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Published in:
Applied Energy

DOI (link to publication from Publisher):
10.1016/j.apenergy.2022.119960

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
Yuan, M., Sorknæs, P., Lund, H., & Liang, Y. (2022). The bidding strategies of large-scale battery storage in 100% renewable smart energy systems. *Applied Energy*, *326*, Article 119960.
https://doi.org/10.1016/j.apenergy.2022.119960

Applied Energy 326 (2022) 119960

Contents lists available at ScienceDirect

Applied Energy

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

The bidding strategies of large-scale battery storage in 100% renewable smart energy systems

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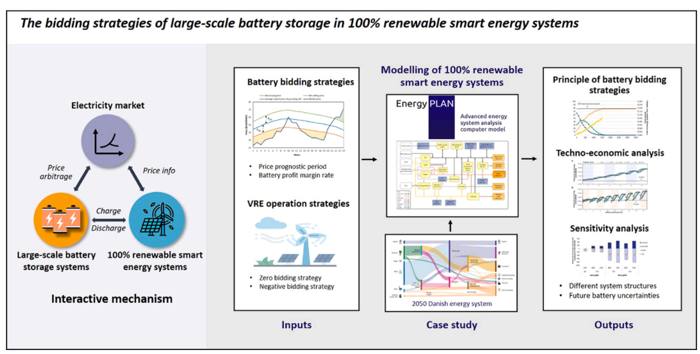
HIGHLIGHTS

- Bidding strategies of large-scale battery storage in 100% RE systems are studied.
- Hourly techno-economic analyses are conducted for both the battery and the energy system.
- The impacts of price prognostic period and battery profit margin rates are identified.
- Large-scale battery storage is not a necessity for the future 100% renewable smart energy systems.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Large-scale battery storage
Bidding strategy
Battery operation
Energy storage
100% renewable energy systems
Smart energy systems

ABSTRACT

Large-scale battery storage solutions have received wide interest as being one of the options to promote renewable energy (RE) penetration. The profitability of battery storages is affected by the bidding strategy adopted by the operator and is highly dependent on the operation of the rest of the energy system. Nevertheless, the coordination between the battery and the energy system has not been investigated in the literature yet. This paper provides a holistic hourly techno-economic analysis of the bidding strategies of large-scale Li-ion batteries in 100% renewable smart energy systems. As a case study, the 2050 Danish energy system is used to demonstrate the relationship between large-scale battery systems and the rest of the energy system. The results show that large-scale battery storage plays a limited role in future energy systems that follow the smart energy system concept. Likewise, the battery solution is only economically feasible in the Danish smart energy system at low battery storage capacities (few hours' duration) with a low-profit margin rate (approx. 100%) and a short prognostic period (approx. 12 h) for operation planning. The finding of this study provides the general strategies of the battery bidding and operation in 100% RE systems.

1. Introduction

Accelerating the energy transition towards a 100% renewable energy

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https://doi.org/10.1016/j.apenergy.2022.119960
Received 6 April 2022; Received in revised form 25 August 2022; Accepted 10 September 2022
Available online 27 September 2022

Nomenclature

BESS	Battery energy storage system
CAES	Compressed air energy storage
CEEP	Critical excess electricity production
CHP	Combined heat and power plant
CO_2	Carbon dioxide
GCA	Danish energy system in cooperative mode
IDA	Danish energy system in independent mode
LAES	Liquid air energy storage
LCOS	Levelized cost of storage
NB	Negative bidding strategy of variable renewable energy
NEC	Number of equivalent cycles in a year
PE	Primary energy
PHES	Pumped hydroelectric energy storage
PP	Power plant
RE	Renewable energy
REF	Reference scenario
VRE	Variable renewable energy
ZB	Zero bidding strategy of variable renewable energy
c	A constant coefficient
i	Discount factor
t	The hours in a year
x	User-specific prognostic period of electricity price (in hours)
ε	The minimum profit margin increase rate specified by the battery operator
α_{charge}	Battery charge efficiency
$\mu_{discharge}$	Battery discharge efficiency
$Charge_t$	Battery charges in hour t
$Discharge_t$	Battery discharges in hour t
FOM_y	Fixed operation and maintenance cost in year y of a lifespan
INV_y	Investment expenditure in year y of a lifespan
$P_t^{Average}$	Average electricity market price of the upcoming user-specific period (x hours)
$P_t^{SellMin}$	Minimum selling price
P_t^{BuyMax}	Maximum buying price
P_t^{Diff}	The difference between the buying/selling prices and the average market price
$P_t^{InitialDiff}$	Initial price difference before considering profit margin
VOM_y	Variable operation and maintenance cost in year y of a lifespan

(RE) era requires joint efforts of all energy sectors in the energy systems, also known as ***Smart Energy Systems***[1] [1]. In a smart energy system approach, the idea is to make the best use of all types of energy production, conversion and storage technologies. Electricity storage technology could be one of the solutions to enhance power system flexibility and integrate high levels of fluctuating RE such as wind and solar energy [2–4]. Among the diverse advanced technologies, the large-scale battery energy storage system (BESS), also referred to as grid-scale or utility-scale BESS, receives wide attention due to its attractive features of flexible installation, rapid response, high energy efficiency and a short construction cycle [5–7].

Driven by the optimization of manufacturing facilities and reduced use of materials, the total installed cost of BESS is expected to decrease by at least 50% by 2030 [8]. Despite the cost-reduction potential of batteries being considerable, their growth still faces the major barrier of high upfront investment and poor cost-effectiveness [5], which leads to few applications in current national energy systems. Some scientific studies also show that batteries have a limited role to play in renewable penetrations considering the economics [9,10]. Improving the available revenue streams is necessary for the future penetration of batteries. Energy arbitrage is one of the direct and major sources of income for batteries [11,12], which refers to the batteries get profits from electricity price differentials by buying energy at a low price and selling it at a higher price.

In the future 100% renewable smart energy system, the battery operator seeks appropriate bidding strategies in the electricity market to maximize profit. From a societal perspective, the operation of batteries should also lower the costs of operating the surrounding energy system while allowing for increased utilisation of RE. This is important as the battery does not stand alone, and it will interact with not only the electricity sector but also other energy sectors in the energy system indirectly, as future RE systems will likely see increased sector integration. This increase in sector integration is sometimes referred to as the concept of ***Smart Energy Systems***, which provides a coherent and integrated understanding of sector synergies to identify the most achievable and affordable strategies towards future 100% RE systems [1].

1.1. Research questions and scope

Focusing on large-scale battery storage in 100% renewable smart energy systems, this paper aims to answer the following research questions:

1) Which principles and strategies should the battery operator follow in the electricity market to maximize the battery profit and minimize the total cost of the energy system? Moreover, what is the relationship between these two economic indicators?
2) Will battery storage be feasible and profitable in a future 100% renewable smart energy system under different energy system conditions? E.g., the different operation strategies of renewable generators.
3) Which kinds of benefits will battery storage bring to the energy system and to what extent?

To investigate the role of batteries in a national smart energy system, the 2050 Danish energy system is used as a case as it has a long-term national energy target of being a low-carbon society independent of fossil fuels by 2050 through extensive utilization of renewable energy. [13]. As a long-term national target could result in many different technical energy system scenarios, two different energy system scenarios made by two different actors are included in this paper. Having more energy system scenarios also allow for a better understanding of how the surrounding energy system affect the market potential of battery storage technologies. Despite different battery storage technologies, such as lithium-ion (Li-ion), sodium sulphur and lead acid batteries, can be used for large-scale applications, currently, Li-ion batteries represent over 90% of the total installed capacity for global market of large-scale battery storage [13]. The Li-ion battery has advantages in high energy density, relatively high round-trip efficiency and relatively mature technology [13]. Due to the reasons mentioned above, we adopt the Li-ion battery for analysis in this paper. The battery revenue from energy

[1] The term Smart Energy Systems was first mentioned in 2009, which is used mostly to express a holistic systems approach as opposed to a single sector approach. It takes an integrated holistic focus on the inclusion of more sectors (electricity, heating, cooling, industry, buildings and transportation) and allows for the identification of more achievable and affordable solutions to the transformation into future renewable and sustainable energy systems.

Table 1
Summary of the existing literature on energy arbitrage of electricity storage system. "–'' means not included.

References	Year	Technology	Contributions	Electricity price consideration	Detailed battery bidding -consideration	Energy system modelling
This paper	2022	Li-ion battery	Optimal bidding strategies in 100% RE system	Different levels of prognostic period from 12 h to a year	Different levels of battery profit margin rates	100% RE system
Lund et al. [33]	2008	CAES	Optimal bidding strategies	Historical 24 h and future 24 h foresight	–	–
Sioshansi et al. [39]	2009	PHES	Parameter influence on profitability	Two-week foresight and backcasting	–	–
Kanakasabapathy and Swarup [40]	2010	PHES	Maximizing profit	Weekly forecast	–	–
Connolly et al. [38]	2011	PHES	Optimal bidding strategies	Historical 24 h and future 24 h foresight	–	–
Jiang and Powell [34]	2015	Battery	Hour-ahead bidding optimization	Historical price training	–	–
Mohsenian-Rad [32]	2016	Battery	Optimal bidding, scheduling, and deployment	Probability distribution functions for prices	–	–
Staffell and Rustomji [11]	2016	Li-ion & NaS batteries	Maximizing profit of arbitrage and reserve	24 h foresight and one-year historical price	–	Only wind farm
Krishnamurthy et al. [12]	2018	Battery	Optimal arbitrage	24 h foresight	–	–
Metz and Saraiva [30]	2018	Li-ion battery	Optimizing the storage dispatch	Non-specified	–	–
Wilson et al. [41]	2018	PHES	Investigate the level of revenues available	24 h foresight	–	–
Lin et al. [37]	2019	LAES	Optimal operation strategies	12 h historical and 12 h future; 18 h historical and 6 h future; 24 h historical	–	–
Arcos-Vargas et al. [31]	2020	Li-ion battery	Optimal electricity scheduling strategies	Non-specified	–	–
Cao et al. [35]	2020	Li-ion battery	Optimal arbitrage	24 h foresight	–	–
Pusceddu et al. [42]	2021	Li-ion & VRB batteries	Synergies between arbitrage and fast frequency response	24 h foresight	–	–
Schneider et al. [36]	2021	Li-ion battery	Economic evaluation for peak shaving and price arbitrage	24 h price series	–	–
Goteti et al. [43]	2021	Not specified	Impact of energy storage on the operation and revenue of existing generation	Actual electricity price	–	Only electricity system
Beuse et al. [44]	2021	Flow battery, PHES, Li-ion battery	Assessment of the electricity system emissions impacts of energy storage systems	Exogenously given by the energy system model	–	Only electricity system

arbitrage is considered, and the other services such as operating reserves [14–16] and deferring network upgrade [17], frequency regulation and black start are excluded from the analyses due to uncertainties related to the size of the future demand of these services and the competition of other technologies for providing these services.

1.2. Literature review and research gaps

The transition towards low-carbon energy systems by integrating electricity storage, such as various kinds of batteries (Li-ion, NAS, VRB), compressed air energy storage (CAES), pumped hydroelectric energy storage (PHES) and liquid air energy storage (LAES), has received widespread attention from academia [18–20]. Researchers have conducted energy system-level analysis for electricity storages or included them in the overall system as one of the key technologies. Energy system modelling tools [21] are the most common approach, including EnergyPLAN [22–24], LUT [25–28] and TIMES [29]. To the best of our knowledge, none of the previous research explores the principle of battery market participation strategy and the corresponding mechanism in a 100% renewable smart energy system.

Aiming at the arbitrage of various electricity storage technologies, a variety of research has been found and summarized in Table 1. The optimal scheduling of electricity storage systems to maximize the arbitrage profit is the most widely studied subject, which commonly adopts mathematical programming formulation such as mixed-integer linear programming [30,31], stochastic programming [12,32] and dynamic programming [33,34], a data-based approaches such as reinforcement learning [35], and self-developed optimization algorithms [11,36]. Given a set of electricity price series and other techno-economic constraints, these optimization approaches can determine the optimal size of storage, quantities and the time of charge and discharge based on different optimization criteria.

