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Optimal sizing and robust feasibility analysis of cloud battery energy storage for a residential community

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ABSTRACT

This paper proposes a novel two-stage framework for optimal sizing and robust feasibility analysis of a cloud battery energy storage (CBES) system for a residential community. In the first stage, the optimal sizing of the CBES is investigated based on the optimal capacity of distributed battery energy storage (DBES) required by individual residential users. Different types of users are assumed based on their installed capacity of rooftop solar photovoltaic (PV) and the type of electricity tariff considered. The optimal capacity, affordable price, and net present cost of DBES are determined in the first stage to support economic integration for each type of residential user. The second stage evaluates the economic feasibility of the battery capacity and price obtained in the first stage from the CBES point of view. To this aim, a robust optimization strategy is developed to model the CBES operator's profit in the worst case of variations of electricity market price and net power trading with the users. Within the novel framework, the analysis simultaneously accounts for a wider set of aspects than previous references, considering optimal battery sizing, feasibility of investments, comparisons with DBES, battery lifetime, and the uncertainties in electricity prices, demand, and renewable energy sources. The results show that while DBES is not economically viable for residential houses, the deployment of CBES becomes economically feasible for the users and the CBES operator.

1. Introduction

With the deep penetration level of photovoltaic (PV) arrays in residential communities, several challenges have emerged. First, feed-in-tariff prices have substantially decreased, discouraging users from further investments in rooftop solar PV systems [1]. Second, the distribution network has faced new challenges due to increasing voltages around noon on bright days, when end-users export the power generated by solar PVs to the grid [2]. The possibility of exceeding grid limits during the mid-hours of bright days could necessitate curtailing part of the PV power generation in these hours [3]. To overcome these problems, the integration of energy storage systems into local energy systems is becoming an urgent requirement.

Battery energy storage (BES) is an ideal candidate to be installed by the users to store excess power from rooftop PVs instead of simply selling power to the grid [4]. Users expect a significant electricity bill reduction by installing a behind-the-meter BES. A specific objective for the user could be to exploit their BES to achieve higher self-sufficiency (i.e., covering as much of the local demand as possible through coordinated local generation and BES) [5]. In this way, the user reduces the exchanges of net power with the grid over time by properly scheduling and managing in real-time the charge and discharge of the batteries in the BES [6]. However, the high price of BES remains the major obstacle to economic investment by users. Therefore, it is necessary to explore innovative business models to adequately reduce the application cost of BES while retaining its technical services for the users. The diffusion of BES for local users is also challenged by alternative options such as vehicle-to-home solutions [7].

In addition to local energy management for a single user, the concept of an energy community has emerged in recent years [8]. In an energy community, a voluntary group of users shares their energy resources to achieve energy, environmental, and social objectives. User participation in an energy community enhances the flexibility of the electrical system

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Nomenclature

Acronyms

BES	Battery energy storage
CB/m	Community batteries
CBES	Cloud battery energy storage
CBES/m	Community battery energy storage
COE	Cost of electricity
CBS/m	Community battery storage
CES	Cloud energy storage
CES/m	Community energy storage
CES/o	Collective energy storage
CRF	Capital recovery factor
CL	Calendar lifetime
DBES	Distributed battery energy storage
GAMS	General Algebraic Modelling System
GST	Goods and services tax
MC	Maintenance cost
NPC	Net present cost
PC	Present cost
PDF	Probability density function
PV	Photovoltaic
RU	Residential user
RTP	Real-time pricing
SB	Shared battery
SES	Shared energy storage
SOC	State of charge
TOU	Time-of-use

Indices and Sets

$i \in \boldsymbol{I}$	Index and set of residential users
$t \in \boldsymbol{T}$	Index and set of time periods (simulation horizon)
$\boldsymbol{V}^{DB}$/ $\boldsymbol{V}^{CB}$	Set of decision variables for first-stage (DBES) and second-stage (CBES) optimization

