event	$\mathbb{E}_{y\in\mathcal{Y}}\left[\mathbb{E}_{\mathcal{T}_{yi}\in T_y}\lvert\mathcal{T}_{yi}\rvert\right]$
EMPNS	Expected Maximum Power Not Served per interruption	GW/event	$\mathbb{E}_{y\in\mathcal{Y}}\left[\mathbb{E}_{\mathcal{T}_{yi}\in T_y}\max(\phi_{yt}\ t\in\mathcal{T}_{yi})\right]$

it gives on the kind of scarcity events a system may encounter. Some of these criticisms, inspired by Stenclik et al. [2], include the lack of information on the duration of a scarcity event; on the magnitude of scarcity events; and of the distribution of loss of load events across Monte Carlo years. Despite this, it remains the industry standard adequacy indicator [32] and is prescribed by law to be the standard in all EU member states [29], justifying its investigation here.

The indicators described in Table 3 make use of the set of scarcity events T_y, which is composed of sets of consecutive timesteps in which there is load shedding in year y.[13] Load shedding is non zero only if the load net of power injection ϕ_{yt} is greater than a threshold ϵ, which in this paper was set to 1 MW. This threshold is explicitly mentioned here to highlight the issue of overcounting scarcity events.[14]

The indicators above were reported in the results with confidence intervals computed based on the central limit theorem [33]. The differences reported in the results are always significant for the set of Monte Carlo years considered, since a consistent random seed was used. This ensured that the availabilities of generators were the same for any year y regardless of the model run.

3.4. Capacity credit calculation

There exist numerous methods to define CCs. These include Effective Firm Capacity (EFC) based definitions [6]; marginal contribution to EENS reduction [34]; peak load reduction or scarcity value [35]; and availability based definitions [36]. This paper investigates how storage operation affects two of these, the incremental or marginal EFC and availability based capacity credit (*AvCC*).

3.4.1. *Effective Firm Capacity (*EFC-EENS, EFC-LOLE*)*

As its name suggests, this capacity credit definition consists of adding a (typically small, that is incremental or marginal) amount of a resource (e.g. storage) to the system and finding the amount of firm capacity which would be required to produce the same improvement in system adequacy. This can be calculated for a single resource, by adding or removing that resource, or a portfolio of the same or similar resources aggregated together as is done here. A full elaboration of the method we use to determine the EFC in this paper can be found in Zhou et al. [6].

Crucially, the EFC may depend on the chosen adequacy indicator measuring the improvement in adequacy resulting from adding the resource at hand and the assumed storage operation. This was one of the findings of National Grid [9], which showed up to a twofold difference in EFC between storage operations when LOLE was used as an indicator and insignificant differences when EENS was used. In this paper both the EENS and LOLE based definitions of EFC were investigated. Unlike National Grid [9], this was done for all resources and not just storage in order to investigate whether storage behaviour affected CCs assigned to other technologies as well.

3.4.2. *Availability based capacity credit (*AvCC*)*

Calculating the EFC of a resource is a laborious task as it essentially involves running several adequacy assessments in order to search for the EFC. An alternative approach, inspired by the Belgian TSO Elia's methodology [36], involves determining 'near scarcity events' $\mathcal{T}_{yi}^{Near} \in T_y^{Near}, \quad t \in \mathcal{T}_{yi}^{Near}$ and calculating capacity credits as the expected availability (generation q_{gyt} or discharge d_{hyt} divided by nameplate capacity K_r) during those time steps over all Monte Carlo years $y \in \mathcal{Y}$:

$$CC_g = \mathop{\mathbb{E}}_{y\in\mathcal{Y},\mathcal{T}_{yi}^{Near}\in T_y, t\in\mathcal{T}_{yi}^{Near}}\left[q_{gyt}/K_g\right] \tag{6}$$

$$CC_h = \mathop{\mathbb{E}}_{y\in\mathcal{Y},\mathcal{T}_{yi}^{Near}\in T_y, t\in\mathcal{T}_{yi}^{Near}}\left[d_{hyt}/K_h\right] \tag{7}$$

While scarcity events are defined as (sets of) timesteps in which load shedding above the threshold ϵ occurs, near scarcity events also include timesteps in which the remaining available

[13] As an example, if $\phi_t = (-1, 1, 2, -1, -2, 3)$ then $T_y = \{(2, 3), (6)\}$.

[14] If this threshold is not used, the reported scarcity events could not only be due to insufficient power, but also to the specifics of the solution method, as in the case of *DDVOLL*; or the optimisation problem formulation as with *Min LOL* and *Max LOL*.

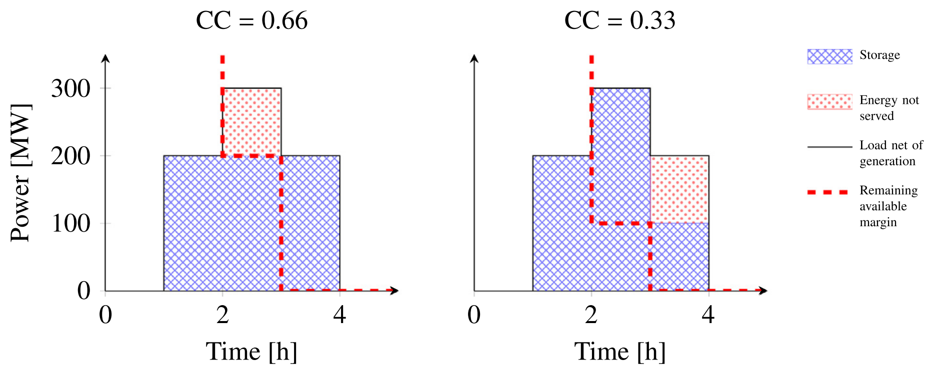


Fig. 4. Illustration of how storage operation can affect its' capacity credit if this is based on resource availability. Storage power and energy capacity are 300 MW and 600 MWh respectively, grey shaded area is the energy served by storage and the dashed red line is the remaining available margin (which includes storage potential for discharge, i.e. the state of charge of storage).

margin, defined as the generation plus the storage state of charge, is below ϵ (set to 1 MW).

This capacity credit definition is in line with the ACER methodology on the calculation of LOLE [29], which states that de-rating factors (a synonym for capacity credits)[15] should "*at least reflect: a) expected availability rate when ENS [Energy Not Served] is positive; and b) energy and activation constraints when ENS is positive*." This methodology must be applied by all EU member states, justifying the inclusion of a capacity credit calculation compatible with it.

This definition is straightforward and computationally inexpensive, as it only requires post processing the results of an adequacy assessment. However, it is not robust to the assumed storage operational strategy, as illustrated by Fig. 4. In the left hand figure, the 600 MWh of the storage unit is discharged at a constant rate of 200 MW, with the maximum power output of the store being 300 MW. This leads to only one scarcity timestep between hours 2 and 3 in which storage discharges at two thirds of its power capacity giving a capacity credit of 0.66. In the right hand figure a greedy strategy is employed, such that again only one near scarcity timestep occurs but this time between hours 3 and 4 where storage discharges at one third of its power capacity, giving a capacity credit of 0.33.