Targeting the bidding strategy of the electricity storage, some studies investigated the impact of different approaches to processing the price information in the market on the arbitrage profit [37]. For instance, Lund et al. [33] proposed two bidding strategies for CAES, i.e., a practical historical strategy and a practical prognostic strategy, based on the average electricity price of the past 24 h and the upcoming 24 h, respectively. The strategies were implemented in an individual plant modeled in EnergyPLAN and were used to find the optimal charge–discharge pairs. Connolly et al. [38] expanded the investigation to PHES and introduced a 24 h optimal strategy which finds the maximum theoretical operational income by inputting an hourly series of electricity prices over the next 24 h. Staffell and Rustomji [11] co-optimized the provision of the arbitrage and reserve for batteries, and the viability of arbitrage with a wind farm was analysed.

Despite the above-mentioned studies contributing to the optimal arbitrage of the electricity storage units, gaps can still be found in research due to the following reasons: 1) The existing studies were carried out mostly for the storage system itself; the coordination with the external energy system was rarely considered (if any only the electricity system), and no one has analysed battery bidding strategies in a 100% renewable smart energy system that considers all energy sectors; 2) Previous studies commonly chose approx. 24 h as the price basis of arbitrage, but with no sufficient evidence provided to support its rationality. From the point view of the coordination between battery systems and the whole energy system, in principle other time horizons may reveal more suitable. Further, the influence of different durations of the

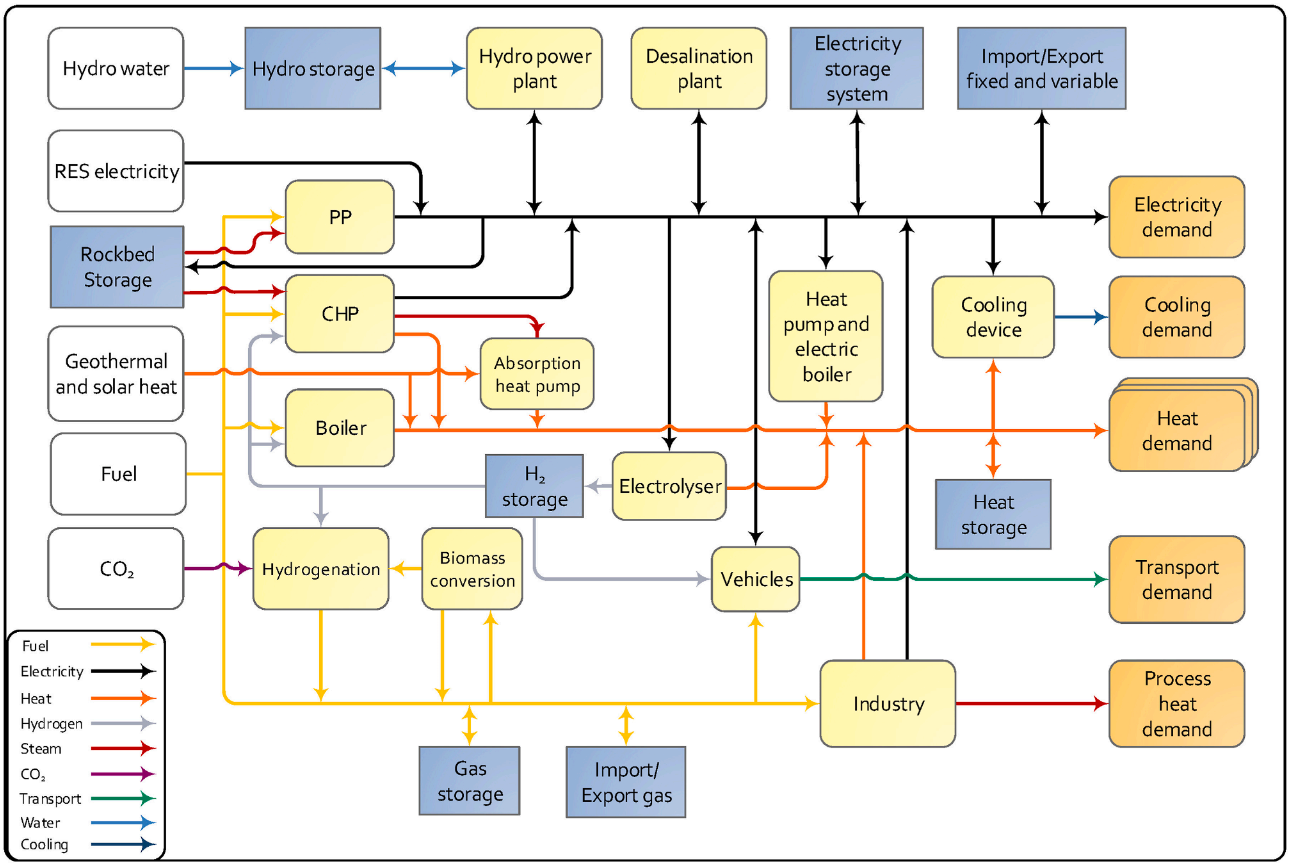

Fig. 1. Energy flows of the smart energy systems constructed in EnergyPLAN [50].

prognostic period should be investigated in depth; 3) The relationship between the battery profitability and the energy system costs is not revealed. This paper analyses the impact of profit margin rates of batteries on the system economy in support of decision making.

1.3. Research Contributions

Filling the above research gaps, this paper presents the first comprehensive techno-economic analysis on the bidding strategies of large-scale batteries in a 100% renewable smart energy system. It is conducted by simulating a series of key battery bidding parameters under different scenarios consisting of various system configurations using the energy system modelling tool EnergyPLAN. The influences of different levels of price prognostic periods and battery profit margin rates, as well as the RE operation modes, on the battery profit and energy system cost are investigated in detail. The results reveal the general relationship between the battery system and the external energy system. The findings of this work are not limited to the studied case of Denmark but aim to serve as a reference also to other countries by using the general analysis framework for a national energy system.

In the following, we first present our methodology framework in Section 2. Second, we describe the reference energy systems of 2050 Denmark and propose corresponding scenarios in Section 3. Then we present the primary results and discuss the bidding strategy of large-scale battery and the surrounding energy system from the techno-economic aspects in Section 4. Later, the impacts of different energy system structure and the sensitivity of the future uncertainties on cost and technical progress are analysed in Section 5. Finally, the conclusions are derived.

2. Methodology

The methodology section first illustrates the approach of modelling 100% RE systems adopted in this paper, followed by describing the basic bidding mechanism of the grid-scale battery in the electricity market and then providing the indicators employed to proceed with the technical–economic analysis.

2.1. The modelling of 100% renewable smart energy systems

This section first introduces the energy system modelling tool EnergyPLAN, and then moves into the simulation strategies of the electricity market and variable RE.

2.1.1. General description of EnergyPLAN

EnergyPLAN [45] is an advanced simulation software that aims at aiding in the design of future 100% RE systems, which has been widely used in literature [46–49]. It simulates the hourly energy balance of a whole national or regional energy system including the electricity, heating, cooling, industry, and transport sectors in a user-specific year, which enables the full advantages of sector synergies expressed in the smart energy system concept [50]. In this paper, EnergyPLAN is employed to simulate the Danish 100% renewable energy systems in 2050, which is described in detail in Section 3.

This modelling framework is illustrated in Fig. 1. An energy system can be constructed by inputting a series of parameters that describe the system components, including energy demands, units and resources of energy production and conversion, technical limitation rules for each unit and the system, as well as costs [51]. Based on a series of endogenous priorities in the model, the annual and hourly operation results of the system will be output, including the energy balance in different technical categories, imports/exports of electricity and gas grid, money

Fig. 2. Illustration of the operation mechanism of the battery in a 24 h prognostic period.

flows, primary energy consumptions, and CO_2 emissions. A detailed description of the modelling of the technologies, resources, and processes can be found in the previous work of the authors, Ref. [50].

2.1.2. Electricity market simulations

EnergyPLAN allows for two principle simulation strategies, being: *Technical* where the aim is to minimize fuel consumption, and *Market Economic* where the aim is to reduce short-term business economic marginal costs of the different technologies. The market economic simulation strategy is chosen to simulate the electricity market in which the battery bids are found. This section provides a general description of the market economic simulation. The detailed executing process can be found in the Section 3.3 of Ref. [50].

As EnergyPLAN simulates the hourly operation of a specific energy system, an hourly electricity market price for surrounding electricity markets is used to identify the relevant import and export of electricity to reduce energy system costs. The hourly price on an external electricity market is an input in EnergyPLAN, which is calculated using an hourly price distribution file for a year to reflect the price fluctuations and two factors representing price elasticity and the corresponding basic price level, respectively, to reflect the response to electricity import/export. EnergyPLAN thereby use the externally given hourly prices alongside the factors to calculate resulting hourly electricity market prices based on the hourly operation of the modelled energy system. Moreover, in the energy system analysis, the electricity market price can go down to zero or negative. It is possible to limit the market price to the minimum and maximum bidding prices allowed in the market, e.g., -500 EUR/MWh and 3000 EUR/MWh, respectively, in Nord Pool Spot. The electricity exchange between the studied system and the external system is limited by the capacity of the defined transmission line.

The least-cost solution of the entire energy system is found based on the identification of the market price at each hour resulting from the demand and supply of electricity. The operators of all production units are assumed to seek to optimize their business-economic profits; thus, the exact production of the various units can be identified when the resulting market price becomes equal to the short-term marginal production price. Similarly, the marginal consumption prices can be determined for various electricity-consuming units.

2.1.3. Operation strategies of variable renewable energy

The electricity market price is affected greatly by the operation of wind turbines and PV, which will further have an indirect impact on the battery bidding in the market. The electricity market price can go to zero or even negative when the simulation is done on hourly basis. Reflecting different levels of flexibility in the price signal, two types of operation strategies of variable renewable energy (VRE) generators are investigated in this paper, which are considered in the scenario design (see Section 3.3).

- **VRE zero bidding strategy (ZB)**

The VRE acts as an active market participant in the ZB strategy, where VRE will stop or reduce production during hours when its operation would result in negative electricity market prices. In other words, the lowest acceptable bid price of the VRE generators is zero in this case. This strategy is expected to represent the current trend where VRE generators are becoming more and more active participants in the energy markets, which in turn helps reduce problems of critical excess electricity production (CEEP). CEEP may occur when the capacity of the transmission line is limited unless other regulations on RE production are employed.

- **VRE negative bidding strategy (NB)**

Contrary to the ZB strategy, the VRE generators in the NB strategy act as passive market participants. The generators produce electricity regardless of the market price, even at very low or negative spot prices. The “negative” indicates that there is no limitation on the lowest bid price of renewable generators except for the minimum price in the electricity market. The NB strategy represents the status of the current electricity market in some countries. The feed-in support schemes that remunerate VRE on the basis of each unit of electricity generation are commonly used in the majority of EU member states, which enables VRE generators to largely feed in electricity at a negative price [52]. In the NB strategy, the problem of CEEP will be larger than for the ZB strategy.

2.2. The bidding strategies of large-scale batteries

The energy arbitrage operation of the battery is incorporated into EnergyPLAN v16.0. This section aims to provide an overview of the mechanism behind it and describe the simulation approach.

2.2.1. Bidding mechanism of batteries

The battery operator updates the market bids on an hourly basis.