Parameters

CRF	Capital recovery factor
$C^{RU,gout}$	Export electricity price of RU (¢/kWh)
$C^{RU,gin}$	Import electricity price of RU (¢/kWh)
CL^{DB}	Calendar lifetime of DBES (year)
$\tau^{ref,thr}$	Energy throughput of the reference battery for one year (kWh)
E_{rate}	Energy rating of battery (kWh)
ir	Interest rate (%)
$MC^{DB,m}$	Annual maintenance cost of DBES ($)
n	Project lifetime (year)
$P^{RU}_{gin,max}$	Limit of import power from grid to the RU (kW)
$P^{RU}_{gout,max}$	Limit of export power to grid by the RU (kW)
$P^{CB}_{g,max}$	Maximum power trading of CBES with grid (kW)
$PC^{DB,c}/PC^{DB,m}$	Capital/maintenance present cost of DBES ($)
$PC^{CB,c}/PC^{CB,m}$	Capital/maintenance present cost of CBES ($)
$Q^{ref,thr}$	Reference battery capacity to compute throughput
R^{bat}	Ratio of power to energy for battery unit size (1/h)
$RC^{DB,r}$	Replacement cost of battery ($)
S^{B}_{min}/S^{B}_{max}	Minimum/maximum SOC of the batteries (per unit or %)
Y^{ref}	Lifetime of the reference battery (years)
$\alpha^{RU}_{net}/\alpha^{RTP}$	Uncertainty deviation
Δt	Time interval (hours)
λ^{RTP}	Price of the market for selling and purchasing energy ($/kWh)
η_{ch}/η_{ds}	Charging/discharging efficiency of battery (%)
Γ^{RTP}/Γ^{RU}	Uncertainty budget

Variables

AB^{RU}	Annual bill of electricity of RU ($)
ASC^{RU}	Annual supply charge of RU ($)
COE^{RU}	Cost of electricity of RU (¢/kWh)
E^{RU}	Electricity demand of RU (kWh)
$E^{DB,tot}$	Total annual energy throughput (charging/discharging) of DBES (kWh)
L^{DB}	Remaining lifetime of DBES at the end of project (year)
NPC^{CB}	Net present cost of CBES ($)
NPC^{DB}	Net present cost of DBES ($)
NPC^{DB}_{tot}	Total net present cost of all DBESs ($)
$P^{DB,ch}/P^{DB,ds}$	Charging/discharging power of DBES (kW)
$P^{CB,ch}/P^{CB,ds}$	Charging/discharging power of CBES (kW)
$P^{CB,gin}$	Purchased power from the grid by the CBES (kW)
$P^{CB,gout}$	Sold power to the grid by the CBES (kW)
P^{PV}	Generated power by solar PV (kW)
$P^{RU,gout}$	Export power to the grid by the RU (kW)
$P^{RU,gin}$	Import power from the grid to the RU (kW)
$P^{RU,net}$	Net power trading of CBES with RUs (kW)
P^{RU}	Power demand of RU (kW)
$PC^{DB,r}/PC^{DB,s}$	Replacement/salvation present cost of DBES ($)
$PC^{CB,r}/PC^{CB,s}$	Replacement/salvation present cost of CBES ($)
PRA^{CB}	Profit from arbitrage of CBES in the deterministic model ($)
PRA^{CB}_{robust}	Profit from arbitrage of CBES in the robust model ($)
Q^{CB}	Battery capacity for CBES (kWh)
Q^{DB}	Battery capacity for DBES (kWh)
RO^{CB}	Robust optimization objective ($)
S^{DB}/ S^{CB}	State of charge of DBES/CBES (%)
Y^{DB}	Replacement year of distributed battery (year)
$X^{CB,g}/X^{CB,cd}$	Binary variables for CBES
$X^{DB,g}/X^{DB,cd}$	Binary variables for DBES
z^{RTP}/q^{RTP}	Dual variables of RTP's robust model
z^{RU}/q^{RU}	Dual variables of RU's robust model
ξ^{RTP}/ξ^{RU}	Auxiliary variables used in the robust model
y^{RTP}/y^{RU}	Auxiliary variables used in the robust model

through the coordinated deployment of demand response and storage resources to cover demand management needs, including electric heating, electric mobility, and electric cooling [9]. From an operational point of view, various solutions have been developed that consider BES [10] or BES and electric vehicles [11]. However, sizing the overall energy system also requires assessing the economic feasibility of the investments to make the energy system profitable. Optimal sizing and feasibility analysis are important aspects of integrating energy storage.

In energy communities, BES systems can be deployed by following two different paradigms:

1. *Distributed battery energy storage* (DBES): the batteries are installed at individual users and are managed independently of each other based on the specific interests of the user. Optimal DBES sizing can improve resilience to grid outages [12] or play a role in managing the local system with renewable energy resources [13]. However, different studies indicate that DBES are not cost-effective, as shown in contexts such as residential users in Australia [14] and Texas [15], and on an educational campus [12]. Moreover, individual users cannot directly participate in the wholesale electricity market or in the provision of grid services, while a specific market can be set up

within a local energy community [16] or a microgrid [17] with customer-owned energy storage.