4. Illustrative example

In this section, we illustrate the effect of storage operation on the range of LOLE, denoted by $\Delta LOLE$. Consider the hypothetical scarcity event shown in Fig. 5. The black line is the load net of generation, $\phi_t^{-\mathcal{H}}$. It is assumed that this is the only scarcity event which happens in the year. In this simple model, the parameters affecting the range of LOLE other than the storage operation are the energy not served in the absence of storage, $\text{EENS}^{-\mathcal{H}}$; the peak amount of load shedding in the absence of storage, $\max(\phi_t^{-\mathcal{H}})$; and the storage characteristics, namely the power and energy capacities K_h and $E_h = K_h/E2P_h$. These parameters define the duration of the scarcity event in the absence of storage, $\text{LOLD}^{-\mathcal{H}}$, which is also equal to $\text{LOLE}^{-\mathcal{H}}$ given the assumption of a single scarcity event.

Fig. 5 shows two storage operations, one which minimises the number of hours in which load shedding occurs (*Min LOL*) and one which maximises them (*Max LOL*). Both of these storage operations are equivalent from a cost minimisation perspective since both avoid the same amount of energy not served. The latter strategy, *Max LOL*, could also be seen as a strategy which minimises peak load net of power injection, $\max(\phi_t)$, or which minimises system costs if the VOLL increases with the depth of load shedding. Indeed, in the case study in Section 5.2 the *Max LOL*, *Min Peak* and *DDVOLL* strategies give the same LOLE within a 95% confidence interval, confirming that these are all similar operational strategies in terms of their effect on the LOLE.

Fig. 6(a) shows that the range of LOLE, $\Delta LOLE$ increases with storage energy capacity up until the point that storage eliminates the scarcity event entirely. Put differently, more storage leads to a greater impact of storage operation on the LOLE. This intuitive result is also confirmed in the case study in Section 5.2.4. In fact, for this contrived example, *maximising the loss of load leads to no reduction in LOLE at all* until all load shedding in the absence of storage is covered by storage. This latter fact can be intuitively understood from Fig. 5 and noting that the LOLE stays constant even if the storage energy capacity increases.

The range of LOLE may also be affected by the nature of the scarcity event in the absence of storage, as illustrated by Fig. 6(b). Greater values of $\max(\phi_t^{-\mathcal{H}})$ mean shorter, more severe scarcity events, and since $\Delta LOLE$ is decreasing in Fig. 6(b) this means that longer, shallower scarcity events mean a greater range in LOLE. This is also confirmed in the case study in Section 5.2.5. The x-axis of Fig. 6(b) stops at 1 since after this value the storage in question also becomes power limited. Though not shown here, clearly the number of events in which this occurred would also affect the range of LOLE.

This illustrative example has focused on the range of LOLE possible due to different storage operation. Other indicators, such as the ELOLD or the EMPNS, are not treated, though it is straightforward to imagine how they might also be affected.

5. Case study

The previous section illustrated how different storage operational strategies can lead to different LOLE values using a stylised model. This section will do the same using state of the art industry methodologies applied to a stylised Belgian system described in Section 5.1. Doing so gives a reasonable indication of the range of LOLE which different strategies could produce for a given EENS.

The general trends observed in Section 4 are confirmed in this case study, namely that the difference in LOLE increases with storage capacity and wider, shallower scarcity events. Additional sensitivities on storage duration and *DDVOLL* parameters are conducted as well as an investigation of which storage operation is uniquely defined. Finally, Section 5.3 compares how capacity credit calculations are affected by storage operation. This case study thus confirms that the issue of storage operation is a cause for concern for adequacy assessments and capacity credit calculations in a real world setting.

[15] Indeed Eli [36] refer to de-rating factors instead of capacity credits in the context of the Belgian CRM.

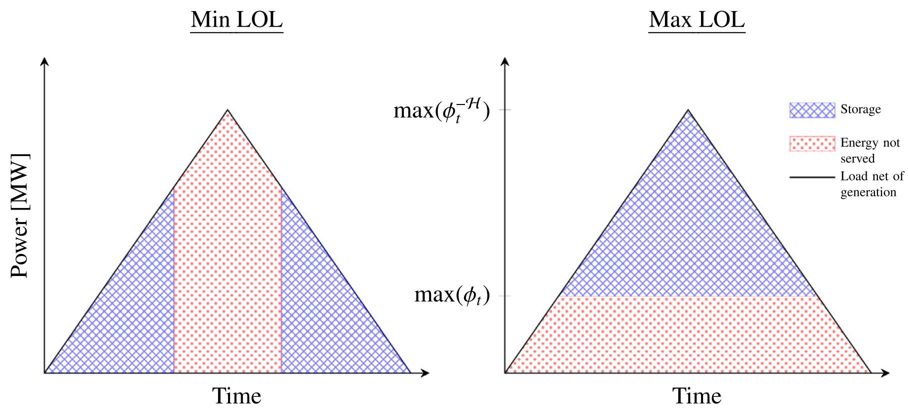
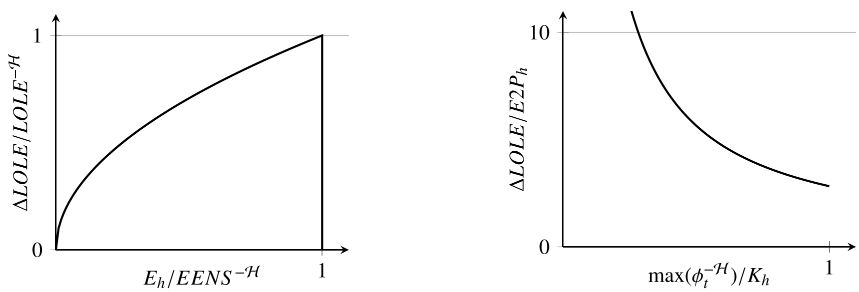


Fig. 5. Illustrative example of two different storage operations, minimising and maximising the loss of load on the left and right respectively.



(a) Relationship between storage energy capacity and range of LOLE. Storage energy capacity is normalised by the energy not served in the absence of storage and the range of LOLE is normalised by the LOLE in the absence of storage.

(b) Relationship between peak load net of generation and range of LOLE. Peak load shedding is normalised by the storage power capacity and the range of LOLE is normalised by the storage energy to power ratio i.e. its duration.

Fig. 6. Range of LOLE as a function storage energy capacity $E_h = K_h/E2P_h$ and peak load net of generation $\max(\phi_t^{-\mathcal{H}})$.

5.1. Stylised Belgian power system

The case study considered is a stylised, islanded, Belgium-like power system with 2.3 GW (15% of peak demand) of 2 h duration storage (4.6 GWh) inspired by the data in Elia [26]. A 2 h duration was chosen because this is in the range of durations listed in Elia [26] and because we suspected in advance that shorter durations would exhibit a more pronounced effect on the results. Further details of the system are described in Appendix A.1.