During each hour t of a year, the battery is traded based on the forecasting of the average electricity market price $P_t^{Average}$ of the upcoming user-specific period (x hours), as shown in Eq. (1). The specific x period is defined as the prognostic period. To generate a profit, the battery only sells during the hours when the market price exceeds the buying prices (the price when the battery buys the electricity from the market). Therefore, a minimum selling price $P_t^{SellMin}$ and a maximum buying price P_t^{BuyMax} exist. The difference between the $P_t^{SellMin}$ and P_t^{BuyMax} is $2{*}P_t^{Diff}$, as shown in Eqs. (2)–(3).

$$P_t^{Average} = \frac{\sum_{k=t}^{t+x} P_k}{x} \tag{1}$$

$$P_t^{SellMin} = P_t^{Average} + P_t^{Diff} \tag{2}$$

$$P_t^{BuyMax} = P_t^{Average} - P_t^{Diff} \tag{3}$$

Fig. 2 illustrates the operation mechanism of the battery in a prognostic period of 24 h. The areas hatched in yellow illustrate the periods when the battery is able to charge, while the area hatched in green illustrates when the battery can bid on the market to discharge. The distance between the orange/green line (maximum buying price/minimum selling price for battery) and the blue line (average market price in the prognostic period) is P_t^{Diff}, which is equally distributed around the average price. P_t^{Diff} is an important operation parameter that can influence the profit of the battery by regulating the trading activity, which is adjustable depending on the requirements of the battery operator by specifying the profit margin rates. Eqs. (4)–(5) calculate P_t^{Diff} by an initial price difference $P_t^{InitialDiff}$ together with a minimum profit margin increase rate ε specified by the battery operator. α_{charge} and $\mu_{discharge}$ are the charge and discharge efficiency of the battery, respectively, and c is a constant representing the variable operational cost (VOC) of consuming one unit of electricity when battery operates, which is consisting of 1) the VOC of the charging (VOC_{charge}), and 2) the VOC of the discharge ($VOC_{discharge}$) corrected for losses in the process. The detailed derivation process of the equations can be found in [53].

$$P_t^{Diff} = (1+\varepsilon)P_t^{InitialDiff} \tag{4}$$

$$P_t^{InitialDiff} = \frac{P_t^{Average}(1-\alpha_{charge}\mu_{discharge}) + c}{\alpha_{charge}\mu_{discharge} + 1} \tag{5}$$

$$c = VOC_{charge} + VOC_{discharge}\alpha_{charge}\mu_{discharge} \tag{6}$$

2.2.2. Simulations of battery bidding in EnergyPLAN

According to the above mechanism, there are two key parameters affecting the bidding activity of the battery, i.e., the prognostic period and the profit margin increase rate. As input data for EnergyPLAN v16.0, the two bidding parameters and other technical specifics of the battery (capacities and efficiencies) can be specified for the batteries modelled in the studied energy system. The possible range for the prognostic period is set by hours in a leap year, i.e., a range from 0 to 8784 h, and the profit margin increase rate is set by percentage. EnergyPLAN outputs the hourly energy charges and discharges of the batteries and the hourly electricity prices on the market for further analysis.

2.3. Metric definitions for technical–economic analysis

2.3.1. Indicators for battery energy storage system

Different indicators for the operation of electricity storage exist in the scientific literature. In this paper, three indicators are used, being: number of equivalent cycles in a year (NEC), profit (annual and per discharge) and levelized cost of storage (LCOS).

- **Number of equivalent cycles in a year**

NEC reflects the degree to which the battery capacity is utilized during a year. It is defined as the total discharged energy during a year divided by the rated capacity of the battery, as shown in Eq. (7). The profitability of the batteries is highly dependent on its utilization of the stored energy. If the excess production of electricity is limited or the electricity price is not attractive enough, the batteries will be faced with the possibility of underuse [54]. NEC is used as a relative indicator for comparison between different sizes of batteries.

$$NEC = \frac{\sum_t discharge_t}{batterycapacity} \tag{7}$$

- **Annual battery profit and average battery profit per discharge**

Eqs. (8) and (9) calculates the annual battery profit [MEUR] and average battery profit per unit of discharged electricity [MEUR/TWh] from price arbitrage, respectively. The annual profit is the sum of the hourly incomes from discharging minus the hourly expenses from charging in a year.

$$\text{Annual battery profit} = \sum_t (discharge_t P_t - charge_t P_t) \tag{8}$$

$$\text{Average battery profit} = \frac{\text{Battery annual profit}}{\sum_t discharge_t} \tag{9}$$

- **Levelized cost of storage**

LCOS [EUR/MWh] quantifies the discounted cost per unit of discharged electricity for storage technology, as shown in Eq. (10). The INV_y, VOM_y and FOM_y represent the investment expenditure, variable O&M cost and fixed O&M cost in year y of a lifespan, and i is the discount factor. The capital and operational expenditures and the discharged energy of each year during the technical lifetime are assumed to be the same, as EnergyPLAN only simulates the energy system for a specific year using annualized cost data, rather than a range of years.

$$\text{LCOS} = \frac{\sum_y (INV_y + VOM_y + FOM_y)(1+i)^{-y}}{\sum_y discharge_y (1+i)^{-y}} \tag{10}$$

2.3.2. Indicators for 100% renewable energy systems

For the national energy system, annual CO_2 emissions, primary energy (PE) consumptions, and CEEP are selected as the main technical indicators, while the economic evaluation is based on the total annual cost of the entire energy system. The total annual cost consists of annualized investment, fixed O&M costs, and variable costs. The variable costs include fuel costs, electricity exchange costs, marginal operation costs, and CO_2 emission costs.

The economic feasibility of the battery integration scheme, defined as the total annual cost of the entire energy system after battery integration, should not exceed the annual cost of the original system without a battery, as the energy system would otherwise incur extra costs.

3. Reference energy systems and scenarios

The 100% renewable energy systems designed for Denmark in 2050 are used to investigate the impacts of the bidding strategy of large-scale batteries under the context of *Smart Energy Systems*. This section first provides an overview of the reference energy systems, then describes the specifics of the BEES employed, and finally describes the generation process of scenarios.

3.1. Description of the 100% renewable energy systems

One energy system is used as the main system for investigation (IDA system), and another energy system (GCA system) is selected for comparison and sensitivity analysis. Both systems show a possible future

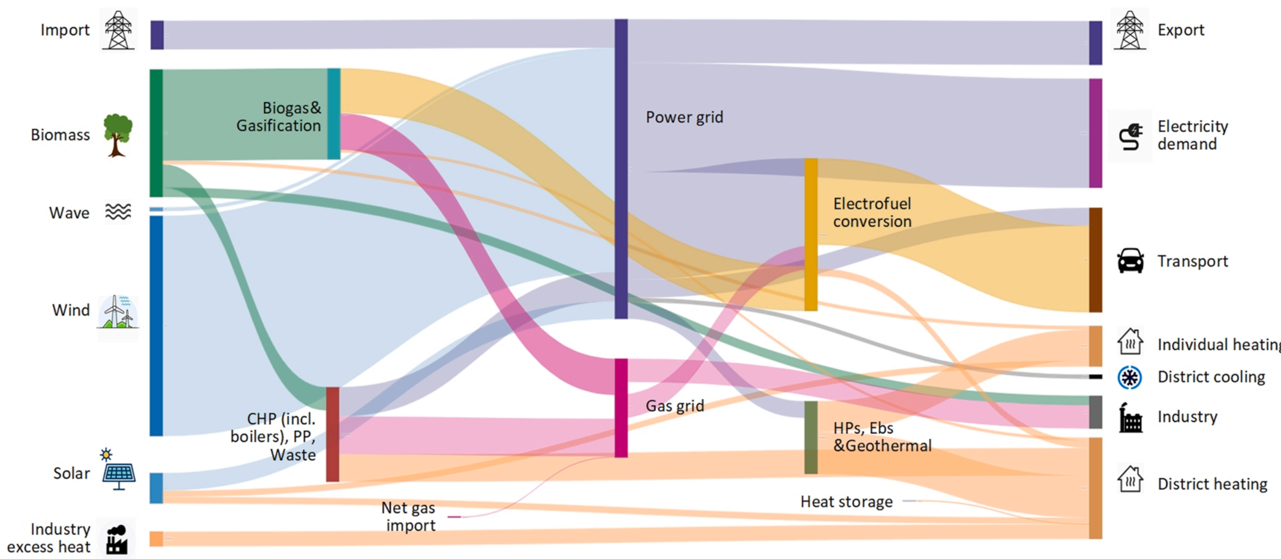

Fig. 3. Sankey diagram of the IDA energy system.

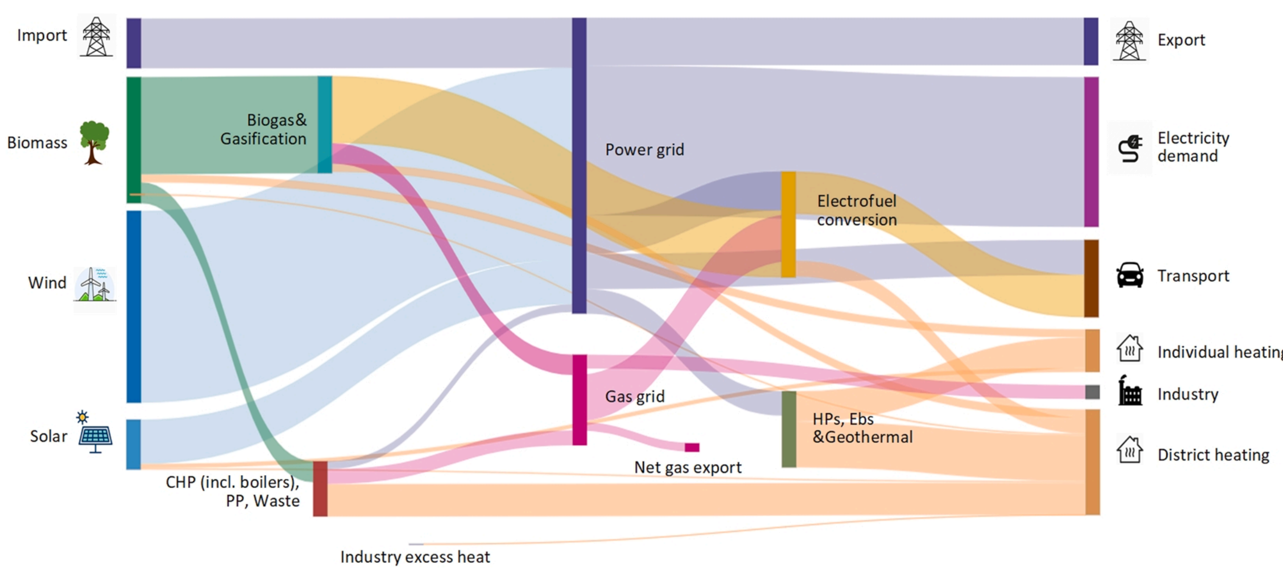

Fig. 4. Sankey diagram of the GCA energy system.

100% renewable energy system in Denmark. The two systems both aim for low-cost sustainable energy supply but vary in development strategies and political ambitions, and neither include grid-scale electricity storage solutions.

The background and general overview of the two energy systems are introduced in this section, and the detailed data of energy demand, technical specifics of production units and costs are provided in Tables A1-A3 in Appendix A.

3.1.1. *Reference energy system: IDA system*

The IDA's Energy Vision 2050 [55] (IDA system) was developed by researchers at Aalborg University for the Danish Society of Engineers. The IDA energy system aims to provide inputs to the political discussion of how Denmark can get to 100% renewable energy in 2050. The IDA system is created based on the Smart Energy System concept and adopts a cross-sectoral approach that integrates all sectors in the energy system to make full use of sector synergies. The IDA system is characterized by strong internal flexibility that enables the domestic energy balance within Denmark as much as possible, therefore it is able to run in an "*Independent Mode*".

A Sankey diagram of the IDA energy system is provided in Fig. 3. Aside from the VRE installation such as onshore and offshore wind and PV, conventional gas-fired combined heat and power (CHP) plants and condensing power plants (PP) that utilize gaseous electrofuel and biomass are installed as well for periods when the VRE production is not sufficient. Some flexible consumption components are integrated as well, e.g., electrolysers and heat pumps in district heating. 7,100 MW electricity transmission line capacity is installed to other countries so as to allow for reduced costs and fuel consumption by being able to trade electricity with other countries. The detailed description of the IDA Energy System can be found in Ref. [55].

3.1.2. *Energy system for comparison: GCA system*

The Global Climate Action energy system [56] (GCA system) is adopted for comparison in this paper. The GCA system is developed by the Danish transmission system operator Energinet based on an analysis of the efficient use of renewable energy considering the highly cross-border and international nature of the Danish energy system. Contrary

Table 2
Unit parameters of one unit (1 MWh) Li-ion battery system in 2050 considering future uncertainties [59].

Uncertainty level	MED	LOW	HIGH
Costs			
Specific investment [MEUR/MWh]	0.255	0.166	0.975
Fixed O&M [% of inv.]	0.19	0.15	0.06
Variable O&M [EUR/MWh]	1.6	0.3	2.5
Technical data			
Investment lifetime [years]	30	20	45
Charge efficiency DC [%]	98.5	98	99
Discharge efficiency DC [%]	97.5	97	98
Charge capacity [MW]	0.5	0.53	0.39
Discharge capacity [MW]	3	3.14	2.33

Table 3
Descriptions of the proposed four main scenarios.