2. *Centralized battery energy storage*: the main idea behind centralized energy storage is to avoid the need for all users to purchase their local energy storage systems and the related battery management systems [18]. Community batteries can be shared on the consumer side, aiming to absorb excess solar PV production and reduce consumer retail costs, providing operational and economic benefits over distributed energy storage [19]. With centralized energy storage, the devices that provide the energy storage service to the end-users are installed at the grid side and are managed in a cloud service center [20]. In this way, there is an economy of scale with respect to purchasing the individual storage systems [21]. Centralized battery energy storage makes a virtual power and energy storage capacity available to each user in the energy community and is an attractive alternative to DBES in the residential sector. Different acronyms are used to indicate centralized battery energy storage. The acronym CES is used to refer to Community Energy Storage [9,22], Cloud Energy Storage [20], or Collective Energy Storage [23]. Other acronyms used are CB (Community Batteries) [24], CBES (Community Battery Energy Storage) [25], CBS (Community Battery Storage) [26], SB (Shared Battery) [27], and SES (Shared Energy Storage) [28].

Table 1 recalls the aspects related to centralized battery energy storage addressed in a selected set of papers. To avoid duplication of the acronyms, in the column referring to the BES types, the text "/m" is added to all acronyms that start with the word "Community", while "/o" is added to the acronym that starts with the word "Collective". The contribution of this paper is identified with the acronym CBES (Cloud Battery Energy Storage) to highlight the specific use of centralized batteries managed by a CBES operator in the context of a residential community.

The main focus of this paper is battery sizing in the CBES solution, considering feasibility aspects related to investments, comparing CBES solutions with DBES of similar size, and taking into account the effects of battery lifetime and different types of uncertainty on electricity prices, electrical load, and renewable energy. These aspects are indicated in Table 1 for the literature contributions considered. In more detail:

- *Battery sizing and feasibility of the investments*: Some studies address the optimal sizing and feasibility analysis of the centralized battery energy storage solutions. Different optimization problems and objective functions are considered. The typical formulation refers to the minimization of the total costs (i.e., the sum of the capital costs and annualized operational costs) in a given period, e.g., 10 years [31], 15 years [30], and

Table 1
Summary of selected studies (ticks ✓ for yes and × for no). BES types are indicated as CB/m (Community Batteries), CBES (Cloud Battery Storage), CBES/m (Community Battery Energy Storage), CBS/m (Community Battery Storage), CES (Cloud Energy Storage), CES/m (Community Energy Storage), CES/o (Collective Energy Storage), SB (Shared Battery), and SES (Shared Energy Storage, also addressed with undefined acronym).

Ref.	BES Type	(Optimal) BES sizing	Feasibility analysis (investments)	Comparison with DBES	Battery lifetime (degradation)	Uncertainty		
						Electricity price	Load	Renewable Energy
[29]	SES	✓	✓	✓	×	×	✓	×
[30]	CB/m	✓	✓	×	✓	×	✓	✓
[31]	CES	✓	✓	×	✓	✓	×	×
[32]	SES	✓	✓	×	×	×	×	✓
[33]	CES	✓	✓	✓	×	✓	✓	✓
[34]	CES/m	✓	×	×	×	✓	✓	✓
[35]	CES	✓	✓	✓	×	✓	✓	×
[36]	CES	✓	✓	×	×	×	✓	✓
[26]	CBS/m	✓	×	×	✓	×	×	×
[25]	CBES/m	✓	✓	×	✓	×	×	×
[37]	CES	✓	✓	✓	×	×	×	×
[38]	CES/m	✓	×	×	×	×	×	✓
[27]	SB	✓	✓	×	✓	×	×	×
[39]	CES/m	✓	✓	×	×	×	×	✓
[40]	CES/m	✓	✓	✓	×	×	×	×
[41]	CES/m	✓	×	×	×	×	×	×
[42]	CB/m	×	✓	×	✓	×	×	×
[43]	CES	×	✓	✓	✓	×	×	×
[44]	CES	×	✓	×	✓	×	×	×
[45]	CES	×	✓	✓	×	×	×	×
[46]	SES	×	✓	✓	✓	×	×	×
[47]	CES	×	✓	✓	×	×	✓	✓
[18]	CES	×	×	✓	×	×	×	×
[48]	CES/m	×	×	✓	✓	×	×	×
[49]	CES/m	×	×	✓	×	×	×	×
[19]	SES	×	×	✓	×	×	×	×
[24]	CB/m	×	×	×	✓	×	×	×
[50]	CES	×	×	×	✓	✓	×	×
[51]	CES/m	×	×	×	✓	×	×	×
[52]	CES/m	×	×	×	✓	×	×	×
[53]	CES/m	×	×	×	✓	×	×	×
[54]	CES	×	×	×	×	✓	×	✓
[55]	SES	×	×	×	×	×	×	✓
[56]	CES	×	×	×	×	×	×	×
[57]	CES/m	×	×	×	×	×	×	×
[58]	CES/m	×	×	×	×	×	×	×
[23]	CES/o	×	×	×	×	×	×	×
[59]	SES	×	×	×	×	×	×	×
[60]	CES/m	×	×	×	×	×	×	×
[61]	CES/m	×	×	×	×	×	×	×
[62]	CES/m	×	×	×	×	×	×	×
This paper	CBES	✓	✓	✓	✓	✓	✓	✓