Table 4 summarises key characteristics of this system. Without storage, it is a highly inadequate system as indicated by the LOLE of 32.2 h/yr. The average duration of a scarcity event is 2.7 h which is moderately greater than the duration of storage which is 2 h. The EMPNS is 0.5 GW/event which is less than the 2.3 GW power capacity of storage. Assuming storage is fully charged before a scarcity event and is not limited by its power capacity, 94.9% of events can be eliminated by storage.

Table 4
Energy and adequacy related data for stylised Belgian case study and 1000 Monte Carlo years. Adequacy indicators are shown for the case without storage. % of events limited by storage energy or power capacity are calculated assuming storage is fully charged before a scarcity event.

Mean yearly load	Peak load	Peak residual load
87 TWh	15.3 GW	14.9 GW

EENS	LOLE	ELOLD	EMPNS
15.5 GW h/yr	32.2 h/yr	2.69 h/event	0.503 GW/event

% of events limited by storage	
Energy capacity	Power capacity
5.1	0.4

5.2. The effect of storage operation on adequacy indicators

In this section, first the LOLE due to storage operational strategy is investigated in a base case in Section 5.2.1; uniqueness of storage operational strategies in Section 5.2.2; and the sensitivity of the difference in LOLE to storage duration, capacity and scarcity event characteristics in Sections 5.2.3–5.2.5 respectively.

Adequacy indicators are reported here with confidence intervals computed based on the central limit theorem [33]. However, the differences reported in the results are always significant for the set of Monte Carlo years considered since a consistent random seed was used. This seed ensured that the availabilities of generators were the same for any year y regardless of the model run.

5.2.1. Base case

Fig. 7 provides a first insight into the magnitude of the effect of storage operation on LOLE. There is an approximately 3 fold difference (1.8 vs 5.9 h/yr) between the *Min LOL* and *Max LOL* operation strategies despite no difference in EENS (see Appendix A.2). Considering that a rule of '1 day in 10 years' or a LOLE of 2.4 h/yr is used in many power systems, this difference could lead to a power system being considered adequate or not. For all intents and purposes, the *Max LOL* and *DDVOLL* strategies produce the same LOLE of 6 h/yr. This result is in line with the simple model of Section 4 in which these two strategies coincide. The LOLE that results when using the *Min Peak* strategy is not

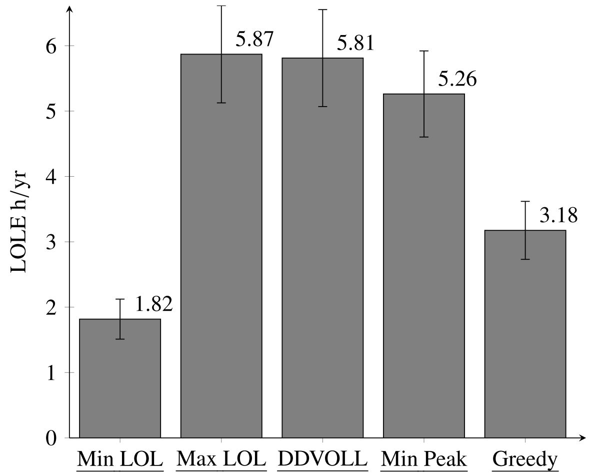


Fig. 7. Effect of storage operation on LOLE (95% confidence intervals). EENS is the same for all storage operations considered (see Appendix A.2). The LOLE in the absence of storage was 32.2 h/yr.

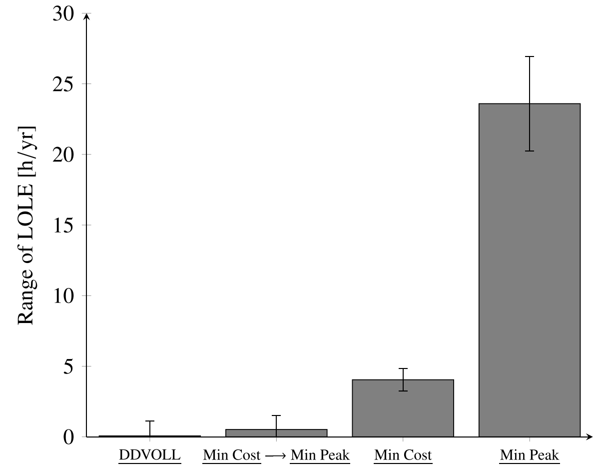


Fig. 8. Range of LOLE for different storage operations keeping EENS constant. This range is computed by running the *Min LOL* and *Max LOL* storage strategies on a result and computing the difference in LOLE between these. *DDVOLL* uniquely defines storage operation, since the range is effectively 0.

statistically different from these last two (95% confidence level), though if just the mean is compared it is about 0.6 h/yr less than *Max LOL* and *DDVOLL*. The *DDVOLL* results were insensitive to the choice of parameters characterising this operation (see Appendix A.3).

This range of LOLE is of the same order of magnitude to that which can be found in state-of-the-art adequacy assessments between sensitivities and scenarios. For example, in Elia [26] the LOLE differs on average by 3.2 h/yr between the EU-BASE and EU-SAFE scenarios.

5.2.2. Uniqueness of storage operational strategy

For a modeller wishing to perform an adequacy assessment or capacity credit calculation, it is important to know whether a storage operation is uniquely defined. For example, the *Min Cost* strategy (not shown here) yielded a similar LOLE as *Greedy*, with values of 3.2 and 3.1 h/yr respectively. However, due to the non-uniqueness of the *Min Cost* strategy, this similarity is coincidental and solver specific. Any value between 1.8 and 5.8 h/yr (the LOLE of the *Min LOL* and *Max LOL* strategies respectively) could have been obtained and a modeller would not know where in that range they would end up.

Fig. 8 investigates which strategies are uniquely defined by plotting the range of LOLE for the different storage operations (see Section 3.2). *DDVOLL* and *Min Peak* exhibit a range of LOLE of 0.13 and 0.52 h/yr, and so could be considered to uniquely define storage operation during scarcity.

Fig. 8 also shows the range of LOLE for the case where the objective is just to minimise peak residual load, which is equal to 23.6 h/yr. This storage strategy, not considered elsewhere in the paper, is the one used by [5]. It is shown here to stress the issue with choosing a non-unique storage operation, namely that the range of possible LOLE values may be substantial.

5.2.3. Sensitivity of the difference in LOLE to storage duration

In this and the following sections, the difference in LOLE of the *Greedy* and *DDVOLL* strategies is compared as opposed to the full range of LOLE when solving an economic dispatch problem. These strategies were chosen since they both uniquely define storage operation and led to the largest range of LOLE while having appeared in the literature. This last aspect is not the case for the *Min LOL* and *Max LOL*, which if compared would give the full range of LOLE possible. *Min LOL* and *Max LOL* may also be considered unusual modes of operation and unlikely to be implemented for an adequacy assessment or capacity credit calculation.

The issue of non-unique storage operation occurs when storage is limited by its energy and not power capacity in the face of scarcity (see Section 1). To this end, the power capacity was reduced while keeping the energy capacity fixed, thereby increasing the duration of storage. The observed difference in LOLE is shown in Fig. 9.