No.	Scenarios	Definition
1	REF@ZB	The reference 100% RE system without battery integration, in which the VRE adopts the ZB operation strategy.
2	REF@NB	The reference 100% RE system without battery integration, in which the VRE adopts the NB operation strategy.
3	Battery@ZB	The large-scale batteries are integrated into the 100% RE system, in which the VRE adopts the ZB operation strategy.
4	Battery@NB	The large-scale batteries are integrated into the 100% RE system, in which the VRE adopts the NB operation strategy.

to the IDA system, the GCA system highly depends on cross-border electricity imports and exports to realize its electricity flexibility, and needs the electricity transmission to maintain a stable electricity system. The GCA system was designed to have strong cooperation across Europe, both in terms of infrastructure and regulation, therefore it can be viewed as an ambitious green system that runs in a way of "*Cooperative Mode*". The GCA system was developed based on the Ten Year Network Development Plan from 2018 by ENTSO-E [57].

A Sankey diagram of the GCA energy system is provided in Fig. 4. Compared to the IDA system, the GCA system contains larger PV installation, but the CHP plant capacity is quite low and the system does not have any separate PP. Also, the capacity of electrolyser is lower at 1,938 MW. The system has a relatively large transmission line capacity at 12,735 MW to satisfy the large need for electricity exchanges. The detailed description of the GCA system and its implementation in EnergyPLAN can be found in our previous report, Ref. [58].

3.2. Technical and cost specifics of BESS

The Li-ion battery is considered in this paper, as it is the most widely used and by many seen as the most promising technology available on the market [13]. The cost and technical level of future batteries are influenced by technological progress, which is very uncertain, and it will affect the feasibility of battery integration into energy systems. In consideration of such uncertainties, this paper employs values for the cost and technical parameters of the 2050 Li-ion BESS that represent three different uncertain levels, i.e., MED, LOW and HIGH.

Table 2 shows the specifics of the adopted 2050 grid-scale battery (type: Samsung SDI E3-R135), which are derived from the Danish Energy Agency [59]. The battery unit investment cost represents the total capital cost of all components in the BESS including rack, battery management system, thermal management system, energy management system, and power conversion system. The replacement of the inverter is already included in the given cost.

3.3. Scenario generation and description

3.3.1. Overview of scenarios

For a quick overview, Table 3 describes the used reference scenarios and two battery integration scenarios considering different VRE operation strategies, as described in Section 2.1.3. All the scenarios are simulated using the proposed methodology. The IDA energy system with the MED-level uncertainty of battery is employed for the main analysis in Section 4 to make the analysis concise, while the GCA energy system and the LOW- and HIGH-level uncertainties are considered for sensitivity analysis in Section 5.

3.3.2. Generation of battery integration scenarios

Three key parameters correlated to the scale and bidding of the battery are employed to generate the battery integration scenarios, including battery sizes, prognostic period for electricity price, and battery profit margin increase rate. The variation of the techno-economic indicators of both the batteries and the entire energy system can be investigated by putting different key parameters into the reference energy system models while maintaining other components of the system unchanged.

For each scenario, 1,521 ($12 \times 6 \times 21$) cases are simulated, which are the different combinations of 12 levels of battery sizes, six levels of prognostic periods, and 21 levels of profit margin increase rates. The details are provided below.

- **Battery energy capacity, charge capacity and discharge capacity**

The battery energy capacity can be calculated using Eq. (11). The charge and discharge capacities of the battery have a proportional relation to the battery energy capacity. The battery storage is assumed to be dimensioned so that it can cover the electricity demand that is only partly flexible or not flexible for a few hours. The partly or not flexible electricity demand includes all electricity demand that is fixed on an annual basis, e.g., conventional electricity demand, electric vehicles and individual heat pumps. Electricity demands that are seen as more flexible are not included, e.g., district heating-based heat pumps and electrolysis, because they do not have a required annual operation or connection to large storage facilities.

$$\text{Battery energy capacity} = \text{hours} \times \frac{\text{Annual electricity demand}}{8784} \tag{11}$$

Here, the battery energy capacity equivalent to the electricity demand from zero up to 24 h with an interval of two hours will be simulated, i.e., 2 h, 4 h and up to 24 h. The battery energy capacity, charge capacity and discharge capacity tested in the IDA and GCA energy systems are provided in Table A4 and Table A5, respectively, in Appendix A.

- **Price prognostic period**

The length of the prognostic period will have an impact on the ability of the battery to respond to the variable future electricity market price. Six levels of prognostic periods are investigated for each variant scenario, i.e., 12 h, 24 h, 48 h, a week, a month, a year.

- **Battery profit margin increase rate**

To explore the techno-economic influence of battery profit margin rate on the batteries and the energy system, a total of 21 levels of profit margin increase rates are simulated from 0 to 2000% with an interval of 100%. The range is determined according to the results of pre-simulation of the reference energy systems.

4. Results and discussions

To help understand the large-scale battery penetration from an energy system-level perspective in the following sections, the principle of battery bidding strategy is illustrated firstly in Section 4.1. Then, the IDA energy system under the MED-level uncertainty of battery is used to

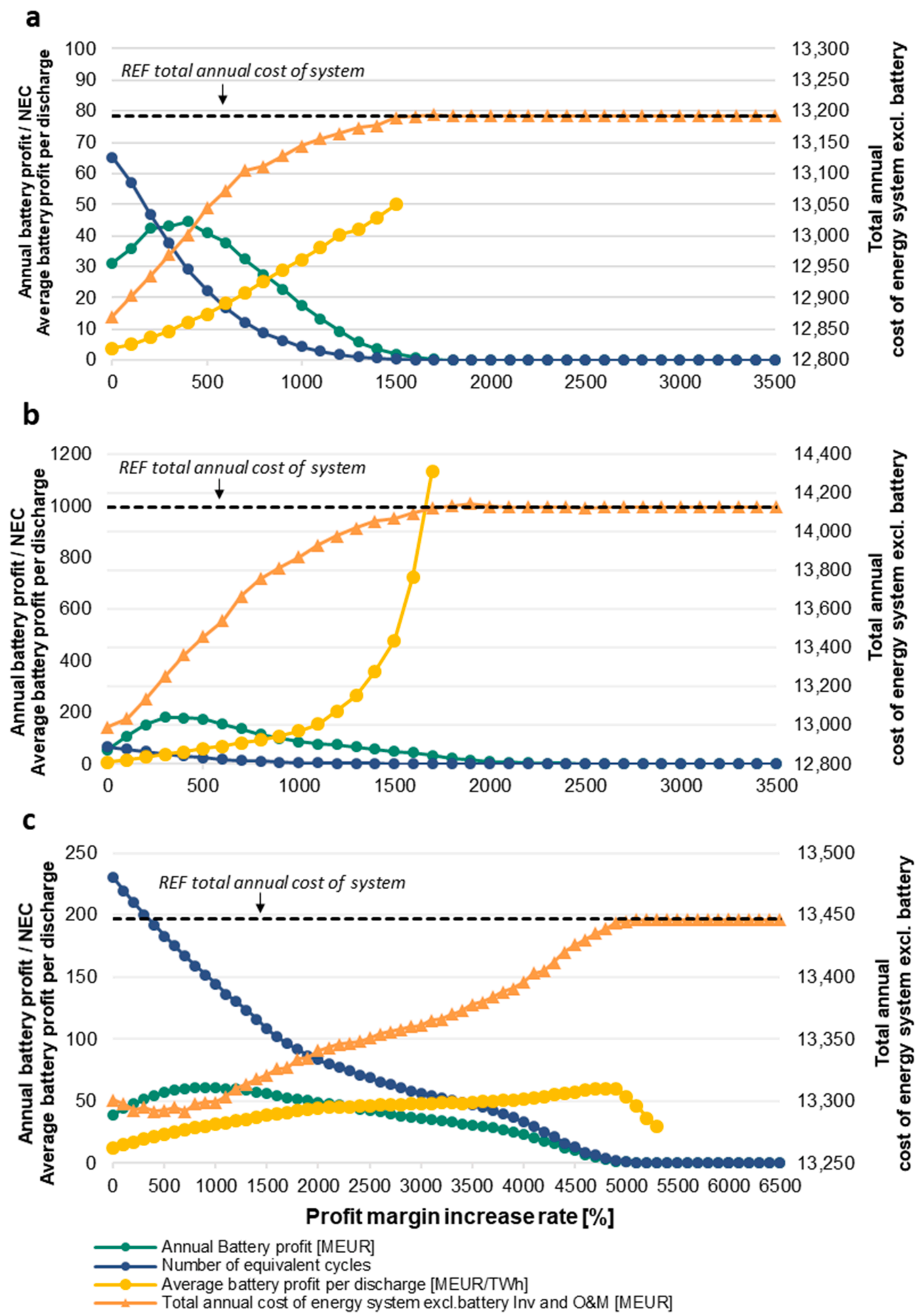

Fig. 5. Principle illustration of the battery bidding strategy in different scenarios while adopting a prognostic period of 24 h. a, results of the Battery@ZB scenario in the IDA energy system with integrating batteries of 24 h capacity. b, results of the Battery@NB scenario in the IDA energy system with integrating batteries of 24 h capacity. c, results of the Battery@ZB scenario in the GCA energy system with integrating batteries of 2 h capacity.

show the primary results and corresponding discussions from the economic and technical aspects in Sections 4.2 and 4.3, respectively. Later, in Section 4.4 the potential cost savings from the substitution of conventional generators with batteries are discussed.

4.1. Principle of battery system bidding strategy

This section shows the general principle of battery bidding strategy utilised (i.e., the key operation parameters —prognostic period and the profit margin increase rate) from the aspects of both the battery itself and the surrounding energy system it belongs to. Specifically, three typical battery integration cases in the IDA energy system and GCA energy system under different scenarios are investigated as examples here. Similar trends can be observed in the curves of other battery specifics.

Fig. 5 shows the variations in total annual profit, average battery profit per discharge, and the number of equivalent cycles of batteries, as well as the total annual cost of the energy system, with the increase of profit margin increase rates. To explore and explain the effect of the battery operation, the first results shown here are excluding battery

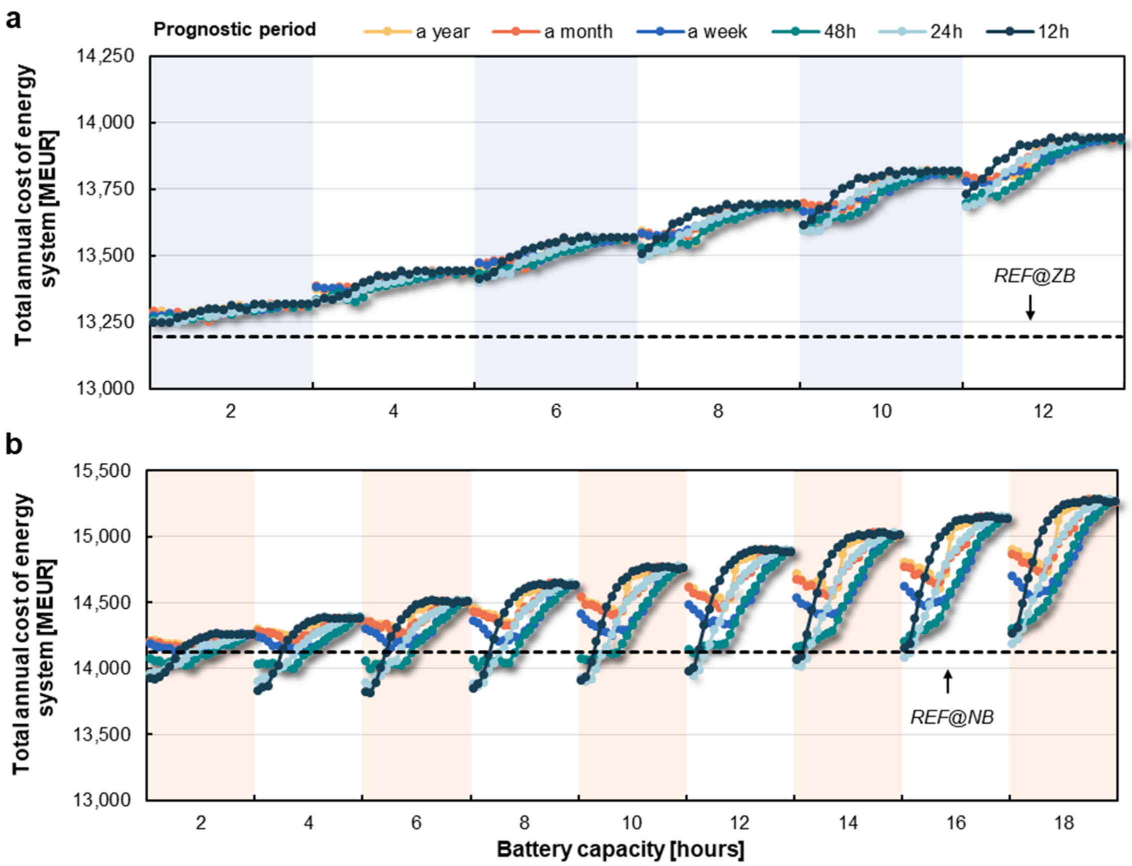

Fig. 6. The total annual cost of the IDA energy system with different battery capacities, prognostic periods, and profit margin increase rates. a, results of the Battery@ZB scenario. b, results of the Battery@NB scenario.

investment and O&M costs. In this way all effects shown are only in relation to batteries effect and interaction with the electricity market. This also then show a best-case situation for the battery since the introducing of battery cost is expected to lower the battery profit. Fig. 5a and b show the cases of Battery@ZB and Battery@NB scenarios in the IDA energy system with 24 h' battery capacity. Fig. 5c presents the case of Battery@ZB scenario in the GCA energy system with 2 h' battery capacity. A prognostic period of 24 h is used for all the cases.