20 years [25]. Some variants determine the total cost as the sum of the energy costs and the life cycle cost of the SES [32], calculate the expected daily costs incorporating energy and capital costs by considering the peak consumption as the relevant variable to decide the investment [29], or compare scenarios with different CES sizes [36]. With a focus based on the network side, the total costs of CES are considered together with the costs of network losses and transformer aging, also adding the results of energy arbitrage, assuming that the CES is owned by the distribution system operator [37]. Further approaches are based on the calculation of the maximum revenues of the users after CES installation and minimum losses in the energy storage cycles within a two-stage robust optimization [35], minimize the operational costs [33], or determine the optimal battery size by maximizing the net present value of the investment [27], also considering the benefits for the network from energy loss reduction and deferral of the network asset upgrade (including additional peaking capacity), as well as energy arbitrage and CO_2 emission reduction [39]. Further benefits can be obtained by providing multiple energy services [25]. Some contributions address battery size optimizations without analysis of the investments. In a local energy market, the aspects considered refer to maximization of the operator and prosumer profits [26] and maximization of the expected reward in the energy management of a price-maker CES [34]. Without considering energy markets, the strategic location and sizing of batteries in the CES are studied to support grid integration, accounting for load factors, network losses, and voltage profile [38]. Without optimization, parametric analysis of the battery size is carried out based on the levelized cost of electricity [40] and [41].