To allow for a fair comparison between storage durations, the EENS was kept constant in all cases. This was achieved using a EFC like calculation in which an amount firm capacity or load was found such that adding these led to the same EENS as that of the base case described in Section 5).[16]

Fig. 9 confirms that the issue of non-unique storage operation occurs only for short term storage, as the LOLE for the *DDVOLL* and *Greedy* strategy converge towards the same solution as storage duration increases (or power capacity decreases). The LOLE resulting from the *DDVOLL* strategy appears to be insensitive to the storage duration once the results are corrected to maintain the same EENS.[17]

5.2.4. Sensitivity of the difference in LOLE to storage capacity

Fig. 10 shows the effect of storage capacity on the difference in LOLE between the *Greedy* and *DDVOLL* strategies. This is done for both the case where the system was kept constant and the case where firm capacity was added to keep the EENS constant at 2.3 GW h/yr(the value at 4.6 GW h of storage).

Whether the system or the EENS is kept constant, increasing the storage capacity increases the difference in LOLE with respect to the case of having no storage at all. However, in the case of keeping the system constant this difference appears to reach a maximum at 2.3 GW h of storage and then decrease. The intuitive explanation for this decrease is simply that the LOLE for both strategies is also decreasing. In the case of the *Greedy* strategy, the LOLE goes from approximately 33 h/yr for no storage to 3 h for 4.6 GW h of storage. It is unsurprising then that the absolute value

[16] The Belgian TSO Elia employs a similar method which it calls a 'GAP volume' calculation [26].

[17] These results may be extrapolated to understand the effect of reducing the round trip efficiency of storage. Reduced discharge efficiencies would effectively reduce the useful energy capacity of storage while keeping the power capacity constant, which is equivalent to a reduced storage duration.

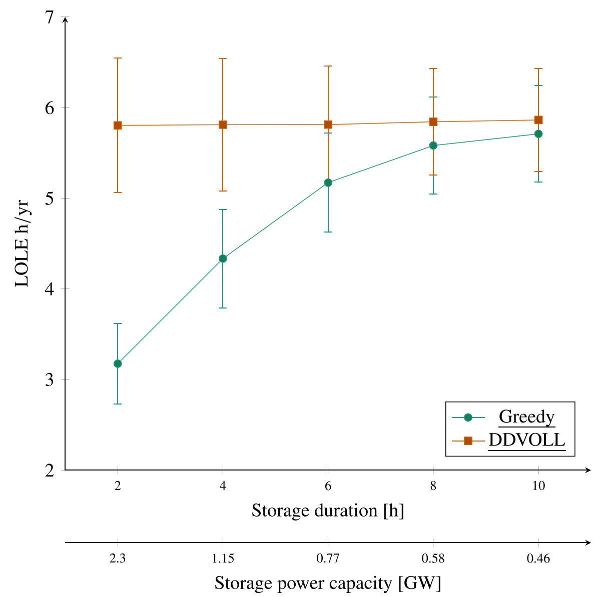


Fig. 9. Increasing storage duration (i.e. decreasing its power capacity while keeping energy capacity constant) while keeping EENS constant by adding firm capacity reduces the difference in LOLE between the *Greedy* and *DDVOLL* strategies (95% confidence intervals shown).

of the difference in the LOLE decreases. Indeed, if the amount of renewable energy in the system is not a limiting factor, then for some (large) storage capacity the LOLE for both strategies would be 0. This would appear to be the case — for 46 GW h (23 GW) of storage the LOLE is 0.5 and 0.2 for the *DDVOLL* and *Greedy* strategies respectively.

5.2.5. Sensitivity of the difference in LOLE to shorter, more severe scarcity events

A complicating factor when conducting the previous sensitivities is that keeping the EENS constant by adding firm capacity changes the nature of the load net of generation, $\phi_t^{-\mathcal{H}}$. However, it was suggested in the illustrative example in Section 4 that this also impacts the range of LOLE.

An additional point of attention is that our case study is an islanded system. This is far from reality for Belgium, which in theory could satisfy more than 60% of its peak demand through imports [26]. One mechanism through which the results could be impacted which we investigate here is that the load net of generation would change, becoming less frequent but more severe for example.

To isolate the effect of modifying $\phi_t^{-\mathcal{H}}$, we scaled the load as described in Appendix A.4. A parameter n determines whether this scaling increases the severity of scarcity events ($n > 1$) or decreases them ($n < 1$). After the scaling the load was shifted so as to maintain the same EENS$^{-\mathcal{H}}$.

Fig. 11 plots the difference in LOLE between the *Greedy* and *DDVOLL* strategies against EMPNS$^{-\mathcal{H}}$ / ELOLD$^{-\mathcal{H}}$, which is a measure of how short and severe scarcity events are in the absence of storage. Similarly to the illustrative example in Section 4, shorter and more severe scarcity events lead to a lower difference in LOLE. This may be explained by the fact that longer and shallower events lead to a greater LOLE$^{-\mathcal{H}}$ which the *DDVOLL* strategy does little to reduce (or conversely the *Greedy* strategy does more to reduce it).

Fig. 11 should nonetheless be interpreted with caution as factors other than the duration and severity of scarcity events may be affecting the results. Table 5 reports the number of events limited by storage energy and power (assuming full charge at the start of a scarcity event) and the EENS, which is also plotted in Appendix A.5 (recall that EENS$^{-\mathcal{H}}$ was kept constant and equal to the value for $n = 1$). Shorter and more severe scarcity events (greater values of n) are more likely to be events limited by both storage power capacity, since $\phi_t^{-\mathcal{H}}$ may take on higher values, and storage energy capacity, since less shortfalls occur but the EENS$^{-\mathcal{H}}$ is kept constant. The former decreases the range of possible LOLE since non-unique storage operation requires storage to be energy limited (see Fig. 9). The effect of the latter is less obvious, since more energy limited events should not necessarily lead to a greater difference in LOLE. The interaction between these two i.e. events for which storage is both power and energy limited is even less clear.

5.3. The effect of storage operation on capacity credits

Fig. 12 compares the effect of storage operation on CC for the three different types of CC described in Section 3.4. In the case of the incremental or marginal EFC based CCs this is calculated for incremental (5%) increases in installed capacity. The error bars shown indicate 95% confidence intervals in the case of the *AvCC* and the bounds on the EFC for EFC based CC calculations which were terminated when the p-value > 0.5.

Of the three calculation methods compared, only *EFC-EENS* produces the same CC regardless of the storage operational strategy. This effect is particularly pronounced for the capacity credit of storage, which differs by approximately 30% for *AvCC* and 35% for *EFC-LOLE*. There is also a notable difference in the CC assigned to storage depending on the calculation method used, which is around 0.1 for *AvCC* and 0.2 for EFC based calculations. These limited results corroborate the finding of National Grid [9] that storage operation affects its capacity credit if it is not calculated based on EENS.

The difference in CC due to storage operation is limited for all other technologies, with the exceptions of Onshore Wind and Solar in the *EFC-LOLE* case. We can offer no explanation at this time for why this is the case.