Under both Battery@ZB and Battery@NB scenarios, with the increase of the profit margin rate, the NEC is found to gradually decrease until zero, while the average battery profit per discharge continues to grow until the battery to the point where the battery barely operates, which is expected as the battery operator increases its threshold to price arbitrage. The annual battery profit first increases until a maximum peak and then decreases to zero. In contrast, the total annual cost of the entire energy system shows a different direction, which first declines and then increases until reaching the cost of the reference system where no battery is integrated.

In Fig. 5c, the benefits for the battery and the energy system do not show apparent conflicts in the 2-hour case. The balance points of profit margin increase rates can be found (at around 800% of the profit margin increase rates) where the battery can maximize its profits, while the energy system is able to lower its costs at the same time. In the 24-hour cases of Fig. 5a and b, however, a zero profit margin increase rate is preferable for the energy system to achieve lowest total annual cost, while a relatively higher profit margin rate at around 300 $\sim$ 500% is optimal for the battery to profit.

To sum up, the choice of battery bidding strategy is case dependent, and the optimal profit margin increase rates need to be adjusted according to different battery specifics. The following sections identify the balance points of the lowest system cost in proposed scenarios including the battery costs.

4.2. Economic analysis: Energy system costs and battery profits

A total of 1,521 cases are simulated respectively for each battery integration scenario Battery@ZB and Battery@NB with using the IDA energy system. This section provides the economic results and analyses.

4.2.1. System total annual cost

Fig. 6 shows the change in total annual cost of the energy system with the increase of battery capacity and profit margin increase rate ε in different scenarios and prognostic periods. The curves in each interval of battery capacity consist of 21 points, which represent the 21 levels of ε from 0 to 2000%. Instead of showing all data of 24 h of battery capacity, here the figure only shows the data up to the economically feasible capacity to ensure a clear comparison of results.

Results show that the battery integration is only economically feasible from an energy system perspective in the case of low-capacity electricity storage, and only in the case where the VRE bids into the electricity market with the lowest possible negative bid. The maximum economically feasible capacity (referring to the cost not exceeding that in the REF scenarios) is 16 h for Battery@NB scenario. Comparing the two scenarios, it is apparent that the cost benefit brought by battery integration is very limited in a system adopting a ZB strategy for VRE, while it is of high potential in the NB scenario. The reason is that the average difference in electricity prices is lower in the ZB strategy as the price rarely, if at all, goes below zero. Thereby the operation strategy of the VRE has a large effect on the profitability of a grid-scale battery.

Moreover, when comparing different prognostic periods, the prognostic periods of 12 h and 24 h show greater advantages in lowering cost. Despite the choice of the optimal prognostic period being case

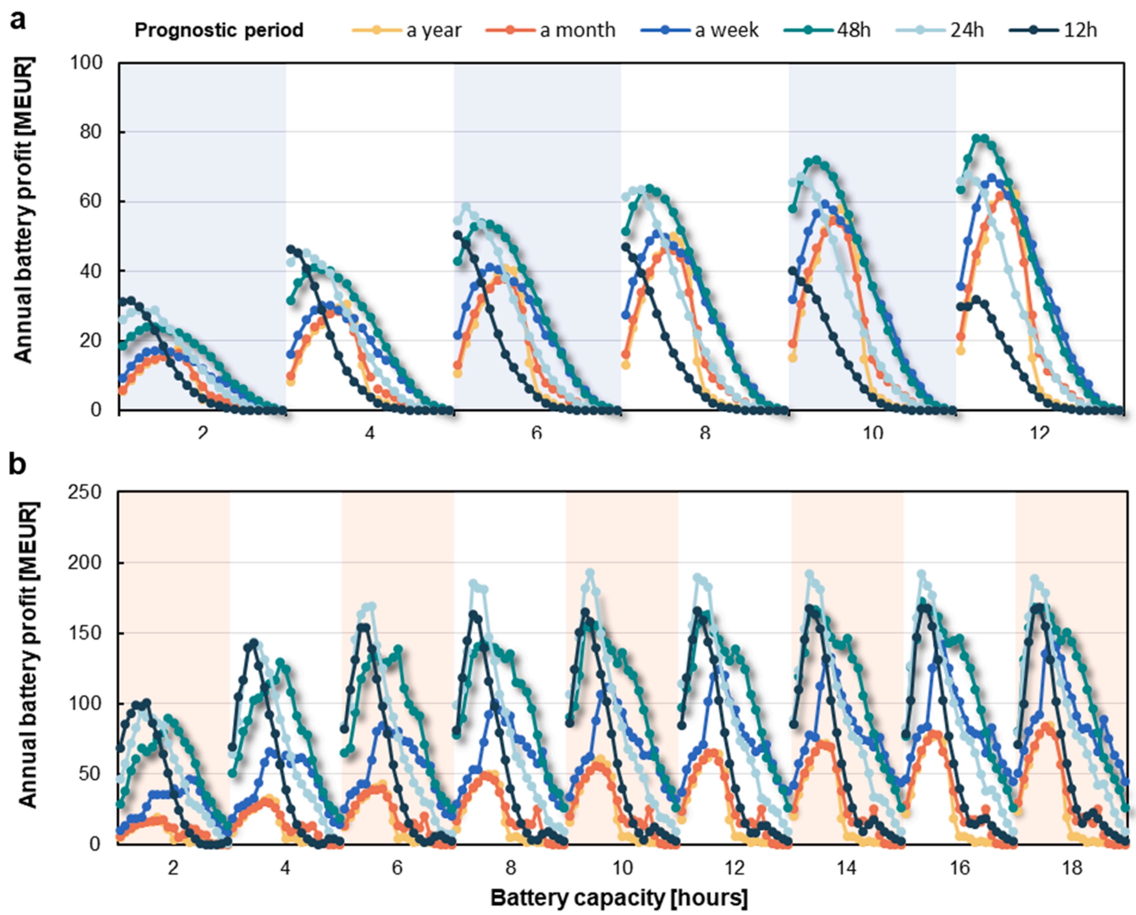

Fig. 7. The annual battery profits under different scenarios with different battery capacities, prognostic periods, and profit margin increase rates. a, results of the Battery@ZB scenario. b, results of the Battery@NB scenario.

Table 4
The economic optimal battery integration solutions of IDA energy system under different scenarios.

Scenarios	REF@ZB	Battery@ZB	REF@NB	Battery@NB
Specifics of batteries				
Battery capacity	–	Infeasible	–	31.58GWh (equiv. 6 h)
Prognostic period	–	–	–	12 h
Profit margin increase rate	–	–	–	100%
Energy system costs [MEUR]				
Total annual cost	13,193	–	14,129	13,816 (↓2.2 %)
Variable cost	1534	–	2471	1782 (↓27.9 %)

dependent, a trend shows that a relatively shorter period (i.e., 12 h) is preferable in a low-capacity storage system (battery capacity less than 10 h), and with the increase of storage capacity, a relatively longer period is preferable.

4.2.2. *Annual battery profits in variant scenarios*

Fig. 7 shows the results of annual battery profit of different scenarios. The structure is the same as Fig. 6. Looking at the battery itself, an optimal turning point of ε that brings the battery the highest profit can be found for each corresponding battery capacity and prognostic period. For a shorter prognostic period, like 12 h or 24 h, the turning point comes earlier at a lower ε, while for a longer prognostic period a relatively larger ε is needed to pursue a higher profit.

4.2.3. *Optimal battery integration solutions in variant scenarios*

The battery integration solutions that achieve the minimum cost for the entire energy system can be identified according to the economic analysis, as provided in Table 4.

The Battery@ZB scenario is regarded as economically infeasible, i.e., it cannot lower the total annual cost of the energy system even in the case of lowest battery capacity tested. This demonstrates that the battery is not a necessity in a well-structured and well-regulated 100% RE system that relies largely on sector synergies, given that the operating mode of renewable generators is matched well with the electricity market.

For the Battery@NB scenario, it can be seen that low-capacity storage solutions (6 h) with a shorter prognostic period (12 h) and lower profit margin rates (100%) have the lowest costs. Electricity storage can bring a significant reduction in the variable cost of the energy systems adopting the NB strategy, with up to 27.9%, and the total annual energy system costs will be reduced by up to 2.2%. Hereby grid-scale batteries can be relevant for energy systems where it is not possible for VRE to close down at periods of low electricity prices, as the batteries can utilise the resulting lower electricity price periods to purchase electricity for later discharge at higher prices.

4.3. *Technical analysis: Impacts of battery integration on the energy system*

This section further analyses the technical aspects of the IDA energy system that adopts the optimal battery integration solutions identified in Section 4.2.3. Since the Battery@ZB has shown to be infeasible in all the tested cases, here only the reference scenarios and the Battery@NB scenario are discussed.

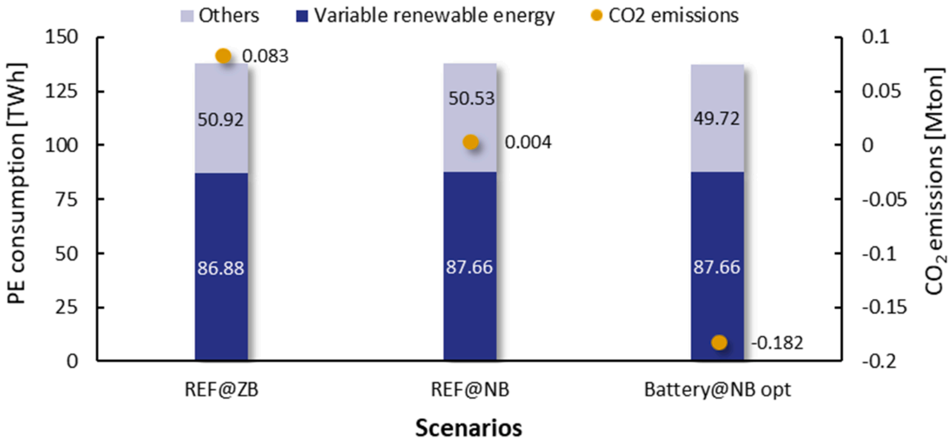

Fig. 8. CO_2 emissions and primary energy consumption of the reference scenarios and the optimal battery integration option of the Battery@NB scenario.