- *Comparison with DBES*: From earlier results, CES has achieved more economic benefits than DBES under different prices to provide the same services to the users, assuming that the unit cost for CES investment is 20% lower than the unit cost for DBES investment. Moreover, given the current investment costs per kWh for energy storage, both CES/m and DBES were economically infeasible for households, becoming more efficient when energy storage is used to increase self-consumption of PV generation [40]. From later contributions that present comparisons between centralized battery energy storage and DBES, there is a consistent indication that the centralized battery energy storage solutions prevail over DBES to provide the same type of services at lower costs or with less investments. These results have been confirmed in various contributions referring to optimal BES sizing and feasibility, with analyses carried out on datasets of residential prosumers, in the U.S. (from PJM data [33] and 14 users [19]), U.K. (200 users [48] and five households [29]), the Netherlands (39 households [40]), Australia (300 users [43]), India (five users in a microgrid [47]), Ireland (200 users [45] and 400 users [18]), and from the OpenEI database [49,63]. Specifically, for cases involving different types of buildings with non-residential users, the average energy storage value across the entire community with the CES/m model is about 1.8 times higher than with the individual energy storage model [49]. From historical data on a residential community at 15-minute intervals for one month, SES shows cost savings up to 14% and improvements in energy storage utilization up to 40% over individual energy storage solutions. From decision-making models, CES can provide energy storage services to users similar to those provided by user-purchased DBES, but at a lower cost [45]. The cooperation for SES to acquire storage capacity by minimizing the expected daily storage cost results in better performance than DBES from a coalitional game approach [29]. Further results from the analysis of an industrial park [35] show that DBES is not appropriate for users with small loads, while the investment in CES is lower than the total cost of DBES. Based on the analysis of 8 nodes of a low-voltage network [37], economies of scale determine significantly lower investment costs for the CES solution. In a network with 13 nodes, CES/m provides greater economic benefits than DBES, while accounting for the effects of renewable energy curtailment to satisfy grid constraints [48].
- *Battery degradation*: Degradation in battery performance, such as reduced capacity or increased resistance, can lead to higher operational costs [64] and accelerate battery aging, thereby shortening its overall lifetime. The battery lifetime is often considered by assuming that the end of life occurs when the maximum capacity of the battery reaches a given percentage of the nameplate capacity, such as 70% [26,42] as indicated in [65], of 80% of the nameplate capacity [27,51] or initial capacity [48]. Battery degradation should be taken into account when conducting a thorough analysis of battery storage systems. However, a specific formulation to assess battery degradation and lifetime is included only in a limited subset of the selected papers. Moreover, there is no uniformity on the model adopted for incorporating battery degradation in the overall formulation of the analysis or optimization of the energy system. Existing models are used, such as the cost model of [66] in [24], the model of [67] in [25], the model of [68] in [46], the model of [69] in [31] and [50], the model of [70] in [52], and the experimental model of [71] in [26]. Battery manufacturers provide the total discharged energy (maximum energy throughput) over the battery's lifetime. Limits on the number of cycles per day are calculated by dividing the maximum energy throughput provided by the manufacturer by the number of days of the battery lifetime [27,42]. The depreciation cost is computed as the ratio of the asset cost to its useful life, and a depreciation factor is also evaluated for regular and irregular cycles [48]. Other approaches based on the events that occur during the battery operation introduce the concept of effective throughput, compared with the total throughput of the battery lifetime [72], determine additional resources to be installed with the related capital costs to compensate for battery degradation [30], or assess the actual lifetime duration under a usage pattern with a given number of events [44], using the Bacon-Watts model for knee-point identification [73] in the capacity degradation analysis [53]. Finally, a simplified assessment can be conducted by setting a fixed degradation cost coefficient (e.g., 0.01 $/kWh, as in [54]).
- *Uncertainty modelling*: The relevant uncertainties refer to the electricity prices, the electrical demand, and the generation from renewable energy sources. The uncertainty characterization is carried out in different ways. For electricity prices, the mean values and standard deviations are obtained from historical data. Normal probability density functions (PDFs) corresponding to these mean values and standard deviations can be used to characterize the uncertainty [33]. Different price scenarios can be constructed by extracting many outcomes from the PDF parameters [50] or by using long short-term memory neural networks [74], resorting to scenario reduction techniques to limit the number of scenarios used in the analysis. In other cases, market prices are modelled as a random process applied to stochastic dynamic programming by assuming stage-wise independent probability density functions [34]. Further approaches do not use probability distributions, defining the uncertainty sets applied in robust optimization models [35], e.g., assuming a percentage of the actual price fluctuations around a predicted value [31]. The uncertainty characterization of the generation from renewable energy and the demand is typically determined starting from historical

data. For photovoltaic systems, the relevant variable is solar irradiance, from which power generation is determined using dedicated models [30,32]. In other cases, generated power data are used to determine the parameters of probability distributions starting from data available from datasets [36,39,38,55] or calculated from forecasts [33,47]. In other applications, renewable generation is modelled as a random process starting from historical data [34], or uncertainty is considered within an information-gap decision-theory framework. The uncertainty characterization of the demand follows aspects like the ones indicated above about the use of historical data for determining the parameters of probability distributions from forecasting results [33,47], the possible creation of scenarios handled with scenario reduction techniques [36], and the definition of uncertainty sets for applications in robust optimization [35]. Specific approaches consider daily peak consumption [29] or electric vehicle demand [30] as random variables.

Further contributions indicated in Table 1 address some aspects outside the scope of this paper, such as the allocation of CES/m available capacity [58], the definition of control strategies for energy management in the energy community with CES/m through model predictive control [62] or in real-time [61], the CES/m system trading in a local energy market [60], the energy management carried out by a SES provider in an energy trading system [57], the SES control by distribution companies and users [59], the CES management for voltage regulation and network losses reduction [56], and the role of CES/o for increasing fairness and equity in renewable energy communities [23].

From the results shown in Table 1, it emerges that none of the studies addresses simultaneously all the aspects indicated in the columns of the table. Moreover, significant aspects include the importance of representing battery degradation by incorporating battery lifetime into the model, and the treatment of uncertainties using a robust approach that does not require the specific representation of the probability distributions of random variables over time.