6. Discussion

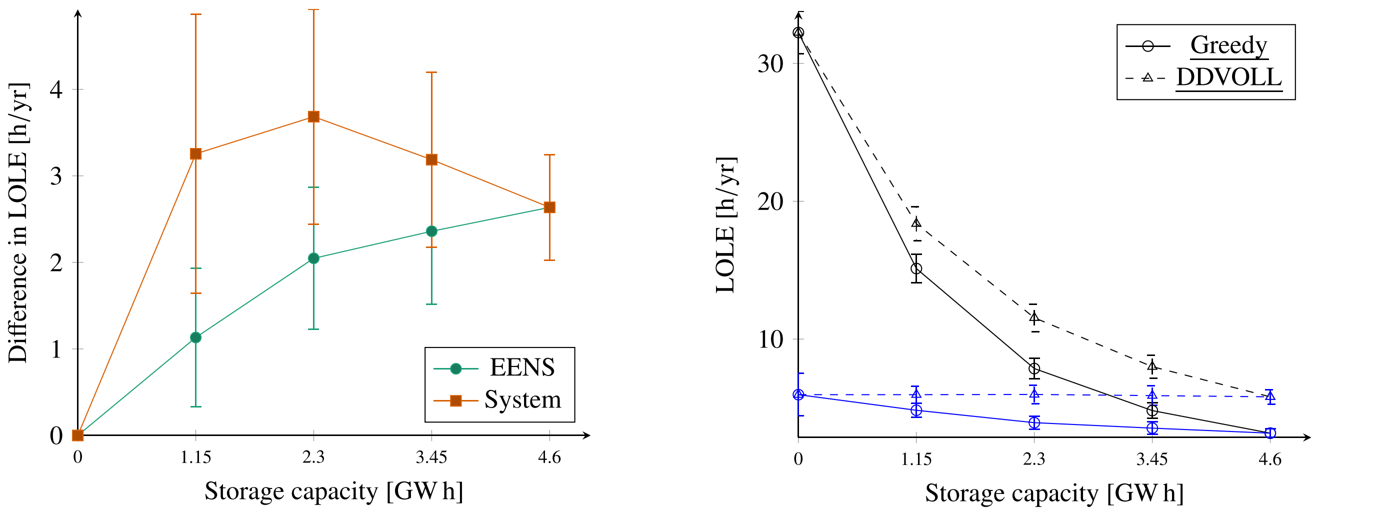
6.1. Drawbacks and areas for future work

This paper investigated the effect of storage operation on adequacy indicators and capacity credits, with a focus on storage operations which would incur the same cost when using an economic dispatch model. This economic dispatch model had features typical of those used in state of the art adequacy assessments [26].

More complex models could include features which would uniquely define storage operation. A non exhaustive list of these features includes storage losses, a time varying VOLL [31] or imperfect foresight. By differentiating the marginal cost of shedding load in time, these features could lead to a unique, cost minimising storage strategy.

The assumption of perfect foresight is treated in Cruise and Zachary [37], and it could be hypothesised that imperfect foresight would lead to a 'greedy' like strategy or a different state of charge before a scarcity event. We believe that investigating the effect of imperfect foresight would be a particularly fruitful extension to this work. It should be noted however that perfect foresight is a typical assumption in adequacy assessments. In its last bi-annual adequacy study Elia assumed perfect foresight over an entire week for example [26].

In this paper it was assumed that all storage participates in the wholesale market and is exposed to time varying prices, or



(a) Difference in LOLE.

(b) Absolute value of LOLE. Black and blue lines are the system and EENS kept constant respectively.

Fig. 10. Increasing storage energy and power capacity (while keeping the duration constant) generally increases the difference in LOLE between the *Greedy* and *DDVOLL* strategies (95% confidence intervals shown) regardless of whether the EENS or the system is kept constant.

Table 5
Shorter and more severe scarcity events (greater values of n) create more events limited by storage power or energy capacity and increase EENS (storage is assumed to be fully charged at the beginning of a scarcity event).

n	Events limited by storage power (%)	Events limited by storage energy (%)	EENS (GW h/yr)
0.9	0.1	4.5	1.99
1	0.4	5.1	2.29
1.1	1.0	6.2	2.82
1.3	4.9	11.0	4.68
1.5	13.9	18.6	7.18

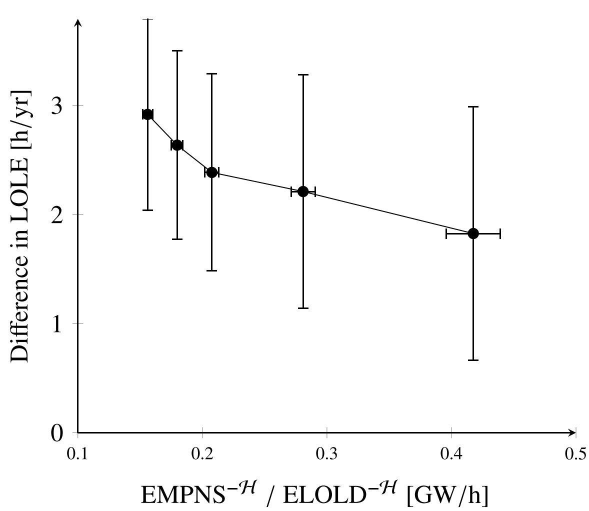


Fig. 11. Shorter and more severe load net of generation $\phi_t^{-\mathcal{H}}$ (here increasing EMPNS$^{-\mathcal{H}}$ / ELOLD$^{-\mathcal{H}}$) reduces difference in LOLE between *Greedy* and *DDVOLL* strategies (95% confidence intervals shown, EENS$^{-\mathcal{H}}$ kept constant).

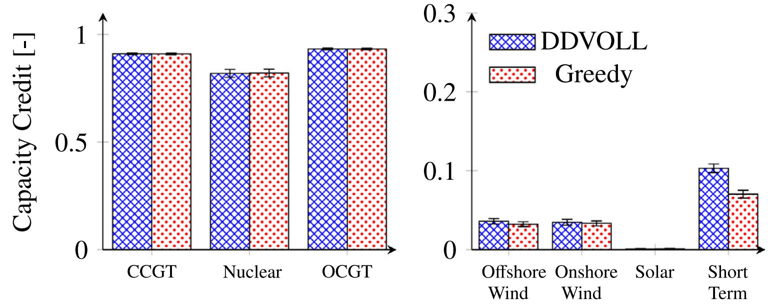
alternatively that storage can be centrally controlled during times of scarcity. This may be reasonable for grid scale batteries but less so for residential batteries. Given the magnitude that the effect storage operation can have on the LOLE, it may be worth modelling these two storage technologies differently so as to better represent how these would be operated during times of scarcity.

We considered an islanded system without interconnectors. While we attempted to address the impacts interconnectors might have by investigating the sensitivity of our results to the types of scarcity events in the absence of storage, further investigation is required to confirm that our results would still be broadly valid. There may also be complex and unintuitive interactions between storage and interconnections that should be investigated. For example, storage may charge using imports to reduce load shed in its own power system during a scarcity event which occurs simultaneously in the system from which it imported. This also raises the question of how to define adequacy and share load shedding in interconnected systems, an issue which is addressed in [38].