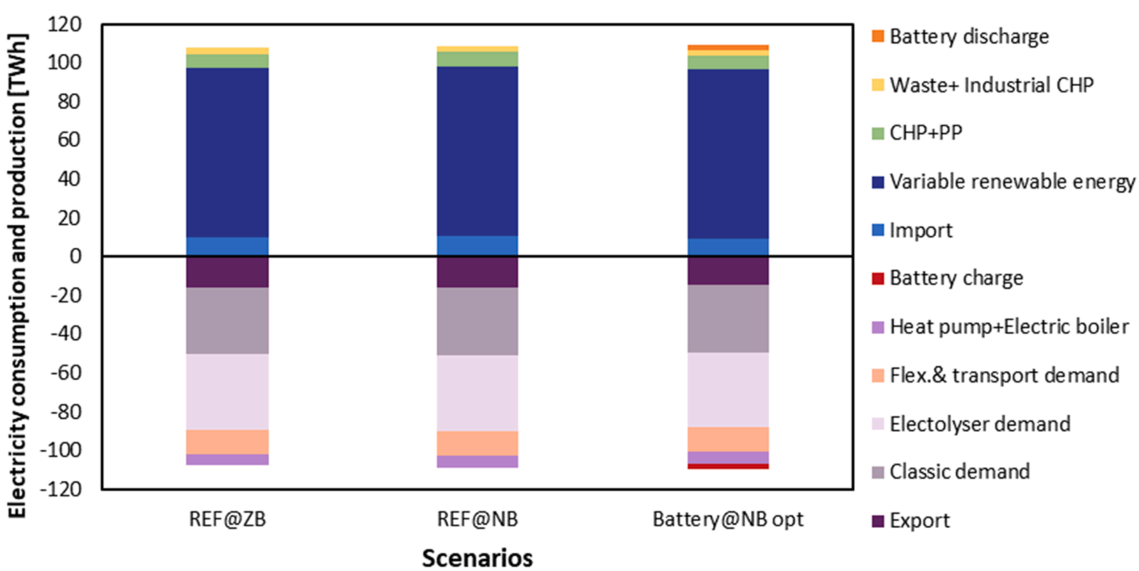

Fig. 9. Overview of the annual electricity production and consumption in different scenarios.

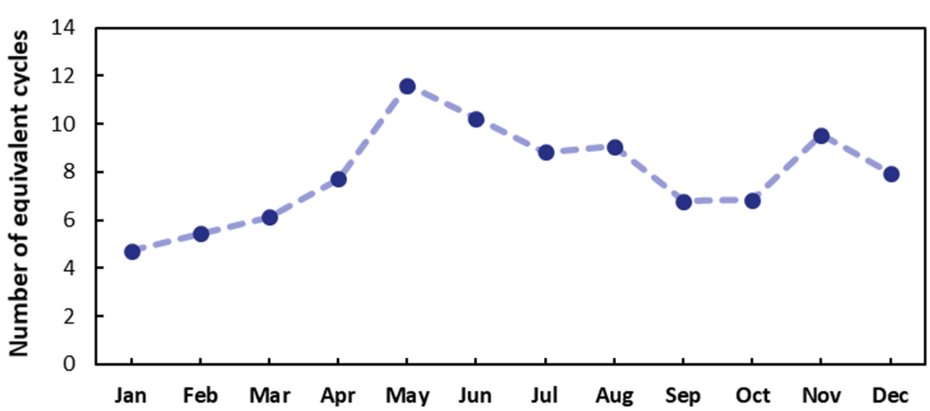

Fig. 10. Monthly battery number of equivalent cycles in the Battery@NB scenario.

4.3.1. Energy and environmental benefits

Fig. 8 shows the comparison of the total annual CO_2 emissions and PE consumptions among different scenarios. The reference scenarios both reach near-zero emissions. The CO_2 emissions are related to a net gas export, where the CO_2 emission factor of the gas is assumed to be the same as natural gas. As the European energy system is transitioning towards being more renewable, the import of gas could in principle be CO_2 neutral gas, such as upgraded biogas, meaning that these emission changes are somewhat uncertain. It can be seen that the battery penetration will help migrate the annual CO_2 emissions to go below zero in the Battery@NB scenario to -0.18 Mton.

In terms of PE consumption, the VRE productions from the REF@NB

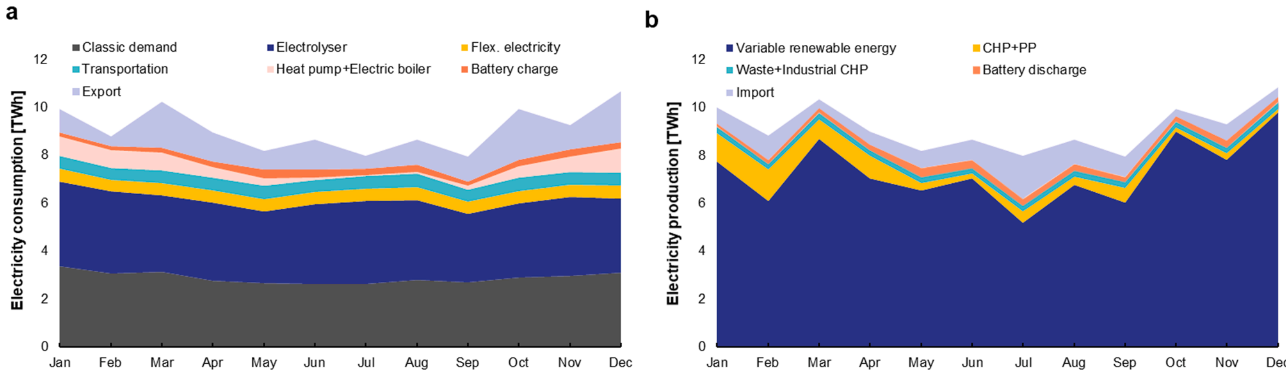

Fig. 11. Monthly electricity consumption and production in the Battery@NB scenario.

Table 5
Results of potential savings by further substituting conventional generators compared to optimal battery integration solutions.

Scenarios	Battery@ZB	Battery@NB
Capacity reduction of conventional generators		
PP	–	0
CHP elec.	–	-6%
Variation of system operation		
Total annual cost of energy System	–	-0.07 %
CO_2 emissions	–	-7.69 %
PE consumption	–	-0.06 %

scenario are higher than the REF@ZB scenario. The differences in VRE between the two scenarios indicate the level of energy not produced due to different reactions to the market prices. Despite not too much, the integration of battery in Battery@NB scenario still shows benefit in reducing PE consumption (0.81 TWh) compared to REF@NB.

4.3.2. Electricity system and seasonal differences

Fig. 9 provides an overview of the annual electricity production (positive) and consumption (negative) in the variant scenarios. From the production side, it can be found that the share of VRE is up to 80% in all scenarios. From the electricity demand side, the IDA energy system has a large number of flexibility components with a 36% share of electrolyser. The battery integration reduces the electricity import and export activity compared to the REF case. Also, the electricity production from CHP plants and PP are reduced as well, with a reduction percentage of 10% in Battery@NB scenario.

The electricity demand, RE production, and battery electricity storage interact with each other. The generation of variable renewable power (PV, onshore and offshore wind) is largely affected by the weather conditions, which contain obvious seasonal differences. In Denmark, wind power predominates in winter, while solar energy does in the summer. Therefore, the seasonal differences of the battery activity can be identified.

Here the economic optimal battery integration case of Battery@NB scenario is used as an example. Fig. 10 shows the monthly number of equivalent cycles of battery and Fig. 11 shows the monthly composition of electricity production and consumption. The electricity demand in winter is much higher than in summer due to a larger heating demand in the winter. The operation of the CHP plant and PP shows a strong electricity demand correlation, which compensates for the seasonal differences of the production of RE generators over a year, especially in the winter. The battery is active in the middle of the year with a peak number of equivalent cycles at 11.6 in May and the lowest at 4.7 in January. The battery electricity storage can further be regarded as compensation for the CHP plant and PP when these conventional generators run in a very low load during the year.

4.4. Potential cost savings by substituting conventional generators

According to the previous analysis in Section 4.3.2, the integration of battery electricity storage will reduce the operation and production of conventional generators, i.e., CHP and condensing PP. Therefore, cost savings could potentially be obtained from reducing the installation capacity of CHP and PP, which have not been included in the previous results. This section explores such potential savings, which is conducted by gradually reducing the capacities of CHP and PP in the energy system, while keeping the battery configuration at the optimal setting until finding the system minimum cost solution. The change of battery configuration is not considered here because this section aims to figure out to what extent the cost can be further saved and to provide a fair comparison among different scenarios. Note that here, only the large CHP extraction plants are assumed to be reduced in capacity.

Table 5 summarizes the results of the identified new CHP and PP configurations and variations of the system economic-technical indicators compared to the optimal battery integration solutions obtained in Section 4.2.3. The data for the Battery@ZB scenario is blank as it is still economically infeasible even with reduced conventional generators. The results show that only 6% of the capacities of CHP plants can be reduced in the Battery@NB scenarios, while the condensing PPs are kept in the system. This indicates that the battery storage has limited ability to serve as an alternative to the traditional generators. Results also show cost saving and decline in CO_2 emissions and PE consumptions. Nevertheless, the impact of CHP and PP on the system's total annual cost is very minor with less than 1%.

5. Sensitivity analysis

Two categories of sensitivity analysis on the battery bidding strategy are conducted in this section from the perspective of the energy system and the battery itself, respectively. The former investigates the impacts of different energy system structures, while the latter focuses on the impacts of different levels of battery uncertainties.

5.1. Battery bidding strategies in various energy systems

The GCA energy system introduced in Section 3.1.2 is employed here to reflect the differences of battery operation in various energy systems. Following the same process of the IDA system, the proposed 1,521 cases are simulated again for the GCA system. As mentioned, the GCA system differs from the IDA system in that the former has a higher electricity transmission line capacity and is dependent on electricity exchange between Denmark and other countries, while the latter is designed to support national energy self-sufficiency as much as possible and employs more flexible technologies on the demand side.

Fig. 12 shows the total annual cost of the GCA energy system under different scenarios with different battery capacities, prognostic periods,

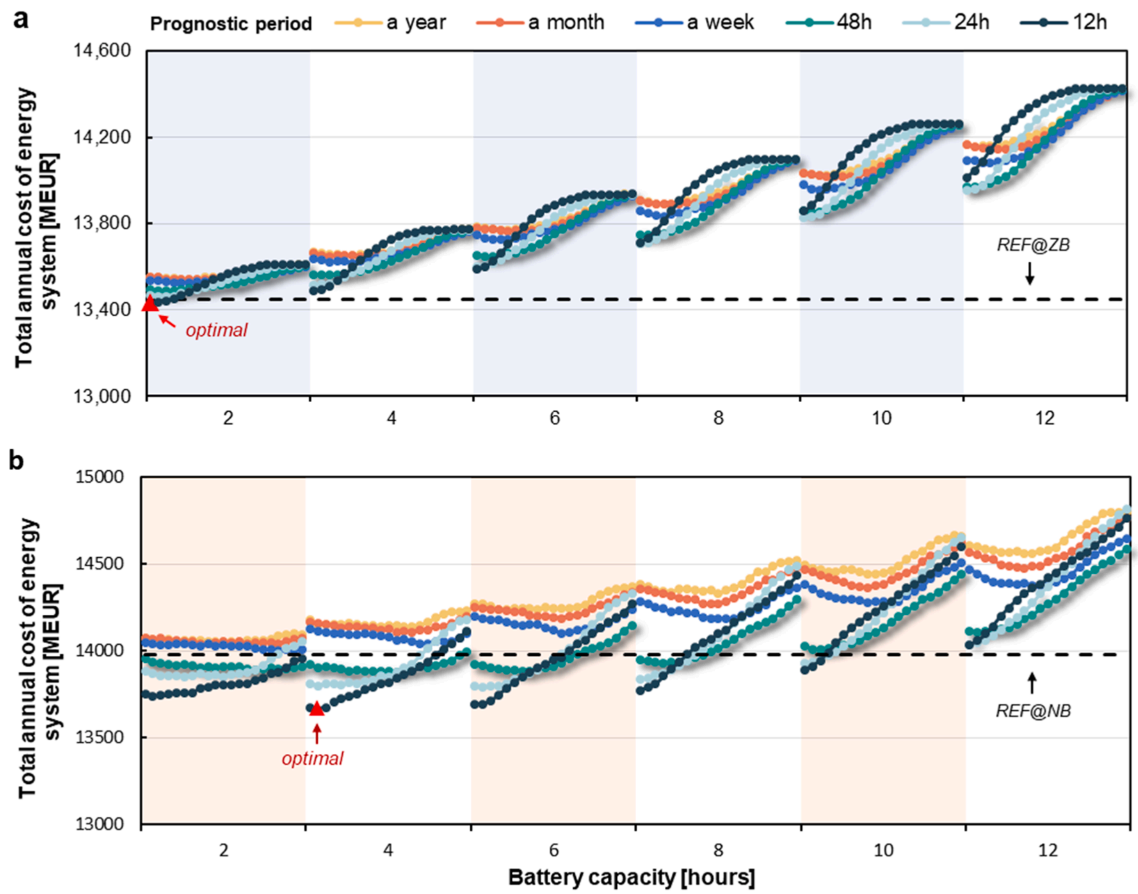

Fig. 12. The total annual cost of the GCA energy system under different scenarios with different battery capacities, prognostic periods, and profit margin increase rates. a, results of the Battery@ZB scenario. b, results of the Battery@NB scenario.