On this basis, the main contributions of this study are as follows:

- The development of a novel two-stage framework for optimal sizing and robust feasibility analysis for the CBES system in a residential community. The specific aspect is that the two stages are linked by using, in the second stage, the total capacity determined for a DBES in the first stage to set up the CBES capacity, ensuring comparability of the outcomes.
- The customization of the CBES service to the needs of an energy community, considering that the exclusive privilege of CBES is the lower unitary cost of the centralized technology, which makes it possible to install a CBES capacity analogous to the total optimal DBES capacity to provide a similar service to the energy community at a lower cost.
- The inclusion of a detailed model of the battery lifetime in the overall framework of analysis.
- The simultaneous modelling of the uncertainties of the electricity market price, generation from renewable energy sources, and load, considering the net power trading with the residential users (RUs).[5]

The framework developed in this paper involves two stages:

(1) In the first stage, optimal sizing of the DBES is conducted for RUs. Optimal sizing is investigated for different household types based on their electricity tariff and the installed rooftop PV capacity. It is assumed that the users use flat or TOU electricity tariffs.

(2) In the second stage, feasibility analysis of the CBES is conducted based on the optimal capacity of the battery resulting from the first stage. A robust optimization approach is utilized in the second stage. The profit of the CBES operator is maximized by optimizing the exchange power between the CBES and the main grid. The CBES exchanges electricity with the main grid under real-time pricing (RTP). The main motivation for adopting robust optimization is to account for uncertainties in electricity market prices and variations in net power trading with RUs to maximize the profit of the CBES operator in the worst-case[6] of variations.

Overall, the two stages have a different focus, with Stage 1 carrying out an optimization from the users' side, while Stage 2 addresses optimization from the CBES operator side. In Stage 1, the optimal DBES capacity for each residential user (RU) is determined by minimizing their cost of energy (COE). These optimal capacities are then aggregated and utilized in Stage 2, where the CBES operator manages the corresponding CBES to maximize profit.

The proposed optimal CBES is examined for a case study in South Australia. For this purpose, real data of load demand, price of battery, solar PV output, as well as electricity prices for Flat, TOU, and RTP are used in the optimization model.

The remainder of this paper is organized as follows. Section 2 describes the CBES concept and the proposed optimization framework. The optimal sizing problem of the first stage optimization is discussed in Section 3. Section 4 explains the feasibility analysis of the second stage optimization. The case study and optimization results of the first and second stages are presented in Section 5. Section 6 concludes the paper and indicates some directions for future work.

2. The CBES concept and the proposed framework

The CBES concept and the proposed optimization framework for optimal sizing and feasibility analysis of the CBES are discussed in this section.

2.1. CBES concept

The introduction of CBES is addressed as a complementary asset to DBES, not as a replacement for existing DBES. By installing DBES, the aim of the RUs equipped with rooftop solar PV is to minimize their cost of electricity (COE). However, there are still several challenges with DBES integration:

(1) The cost of the DBES technology is high due to the small battery capacity.

(2) DBES cannot participate in the market's energy arbitrage due to regulatory policies for small-scale batteries; and,

(3) In most cases, the householders are unable to use RTP tariffs and are instead required to use Flat or TOU tariffs, which reduce the DBES's profitability.

In this paper, a mathematical model is developed to determine the optimal capacity of DBES considering the power generation of the PV system and the electricity tariff. It is shown that the current price of DBES is not economically viable for users to invest in, so a new solution is required to reduce the cost of installing DBES. An efficient solution is to use a large amount of aggregated battery storage to provide

[5] The net power trading with the RUs is defined, at each time step of the analysis, as the sum of the power that users received from the grid minus the sum of the extra power that users injected into the grid. Therefore, this parameter is considered as an uncertain parameter to address the uncertainties of both the load and output power of PV systems.

[6] The robust optimization approach determines the best solution in worst-case conditions and could lead to over-conservative results [75]. Less conservative results can be obtained from adaptive robust optimization and distributionally robust optimization approaches. However, in this paper the robust optimization approach is used intentionally to check whether the CBES solution is better than the solution with DBES also in worst-case conditions of parameter uncertainty.

commercial cloud capacity to end users. This is the main idea of CBES: sharing energy storage capacity among users to achieve the revenue of a large-scale BES, rather than using only small-scale DBES.

Fig. 1 shows a general scheme of a CBES for RUs in an energy community. As indicated, there are three sectors in the CBES: (1) CBES users, (2) CBES operator, and (3) CBES facilities. The CBES facilities are the installed BESs in the system. The CBES can install different battery technologies, such as Lead-acid, Lithium-ion, or flow batteries, to take advantage of a variety of characteristics for investment cost, ageing, charging/discharging rate, maintenance cost, and efficiency.