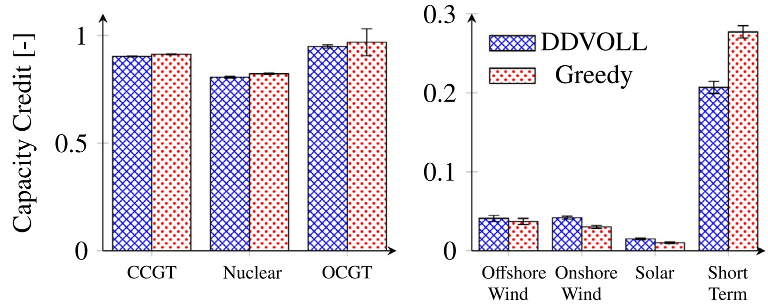
6.2. Implications for stakeholders

It may be tempting to view the effect of non-unique storage operation on adequacy indicators and capacity credits as a merely an academic issue. After all, storage operation in a real world setting would take into account many more parameters than the ones in the economic dispatch model used here, leading to unique optimal strategy for a storage operator.

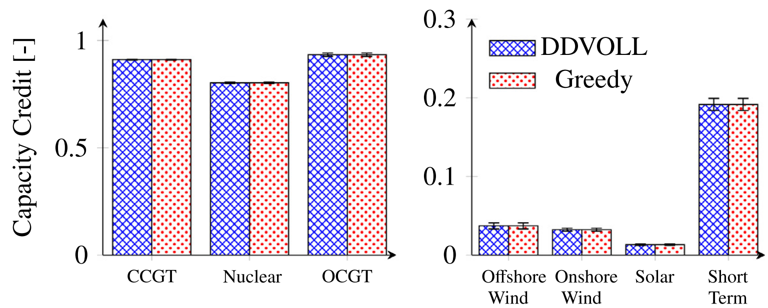
However, economic dispatch models such as the one employed here are widely used for adequacy assessments and capacity credit calculations, and the results of either of these exercises may have important repercussions. Adequacy assessments are ultimately used to justify whether interventions such as CRMs are necessary to ensure resource adequacy, while capacity credits are important parameters in CRMs. Getting either of these exercises wrong could lead to an inadequate or an overbuilt



(a) Capacity credits calculated based on availability during scarcity, AvCC.



(b) Capacity credits calculated based on LOLE and equivalent firm capacity, EFC-LOLE.



(c) Capacity credits calculated based on EENS and equivalent firm capacity, EFC-EENS.

Fig. 12. Capacity credit calculations for the *Greedy* and *DDVOLL* strategies and three different capacity credit definitions. Only *EFC-EENS* is insensitive to the storage operational strategy.

power system [34]. The rolling blackouts in California in 2021 are a recent reminder of the dangers of the former. For these reasons it is important to consider what strategy it is assumed a storage operator would implement during scarcity events, be it implicitly through the marginal cost of shedding load or explicitly by enforcing a storage operation during scarcity, and whether this reflects realistic storage operation.

We stress that we have focused on the effect of storage operation on the LOLE here because it is the industry standard indicator [32] and is prescribed by law to be the reliability standard in all EU member states [29]. As mentioned in Section 3.3, it has been criticised for the lack of information on the duration of a scarcity event; on the magnitude of scarcity events; and on the distribution of loss of load events across Monte Carlo years [2]. [39] additionally criticise indicators based solely on characterising scarcity events. We will not elaborate on these criticisms here. Instead, we hope that this paper may be used to inform the debate on which indicator(s) are most suitable for modern power systems.

6.2.1. Adequacy assessments

It is evident that the choice of storage operation affects adequacy indicators other than EENS. This paper focused on the LOLE, where it was shown that this metric can differ by 3 or 4 h depending on the chosen storage operation. The magnitude of this difference was shown to decrease with storage duration and increase with storage penetration and shorter, more severe scarcity events. The effect of storage operation on adequacy indicators such as the LOLE may be limited for now due to the limited penetration of short term storage in the power system. However, the increasingly rapid energy transition may change this in the years to come and so this effect could prove significant.

A mismatch between assumed storage strategy in an adequacy assessment and realistic operation of storage could have undesirable consequences. If an assessment yielded a LOLE of 2 h when in reality it is 6 h and the desired LOLE is less than 3 h, then an intervention could not be justified by the assessment even though it is in fact necessary. Ultimately this would lead to an inadequate system. This is of course true for any mismatch between an adequacy assessment and the true adequacy of a power system, whether that mismatch is caused by storage operation or not.

Given this, modellers conducting adequacy assessments should be explicit about the storage operation that they choose and transparent about how they implement it in their models. Solving a cost minimisation problem with a single VOLL does not satisfy these requirements, as this paper has demonstrated throughout that this does not uniquely define storage operation.

Exactly which operation is chosen will be context specific. While minimising the depth of a shortfall is likely the most sensible option, since it avoids shedding load with a higher VOLL, it may not be so easy to predict the shape of a shortfall. In this case a greedy strategy, which is EENS minimising, may be considered more suitable. There may even be cases where minimising the LOLE would be desirable, since longer duration scarcity events may have worse impacts on the public's trust in the system operator than shorter, more severe events. Naturally the modelled storage operation should best reflect what would happen in practice. What this operation is may be unclear however, given the limited experience of many system operators (particularly in Europe) to scarcity events and novelty of short term storage technologies.

6.2.2. Capacity remuneration mechanisms

As with adequacy assessments, a mismatch between assumed and realistic storage operation when calculating capacity credits could have undesirable consequences when operating a CRM such as a capacity market. If a capacity credit is underestimated, clearing the market could yield an overly adequate and therefore more expensive power system, and vice versa if it is overestimated.

This paper confirmed that CCs based on the concept of EFC and EENS are robust to changes in storage operation. EFC based on LOLE or the availability based method *AvCC* led to differences in CC between storage strategies of approximately 30%.

However, robustness to storage operation is not the only consideration in choosing a CC calculation method. In a previous work, we hinted at the problem of a CC definition which does not reflect the end use correctly [35]. In this case there is a discrepancy between peak load reduction potential and scarcity value based definitions for reaching a capacity target which minimises total costs. The choice of CC methodology should perhaps then reflect its end use. For example, if a CC is used in a CRM (as is often the case) then it may be necessary for the capacity target and CC to be consistent with each other. This means that if the capacity target is set so as to reach a LOLE target, then the CC calculation would also based on LOLE. We leave analysis of this potential issue for future work.

Given the issues that storage operation presents, alternative CRM designs may also be desirable. One such design is given in Zachary et al. [7], where an EENS target is used as opposed to a capacity target. Since the EENS is insensitive to the operation of storage this issue is resolved assuming that the CC is also calculated using EENS.