Table 6
Comparison of the optimal battery integration solutions between the IDA energy system and GCA energy system under different scenarios.

Scenarios	Battery@ZB		Battery@NB	
	IDA	GCA	IDA	GCA
Specifics of batteries				
Battery capacity [GWh]	–	13.72 (equiv. 2 h)	31.58 (equiv. 6 h)	27.44 (equiv. 4 h)
Prognostic period [hours]	–	12	12	12
Profit margin increase rate [%]	–	0	100	100
Performance of batteries				
Battery profit [MEUR]	–	64.1	110.1	112.3
Number of equivalent cycles	–	257.2	94.8	187.3
Average battery profit [MEUR/TWh]	–	18.6	37.7	22.4
LCOS [EUR/MWh]	–	50.6	132.4	68.5

and profit margin increase rates. The red triangle represents the economic optimal solution. It can be found that when the VRE adopts the ZB strategy in the electricity market, the GCA system shows a higher potential of battery integration compared to the IDA system (battery capacity: 2 h vs infeasible). The two battery bidding parameters (i.e., prognostic periods and profit margin increase rates) in the IDA system show similar trends as the GCA system. The choice of the prognostic period is related to the battery capacity, while a low profit margin increase rate (less than 200%) is preferable under most kinds of battery sizes from the perspective of the energy system.

Table 6 shows the comparison of the battery specifics and

Table 7
Specifics of batteries and the energy system in the LOW-level uncertainty cases.

Scenarios	Battery@ZB		Battery@NB	
	IDA	GCA	IDA	GCA
Specifics of batteries				
Battery capacity [GWh]	10.53 (equiv. 2 h)	13.72 (equiv. 2 h)	42.11 (equiv. 8 h)	41.15 (equiv. 6 h)
Prognostic period [hours]	12	12	24	12
Profit margin increase rate [%]	0	100	600	0
Variation of the batteries and energy system performance compared to MED cases				
Battery profit	29.3 MEUR [a]	-1%	-7%	-15%
Number of equivalent cycles	159.6 MEUR [a]	-1%	-29%	0%
Average battery profit	18.0 MEUR/TWh [a]	1 %	-2%	-43%
LCOS	74.2 EUR/MWh [a]	-8%	32%	-8%
CO_2 emissions	–222% [b]	-5%	-36%	-1%

[a] The IDA system is infeasible under the Battery@ZB scenario for battery integration, so the numbers here show the battery performance rather than the variations.
[b] The numbers here show the variations compared to the reference scenario, because the IDA system is infeasible here.

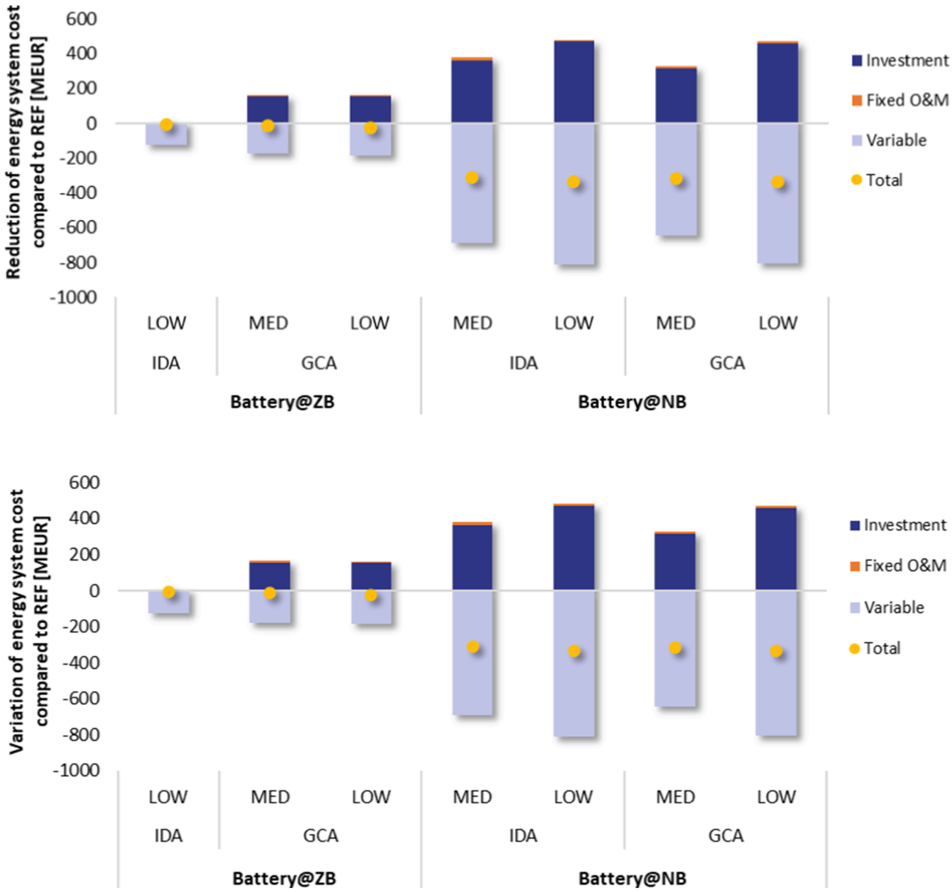

Fig. 13. Cost components of energy systems in different scenarios.

performance of the optimal battery integration solutions between the IDA energy system and the GCA energy system under different scenarios. A smaller size battery tends to operate more actively in one year with a higher number of equivalent cycles. Among the four cases, the Battery@ZB scenario in the GCA energy system has the highest annual equivalent cycles at 257 and the lowest LCOS at 50.6 EUR/MWh. Higher electricity exchanges in the GCA system promote battery activity compared to the IDA system. In the Battery@NB scenario, the GCA energy system owns almost half LCOS of that in the IDA energy system.

5.2. Impacts of future uncertainties on battery penetration

The sensitivity of the battery penetration to the future uncertainties is investigated in this section by simulating the LOW- and HIGH-level uncertainty. These uncertainties are related to the technology development of the batteries. Results show that the HIGH-level battery is not economically feasible in any energy system and even the lowest-capacity battery (2 h) cannot bring down the total annual system cost.

Table 7 shows the economically optimal battery configuration and corresponding technical indicators of the batteries and energy systems in the LOW-level cases. It is shown that the LOW-level case brings greater environmental and technical benefits compared to the MED-level case. Also, in the Battery@ZB scenario, the low capacity battery (2 h) is feasible in the IDA energy system. The CO_2 emissions are lower from the perspective of the entire energy system, while the annual battery profit and number of equivalent cycles decrease from the perspective of the battery itself.

Fig. 13 shows the cost components of the energy system in different scenarios. Looking at the overall economic performance, the role of battery integration in cost reduction is moderate under the Battery@ZB scenario with only a 0.2% reduction in the GCA system compared to the reference scenario, while the reduction in the Battery@NB strategy is up to 2.4%. From an uncertainty perspective, it can be seen that, despite the differences in cost components, especially the investment and variable costs are high, while the differences in total annual cost between the MED and LOW-level are minor. The LOW-level tends to install higher capacity batteries compared to the MED-level, which results in higher investment costs but lower variable costs due to the reduced fuel consumption, CO_2 emissions and electricity import.

6. Conclusions

This paper provides a comprehensive techno-economic analysis of the bidding strategies of large-scale battery storage in 100% renewable smart energy systems for the first time, with a case study of the Danish energy system in 2050 modelled in the energy system modelling tool EnergyPLAN. Two VRE operation strategies (zero bidding and negative bidding), two energy systems (cooperative mode and independent mode), and three levels of uncertainties in battery cost and technical development are considered. The feasibility and corresponding impacts of battery integration on the energy system are investigated by executing a series of experiments on key bidding parameters, i.e., battery sizes, price prognostic periods, and profit margin increase rates.

Results show that only at relatively small sizes, the batteries prove to be economically feasible for energy arbitrage and only in MED- and LOW-level cost cases. The profit margin rate of batteries has a significant impact on the energy system cost. The battery profitability and the energy system cost will not have apparent conflicts when the battery capacity is low, and a lower profit margin rate (less than 100% in this paper) is preferable in such case, which is beneficial to both the high battery profit and the low energy system cost.

Results show that the prognostic period correlates with the battery

Table A1
Input data of the 2050 reference energy systems in EnergyPLAN [58].

Input	IDA 2050	GCA 2050
1. Electricity		
1.1 Electricity demand		
Fixed electricity demand (TWh/year)	32.92	39.12
Flexible electricity demand (1 day) (TWh/year)	2.7	3.91
Max-effect for flexible electricity demand (1 day) (MW)	922	705
Flexible electricity demand (1 week) (TWh/year)	0.74	–
Max-effect for flexible electricity demand (1 week) (MW)	504	–
1.2 Electricity production		
Wind (onshore)		
Capacity (MW)	5000	6,164
Annual production (TWh)	10.9	14.55
Offshore Wind		
Capacity (MW)	14,000	12,785
Annual production (TWh)	52.93	50.59
Photo Voltaic		
Capacity (MW)	5000	11,450
Annual production (TWh)	4.91	14.57
Thermal power production		
Large CHP units condensing power capacity (MW)	4500	391
Large CHP units condensing power efficiency	0.615	0.404
Capacity of large steam turbines operating on excess heat from gasification (MW)	–	100
Annual electricity production by large steam turbines operating on excess heat from gasification (TWh)	–	0.51
1.3 Electricity exchange		
Transmission line capacity (MW)	7100	12,735
2. District heating		
2.1 Decentralised district heating		
District heating production (TWh/year)	12.94	17.5
Fuel boiler capacity (MW)	4400	5,928
Fuel boiler efficiency	0.95	0.92
Small-scale CHP - Electric capacity (MW)	1500	1,586
Small-scale CHP - Electric efficiency	0.52	0.352
Small-scale CHP - Thermal capacity (MW)	1125	2,370
Small-scale CHP - Thermal efficiency	0.39	0.526
Fixed boiler share (%)	0.5	33
Grid loss	0.2	0.15
Thermal storage capacity (GWh)	56	15
Solar thermal input (TWh/year)	1.75	0.51
Solar thermal storage (GWh)	30	–
Industrial CHP heat produced (TWh/year)	–	1.18
Industrial CHP electricity produced (TWh/year)	1.2	0.254
Industrial CHP heat demand (TWh/year)	–	1.252
Compression heat pump electric capacity (MW)	300	306
Compression heat pump COP	3.5	3.5
Compression heat pump maximum share of load	0.5	0.5
Electric boiler capacity (MW)	300	20
Industrial excess heat (TWh/year)	1.29	0.525
2.2 Central district heating		
District heating production (TWh/year)	22.3	17.5
Fuel boiler capacity (MW)	7600	5,928
Fuel boiler efficiency	0.95	0.891
Large CHP - Electric capacity (MW)	3500	391
Large CHP - Electric efficiency	0.52	0.404
Large CHP - Thermal capacity (MW)	2625	393
Large CHP - Thermal efficiency	0.39	0.406
Fixed boiler share	0.5	1
Grid loss	0.2	0.15
Thermal storage capacity (GWh)	56	15
Industrial CHP heat produced (TWh/year)	–	0.42
Industrial CHP electricity produced (TWh/year)	–	0
Industrial CHP heat demand (TWh/year)	–	0
Compression heat pump electric capacity (MW)	400	714
Compression heat pump COP	3.5	3.5
Compression heat pump maximum share of load	0.5	0.81
Electric boiler capacity (MW)	600	465
Industrial excess heat (TWh/year)	4.05	–
3. Fuel Distribution and Consumption		

Table A1 (*continued*)