The CBES users in this study are the RUs acting as prosumers in a residential community. These prosumers can purchase or rent the required capacity from the CBES to reduce their electricity cost through a contract assignment with the CBES operator. This contract has the following conditions:

- The assigned capacity of the CBES for the prosumers is charged or discharged similarly to the behind-the-meter DBES. Therefore, the optimal charging/discharging decisions of the RUs regarding their assigned capacity are sent to the CBES operator, and the CBES operator must guarantee these decisions for the RUs.
- The net present cost (NPC) obtained from the optimal sizing problem of the DBES, which shows the investment and maintenance costs of the assigned capacity in the contract period, must be paid by the RUs to the CBES.[7]

Therefore, the capacity of the CBES is determined regarding the assigned capacities requested by the RUs. The CBES operator is responsible for running the CBES in accordance with the charging/discharging requests from the RUs. Then, the operator can maximize the profit of the CBES according to the electricity market price for exchanging power with the grid.

2.2. Proposed framework

The determination of the optimal assigned battery capacity for the RUs that considers the decision-making of the CBES operator is essentially a two-stage optimization problem [76]. In this study, the optimal capacity of the CBES will be determined based on the individual users' requirements. On the other hand, users cannot participate in the market with their individual batteries. For this purpose, a two-stage optimization framework is developed for optimal sizing and feasibility analysis of CBES. In this model, the CBES operator knows the optimal battery capacity for each user from the results of the first stage problem. The total capacity of CBES is equal to the total capacity of the DBESs in the residential community. The second stage problem is only dedicated to maximizing the profit of the CBES. It is notable that the conventional single-stage optimization frameworks for the CBES only investigate the profitability for the CBES operator and do not analyze the optimal sizing and economic terms for the users. However, the users are subject to different electricity pricing tariffs and are equipped with different PV sizes, which makes the economic analysis and optimal BES capacity vary across users. Hence, the optimal sizing must be investigated first for different users, and then the feasibility analysis is carried out for the CBES.

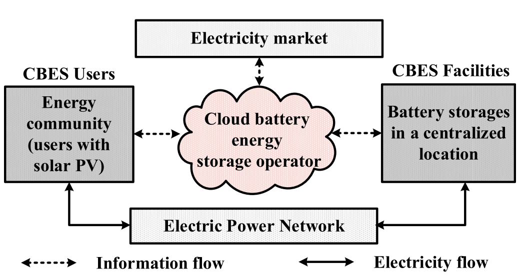

Fig. 1. A general scheme of CBES for residential users.

Fig. 2 shows the proposed optimization framework. In the first stage, optimal sizing of DBES is developed for RUs. The decision variable at this stage is the DBES capacity for different users. It is assumed that only the users with rooftop solar PV can purchase DBES for their homes; thus, users who decide to buy and manage a local BES, regardless of cost, are excluded from the evaluation of the DBES capacity. The COE of the RUs is selected as the objective function. The COE is a widely used index for evaluating the economic aspects of electricity systems in residential case studies [3]. The associated constraints with DBES (i.e., state-of-charge (SOC) and available input/output powers), as well as the power trading constraints with the grid, are considered.

When the optimization procedure of the first stage is terminated, the following results are extracted to be used in the second stage: (*i*) total DBES capacity of all users, (*ii*) the affordable battery price for economic investment by the users, (*iii*) the total NPC of DBES, and (*iv*) the users' charging/discharging pattern of DBES.

In the second stage, the results from the first stage are used to assess the economic feasibility of the CBES. In this stage, a robust optimization model is developed. The objective of this stage is to maximize the profit of CBES in the worst case of variations of the electricity market price and the net power trading with the RUs. The decision variable is the exchange power between the CBES and the main grid. The CBES is obliged to meet the charging/discharging pattern of the users (obtained from the first stage). Once the profit of the CBES is maximized, the NPC of the CBES is calculated and is then compared to the total NPC of DBES in the first stage. If the NPC of the CBES is lower than the total NPC of the DBES, the application of the CBES is economically feasible in the system.