6.2.3. Using the LOLE as an adequacy target

We have extensively illustrated that storage operation may have a significant impact on the LOLE with no impacts on system costs. LOLE is simply not a suitable adequacy indicator in a cost minimisation framework. This may be one more reason to move away from the industry standard LOLE target and towards a more comprehensive set of targets [2].

However, this is currently not a viable option for European Member states, since legislation requires the LOLE to be used as the adequacy target [29]. Specifically, ACER's methodology says that the target should be calculated as follows:

$$\mathrm{LOLE} = \frac{CONE^{fix}/K}{\mathrm{VOLL} - CONE^{var}} \tag{8}$$

Where $CONE^{fix}$ and $CONE^{var}$ are the fixed and variable costs of new entry (for example OCGT or demand response) and K is a de-rating factor which reflects the availability of the new entry

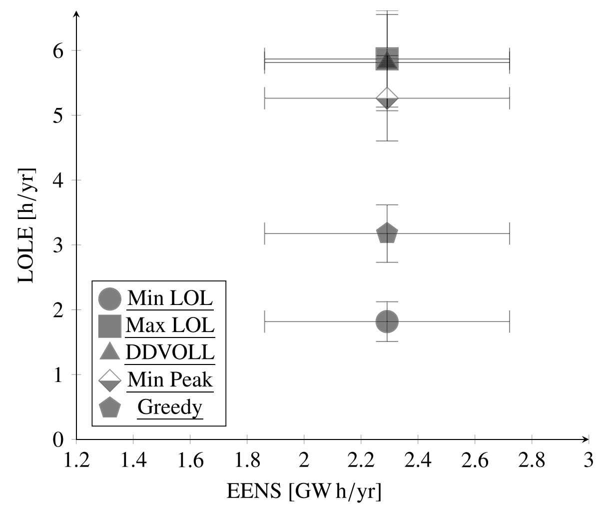


Fig. 13. EENS vs LOLE for base case.

resource during scarcity events. The principle behind this equation is that the marginal cost of reducing EENS should balance the marginal cost of additional resources (i.e. the cost of new entry). As explained in Zachary et al. [7], the above equation holds if all resources are (or can be approximated as) firm capacity or if there is a one to one mapping between adequacy indicators.

The ACER methodology specifies that the VOLL used should reflect the consumers who are likely to be disconnected should load shedding take place. Put differently, it is recognised that the VOLL is depth dependent, a fact which was shown here to uniquely define storage operation (see Fig. 8), even though only one expected VOLL is used in (8).

Setting a LOLE target in this way appears problematic given the non-uniqueness of storage operation when minimising costs, since a range of LOLE is then possible. Assuming that (8) still holds in this case, the only parameter that may change to reflect storage operation would appear to be the de-rating factor K.[18] Taken to the extreme, if the LOLE range is between 2 and 6 h/yr, as was the case in Fig. 7, then the range of possible K values should differ by a factor of 3. However, if K is interpreted as the CC of the new entry resource[19] e.g. OCGT, then this range is not possible, since the CC of conventional resources is insensitive to the storage strategy (see Fig. 12).

Clearly storage operation raises questions regarding the use of (8) to set the LOLE. How these might be resolved will be the subject of future work. However, we tentatively suggest here already that (8) prescribes a particular type of storage operation in order for it to be valid.

7. Conclusion

This paper investigated the effect of storage operation on adequacy indicators, in particular the Loss of Load Expectation (LOLE), and capacity credits. A simple, single scarcity event model was used to illustrate how storage may be operated in such a way that the Expected Energy Not Served (EENS) is kept constant while the LOLE changes. That storage may be operated in this way implies that solving a cost minimisation problem with a

[18] Indeed in the ACER methodology it is stated that (8) holds if "energy constraints are properly represented through the de-rating capacity factor".

[19] The ACER methodology states that the de-rating should 'at least' reflect availability during scarcity as well as energy and activation constraints. This definition, which is not justified, appears to be in line with the definition of *AvCC*.

Table A.6
Key input data for stylised Belgian case study inspired by Elia [26].

Resource	Capacity [GW]	Unit size [GW]	Mean availability [–]
Nuclear	3.0	0.75	0.95
CCGT	5.5	0.1	0.93
OCGT	2.5	0.05	0.94
Offshore Wind	4.4	–	0.43
Onshore Wind	5.4	–	0.29
Solar PV	12.2	–	0.11
Storage (2h)	2.3	–	1.0
Other	2.0	–	1.0
Total	38.6	–	–

Resource	FOR [1/yr]	Mean FO duration [h]
Nuclear	1.6	240
CCGT	7	101
OCGT	3.1	201

Table A.7
Sensitivity of LOLE to the $VOLL^{min}$ and $VOLL^{max}$ parameters when applying the *DDVOLL* strategy. The LOLE does not change within the 95% confidence intervals, indicating that it is insensitive to these parameters.

$VOLL^{min}$	$VOLL^{max}$	LOLE [h/yr] (95% confidence interval)
1.0	1.01	5.81 ± 0.37
1.0	1.1	5.81 ± 0.37
1.0	2.0	5.84 ± 0.38
10.0	10.1	5.81 ± 0.37
10.0	11.0	5.81 ± 0.37
10.0	20.0	5.84 ± 0.38

single Value of Lost Load (VOLL) does not uniquely define storage operation.

In a stylised case study of the Belgian power system and an economic dispatch model, this paper found a range of LOLE between 2 and 6 h depending on the storage operation. The difference in LOLE decreased with storage duration, confirming that this difference occurs when storage is energy limited. This difference also increased with storage penetration and shorter, more severe scarcity events. In addition, including a depth dependent VOLL uniquely defined storage operation.

Storage operation affected two out of the three capacity credit calculations investigated, while the one based on EENS was unaffected. Differences of approximately 30% in the capacity credit assigned to storage were observed while the capacity credits of other technologies were unchanged.

These results motivate explicit assumptions regarding storage operation in adequacy assessments and capacity credit calculations. This implies that the assumed storage operation should be uniquely defined for the results to be transparent and reproducible. Failing to do so could ultimately lead to designing inadequate or overly expensive power systems.

We suggest that non-unique storage operation may also lead to issues of consistency, for example if the Capacity Credit (CC) of a storage unit is calculated based on one adequacy indicator and used to satisfy a capacity target in a Capacity Remuneration Mechanism (CRM) based on another. We also suggest that storage operation complicates the economic justification for using the LOLE as an adequacy target. Both of these points may be the subject of future work.

CRediT authorship contribution statement

Sebastian Gonzato: Conceptualization, Methodology, Software, Writing – original draft. **Kenneth Bruninx:** Conceptualization, Methodology, Writing – review & editing. **Erik Delarue:** Supervision, Writing – review & editing.

Data availability

All data and code can be found at https://gitlab.kuleuven.be/u0128861/storage-operation-and-lole.

Acknowledgements

The authors would like to thank Stan Zachary, Chris Dent and Amy Wilson, whose paper was the initial inspiration for this work. In addition the authors would like to thank Andreas Tirez, François Beaude, Vasilis Papandreou and Rafael Feito-Kiczak for discussions which helped refine this paper. Any remaining errors are the sole responsibility of the authors.