Input	IDA 2050	GCA 2050
3.1 Fuel Distribution for Heat and Power Production These relations indicate the fuel mix used for each plant type (Coal / Oil / Gas / Biomass) .		
Small-scale CHP units	0/0/1/0	0 / 0 / 2 / 0.73
Large CHP units	0/0/1/0	0 / 0 / 1 / 0
Boilers in decentralised district heating	0/0/0/1	0 / 0.12 / 1.19 / 5.61
Boilers in central district heating	0/0/0/1	0 / 0 / 0.15 / 0.02
Condensing operation of large CHP units	0/0/1/0	0 / 0 / 1 / 0
Condensing power plants	0/0/1/0	–
3.2 Additional fuel consumption (TWh/year)		
Gas in industry	–	4.58
Biomass in industry	3.41	–
Natural gas, various	8.41	–
4. Transport		
4.1 Conventional fuels (TWh/year)		
Grid gas	0	8.16
JP (Jet fuel) - electrofuel	10.12	11.17
Diesel - electrofuel	21.01	0
Petrol - electrofuel	0	2.78
4.2 Electricity (TWh/year)		
Electricity - dump charge	2.64	5.94
Electricity – smart charge	6.46	11.51
Max. share of cars during peak demand	0.2	0.2
Capacity of grid to battery connection (MW)	16,396	29,213
Share of parked cars grid connected	0.7	0.7
Efficiency (grid to battery)	0.9	0.9
Battery storage capacity (GWh)	14.2	25.3
5. Waste conversion		
5.1 Waste incineration in decentralised district heating		
Waste input (TWh/year)	–	1.121
Thermal efficiency	–	0.894
Electric efficiency	–	0.076
5.2 Waste incineration in central district heating		
Waste input (TWh/year)	7.3	0.169
Thermal efficiency	0.7093	0.976
Electric efficiency	0.2591	0
6. Individual heating		
Coal boilers		
Fuel consumption (TWh/year)	–	0.2
Efficiency	–	1
Solar thermal input (TWh/year)	–	0
Biomass boilers		
Fuel consumption (TWh/year)	1.59	2.64
Efficiency	0.9087	0.89
Solar thermal input (TWh/year)	0.25	0
Heat pumps		
Heat demand (TWh/year)	13.07	11.36
COP	4.53	3.14
Solar thermal input (TWh/year)	2	1.367
Electric heating		
Heat demand (TWh/year)	–	0.26
7. Liquid and gas fuel		
7.1 Biogas production		
Biomass input (TWh/year)	0	26.24
Biogas production (TWh/year)	11.7	18.78
Biogas upgrade to grid efficiency	1	1
Input to gas grid (TWh/year)	5.24	6.61
7.2 Gasification plant		
Biomas input (TWh/year)	21.11	13.14
Electricity share	0.011	0.0175
Steam share	0.13	0.13
Steam efficiency	1.25	1.25
Coldgas efficiency	0.93	0.846
DH central share	0.05	0.2085
7.3 Electrolysers		
lectrolyser capacity (MW-e)	8510	1938
Electrolyser efficiency (Biomass hydrogenation)	0.74	0.891
Electrolyser efficiency (Biogas hydrogenation)	0.74	0.868
Hydrogen storage [GWh]	532	7.66
7.4 CO_2 hydrogenation		
Liquid fuel output (TWh/year)	15.51	
CO_2/Liquid fuel (Mton/TWh)	0.252	
Hydrogen/Liquid fuel (Mton/TWh)	1.153	

(*continued on next page*)

Table A1 (*continued*)

Input	IDA 2050	GCA 2050
Electricity/CO_2 (TWh/Mton)	0.289	
7.5 Biomass hydrogenation		
Liquid fuel output (TWh/year)	15.62	10.72
Liquid fuel efficiency	0.992	0.764
Hydrogen share	0.38	0.298
DH central share	0.05	0.0955
7.6 Biogas hydrogenation		
Gas fuel output (TWh/year)	8.41	15.33
Gas fuel efficiency	0.82	0.8
Hydrogen share	0.37	0.365
DH decentral share	0.05	0.2
7.7 Fuel storage Gas (GWh)	6000	–

size, which should be determined case by case in order to achieve greater economic benefits. The general recommendation of this study is that a shorter prognostic period is suitable for low capacity batteries (12 h for most cases presented in this paper), and a relatively longer prognostic period, e.g., 24 h or longer, is better for batteries with higher capacity.

Table A3
Variable operation and maintenance costs of the 2050 reference energy systems.

Technology [MEUR/unit]	Unit	IDA	GCA
Small and large CHP units	MWh_e	4	4.69
Heat Pump gr 2 + 3	MWh_e	0.43	0.43
Boilers gr. 2 and 3	MWh_{th}	0.5	1.05
Electr. boiler Gr 2 + 3	MWh_e	0.5	0.4
Large power plants	MWh_e	4	4

Table A2
Costs and technical life of technologies in the 2050 reference energy systems [58].

Technology	Unit	Costs [MEUR/unit]		Fixed O&M [% of investment]		Technical life [Year]	
		GCA	IDA	GCA	IDA	GCA	IDA
1. Heat and electricity							
Small CHP units	MW_e	1.32	1.1	2.48	2.36	25	25
Large CHP units	MW_e	0.8	0.8	3.25	3.25	25	25
Steam turbines	MW_e	0.481	–	3	–	25	–
Heat Storage CHP	GWh	3	3	0.7	0.7	20	20
Waste CHP	TWh/year	215.62	215.62	7.37	7.37	20	20
Heat Pump gr 2 + 3	MW_e	2.66	2.66	0.26	0.26	25	25
Boilers gr. 2 + 3	MW_{th}	0.315	0.67	4.87	4.3	25	25
Electr. boiler Gr 2 + 3	MW_e	0.06	0.06	1.53	1.53	20	20
Large power plants	MW_e	0.76	0.76	3.25	3.25	25	25
Interconnection	MW_e	1.2	1.2	1	1	40	40
Indust. CHP Electr.	TWh/year	60.6	60.6	2.15	2.15	31	31
Indust. CHP Heat	TWh/year	68.3	68.3	7.3	7.3	25	25
2. Renewable energy							
Wind - onshore	MW_e	0.7	0.7	1.62	1.62	30	30
Wind - offshore	MW_e	1.78	1.78	1.82	1.82	30	30
Photo Voltaic	MW_e	0.73	0.49	1.56	1.59	40	40
Wave Power	MW_e	–	1.6	–	4.9	–	30
Solar Thermal	TWh/year	307	307	0.15	0.15	30	30
Heat storage solar	GWh	–	3	–	0.7	–	20
Indust. Excess heat	TWh/year	30	40	1	1	30	30
3. Liquid and gas fuels							
Biogas Plant	TWh/year	159.03	159.03	14	14	20	20
Gasification Plant	MW	1.397	1.33	2.4	2.4	20	20
Biogas Upgrade	MW	0.25	0.25	2.5	2.5	15	15
Gasification Upgrade	MW	0.68	0.68	1.7	1.7	20	20
Carbon recycling	MtCO/y	–	60	–	4	–	20
LiquidFuel synth (CO_2)	MW	–	0.3	–	4	–	25
LiquidFuel synth (biomass)	MW	0.3	0.3	4	4	25	25
Methanation (biogas)	MW	0.2	0.2	4	4	25	25
JP Synthesis	MW	0.37	0.37	4	4	25	25
SOEC Electrolyser	MW-e	0.4	0.4	3	3	20	20
Hydrogen Storage	GWh	–	7.6	–	2.5	–	25
4. Heat infrastructure							
Indv. Boilers	1000-units	5.9	5.9	7.12	7.12	20	20
Indv. Heat Pump	1000-units	7	7	2.75	2.75	19	19
Indv. Electric heat	1000-units	2.5	–	0.84	–	30	–
Indv. Solar thermal	TWh/year	1233	1233	1.68	1.68	30	30
5. Additional							
Electric grid	–	2210	2475	1	1	45	45
District heating grid	–	16,703	16,703	1.25	1.25	40	40
Interconnections	–	1333	743	1	1	45	45
Compression cooling (Refrigeration)	–	559	559	0	0	15	15
Compression cooling (room temp)	–	5031	2795	4	4	15	15
District cooling (only for room temp)	–	–	413	–	2	–	25
Combined district cooling & heating (only for room temp)	–	–	1239	–	2	–	25
Electricity savings in households	–	1364	1364	0	0	10	10
Electricity savings in industry	–	2595	3491	0	0	15	15
Fuel savings in industry	–	10,011	10,011	0	0	20	20
Flexible electricity demand in households	–	222	222	1	1	20	20
Flexible electricity demand in industry	–	244	244	1	1	20	20
District heating grid expansion	–	5448	5448	1.25	1.25	40	40
Heat savings existing buildings	–	32,592	32,592	0	0	50	50

Table A4
Inputs of the battery storage capacities [GWh], charge capacities [MW] and discharge capacities [MW] in the IDA energy system under different uncertainty levels.

Hours of storage	Storage capacity	MED		LOW		HIGH	
		Charge capacity	Discharge capacity	Charge capacity	Discharge capacity	Charge capacity	Discharge capacity
2	10.53	5264	31,585	5580	33,059	4106	24,531
4	21.06	10,528	63,169	11,160	66,117	8212	49,062
6	31.58	15,792	94,754	16,740	99,176	12,318	73,592
8	42.11	21,056	126,339	22,320	132,235	16,424	98,123
10	52.64	26,321	157,923	27,900	165,293	20,530	122,654
12	63.17	31,585	189,508	33,480	198,352	24,636	147,185
14	73.70	36,849	221,093	39,060	231,411	28,742	171,715
16	84.23	42,113	252,678	44,640	264,469	32,848	196,246
18	94.75	47,377	284,262	50,220	297,528	36,954	220,777
20	105.28	52,641	315,847	55,800	330,587	41,060	245,308
22	115.81	57,905	347,432	61,380	363,645	45,166	269,839
24	126.34	63,169	379,016	66,960	396,704	49,272	294,369

Table A5
Inputs of the battery storage capacities [GWh], charge capacities [MW] and discharge capacities [MW] in the GCA energy system under different uncertainty levels.

Hours of storage	**Storage capacity**	**MED**		**LOW**		**HIGH**	
		Charge capacity	Discharge capacity	Charge capacity	Discharge capacity	Charge capacity	Discharge capacity
2	13.72	6859	41,154	7271	43,075	5350	31,963
4	27.44	13,718	82,309	14,541	86,150	10,700	63,926
6	41.15	20,577	123,463	21,812	129,225	16,050	95,890
8	54.87	27,436	164,617	29,082	172,300	21,400	127,853
10	68.59	34,295	205,772	36,353	215,375	26,750	159,816
12	82.31	41,154	246,926	43,624	258,449	32,100	191,779
14	96.03	48,013	288,081	50,894	301,524	37,450	223,743
16	109.74	54,872	329,235	58,165	344,599	42,801	255,706
18	123.46	61,732	370,389	65,435	387,674	48,151	287,669
20	137.18	68,591	411,544	72,706	430,749	53,501	319,632
22	150.90	75,450	452,698	79,977	473,824	58,851	351,596
24	164.62	82,309	493,852	87,247	516,899	64,201	383,559

In addition, the limited role of batteries in the smart energy system IDA demonstrates that the large-scale battery is just one of the solutions towards future 100% RE systems for energy arbitrage, but may not be a necessary solution. When the variable renewable generators work as active market participants by using the zero-bidding strategy, the room for battery arbitrage will shrink. The smart energy system itself is efficient enough without the battery storage, as it employs flexible production and demand components in a cross-sector approach.

It should be noted that this paper only investigates arbitrage, and the batteries could be relevant for providing other services such as frequency regulation and black start. Some evidence also shows that providing other services alternately aside from just delivering arbitrage can bring significant extra revenues for the battery and increase the final profitability of the battery application [11,42,60]. In the future study, the other services that the battery provided mentioned above can be included in the economic feasibility analysis. Also, a comparison analysis between batteries and other types of electricity storage technology can be further conducted.

CRediT authorship contribution statement

Meng Yuan: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Peter Sorknæs:** Conceptualization, Methodology, Formal analysis, Resources, Writing – review & editing, Supervision. **Henrik Lund:** Conceptualization, Methodology, Software, Writing – review & editing, Supervision. **Yongtu Liang:** Supervision, 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.

Data availability

Data will be made available on request.

Acknowledgement

The work presented here was funded by the China Scholarship Council (No. 201906440059), the National Natural Science Foundation of China (No. 51874325), the SENTINEL project of the European Union's Horizon 2020 research and innovation programme under grant agreement No 837089, and the RE-INVEST project supported by the Innovation Fund Denmark under Grant No. 6154-00022B. The authors would like to thank Mette Reiche Sørensen and Pernille Sylvest Andersen for their help in proofreading.

Appendix A

See Tables A1-A5.

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