S. Gonzato is supported via the Energy Transition, Belgium Funds project EPOC 2030–2050 organised by the FPS economy, S.M.E.s, Self-employed and Energy. Until May 2022, K. Bruninx was a post-doctoral research fellow of the Research Foundation — Flanders (FWO) at the University of Leuven and EnergyVille, Belgium. His work was funded under post-doctoral mandates no. 12J3317N, sponsored by the Flemish Institute for Technological Research (VITO), Belgium, and no. 12J3320N, sponsored by FWO, Belgium.

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

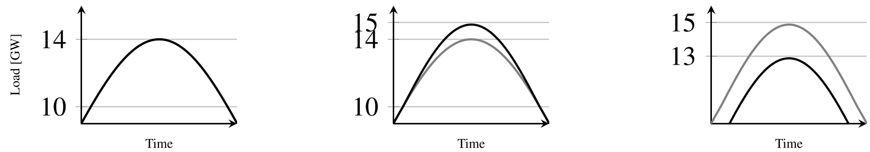
A.1. Case study data

The case study considered is a stylised Belgium-like system. To isolate the effects of storage strategy, no imports or exports are considered. Installed capacities and forced outage rates are inspired by those used in Elia's latest adequacy study and for the year 2032 [26] with a key difference being the addition of 3 GW of nuclear capacity.[20] All storage, be it electric vehicles, residential or grid scale batteries, was aggregated into one storage technology (the pumped hydro reservoir of Coo was omitted). Storage was assumed to always be available. Load data was obtained from the Ten Year Network Development Plan National Trends scenario [40] and Variable Renewable Energy Sources (VRES) availabilities from ENTSO-E's Mid Term Adequacy Forecast [27] (which uses the Pan European Climate Database), both from the year 2020. The data for this base case is summarised in Table A.6. Unless otherwise specified, 1,000 Monte Carlo years of weather profiles and forced outage draws were employed.

A.2. Base case EENS vs LOLE

Fig. 13 shows the LOLE as a function of the EENS. Clearly the EENS changes very little (it is the same in all cases to 6 decimal places, 2.2913374 GW h/yr) while the LOLE ranges between 5.87 and 1.817 h/yr.

20 Belgium was set to retire its nuclear power plants by 2025, though high gas prices and the war in Ukraine have led to an extension of the lifetime of these units. In this case study, the 3 GW of nuclear capacity was kept to make up for lack of import capacity. Without it, the system would be unrealistically inadequate.



(a) Original load profile.

(b) Load profile with a scaling applied for values above 10 GW (solid line) and original load profile (grey line).

(c) Scaled load profile shifted down by 2 GW (solid line) and the scaled load profile before the shift (grey line). Load profile is shifted down such that the EENS for the load net of generation ϕ^{net} timeseries is the same after scaling.

Fig. 14. Illustration of how load profile is scaled to create shorter more severe scarcity events. Load is then shifted downwards such that EENS without storage, $\mathrm{EENS}^{-\mathcal{H}}$, is kept constant.

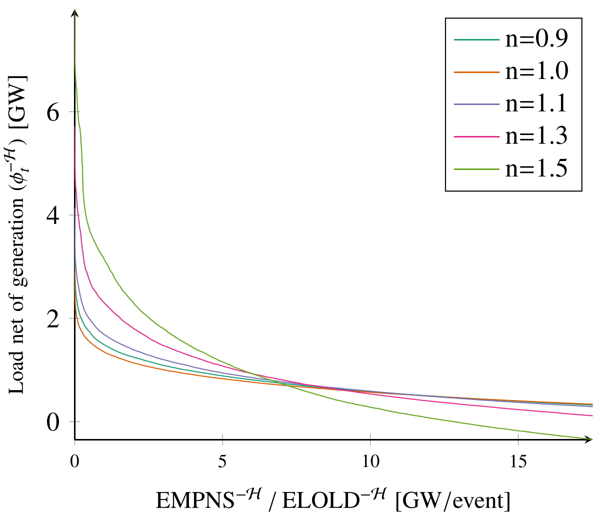


Fig. 15. Load net of generation ($\phi_t^{-\mathcal{H}}$) duration curves illustrating how higher values of n lead to fewer but greater peak values. Curves were constructed by sorting in descending order 1,000 Monte Carlo years worth of $\phi_{yt}^{-\mathcal{H}}$ and then taking the mean value for each hour.

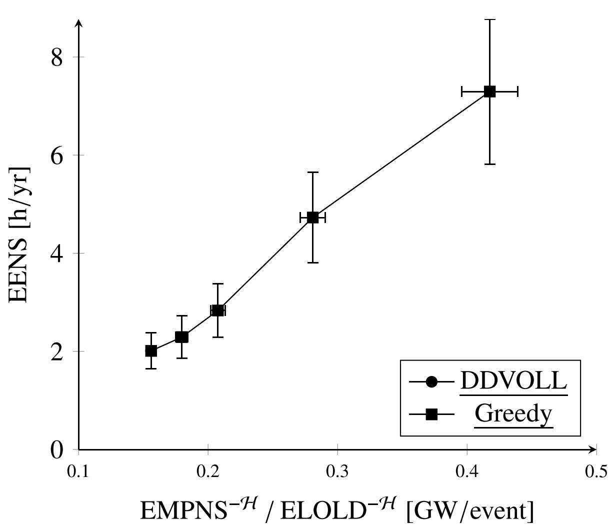


Fig. 16. EENS as a function of the duration and severity of scarcity events (which increases with increasing $\mathrm{EMPNS}^{-\mathcal{H}}/\mathrm{ELOLD}^{-\mathcal{H}}$). Note that EENS was kept constant.

A.3. Sensitivity of the LOLE to the choice of parameters for the DDVOLL *strategy*

It could be that the LOLE obtained using the *DDVOLL* strategy also depends on this strategy's parameters. Table A.7 shows the LOLE for various values of the upper and lower limit on the VOLL, clearly showing that it is largely insensitive to these.

A.4. Scaling and shifting load

Load scaling was achieved by applying the transformation described below:

$$f(D_t) = \begin{cases} D_t & \text{if } D_t \leq 10 \text{ GW} \\ 10 + (D_t - 10 + 1)^n - 1 & \text{if } D_t > 10 \text{ GW} \end{cases} \tag{9}$$

After this transformation, the load was shifted so as to maintain the same EENS. This is graphically illustrated in Fig. 14.

The load changes only for values above 10 GW, which is approximately equivalent to the amount of de-rated conventional capacity. Values of n below 1 'flatten' the load above this threshold while values above 1 make it 'peakier'. The peak hours of the resulting load net of generation $\phi_t^{-\mathcal{H}}$, corrected to have the same $\mathrm{EENS}^{-\mathcal{H}}$ as $n = 1$, are shown in Fig. 15.

A.5. EENS for shorter, more severe scarcity events

Fig. 16 shows how keeping $\mathrm{EENS}^{-\mathcal{H}}$ constant nonetheless leads to a different EENS for the results shown in Section 5.2.5.

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