The proposed two-stage optimization framework is used for an energy community in a distribution network with a number of RUs. The proposed approach assumes that no constraints of the distribution network are violated during CBES operation. This assumption is also motivated by the fact that with the use of CBES, power flow variations are typically smoothed, increasing the possibility of remaining inside the

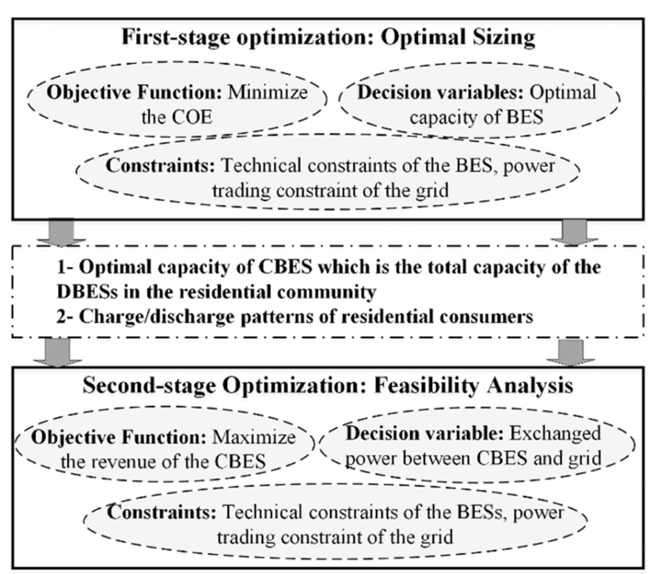

Fig. 2. Two-stage optimization framework for optimal sizing and feasibility analysis of CBES in a residential community.

[7] This obtained NPC is compared with the NPC determined in the second-stage problem to feasibility analysis of using the CBES. The procedure of this settlement between the RUs and CBES system is beyond the scope of this paper.

network constraints more easily. It is notable that the optimal capacity determined in the first stage is also uncertain due to weather and load variations. However, it was shown in [14] that the size of DBES is nearly the same across 10 real-data scenarios for weather and load in the same case study used in this paper.

3. First Stage Optimization: Optimal DBES Sizing

The problem formulation of the first stage optimization is presented in this section. In this stage, optimal sizing of DBES is formulated to achieve the optimal battery capacity for different users. The set of RUs is denoted as $\boldsymbol{I}$, the set $\boldsymbol{T}$ contains the successive time steps considered, and the time interval of analysis (in hours) is denoted as Δt.

The COE of the RUs is selected as the objective function. The optimal sizing problem in the first stage optimization, solved for each user $i \in \boldsymbol{I}$, separately, is formulated as follows:

$$\underset{\boldsymbol{V}_i^{\mathrm{DB}}}{\text{minimize}}\left\{COE_i^{\mathrm{RU}}\right\}, \quad i \in \boldsymbol{I} \tag{1}$$

$$COE_i^{\mathrm{RU}} = \frac{NPC_i^{\mathrm{DB}}\mathrm{CRF} + AB_i^{\mathrm{RU}}}{E_i^{\mathrm{RU}}} \tag{2}$$

subject to:

$$0 \le Q_i^{\mathrm{DB}} \le \mathrm{Q}_{\max}^{\mathrm{DB}} \tag{3}$$

$$P_i^{\mathrm{PV}}(t) + P_i^{\mathrm{RU,gin}}(t) + P_i^{\mathrm{DB,ds}}(t) = P_i^{\mathrm{RU,gout}}(t) + P_i^{\mathrm{DB,ch}}(t) + P_i^{\mathrm{RU}}(t) \tag{4}$$

$$S_i^{\mathrm{DB}}(t) = S_i^{\mathrm{DB}}(t-\Delta t) + \frac{\left(P_i^{\mathrm{DB,ch}}(t)\,\eta_{\mathrm{ch}} - P_i^{\mathrm{DB,ds}}(t)\big/\eta_{\mathrm{ds}}\right)\Delta t}{Q_i^{\mathrm{DB}}} \tag{5}$$

$$\mathrm{S}_{\min}^{\mathrm{B}} \le S_i^{\mathrm{DB}}(t) \le \mathrm{S}_{\max}^{\mathrm{B}} \tag{6}$$

$$0 \le P_i^{\mathrm{DB,ch}}(t) \le Q_i^{\mathrm{DB}}\,\mathrm{R}^{\mathrm{bat}}\left(1 - X_i^{\mathrm{DB,cd}}(t)\right) \tag{7}$$

$$0 \le P_i^{\mathrm{DB,ds}}(t) \le Q_i^{\mathrm{DB}}\,\mathrm{R}^{\mathrm{bat}}\,X_i^{\mathrm{DB,cd}}(t) \tag{8}$$

$$0 \le P_i^{\mathrm{RU,gin}}(t) \le \mathrm{P}_{\max}^{\mathrm{RU,gin}}\left(1 - X_i^{\mathrm{DB,g}}(t)\right) \tag{9}$$

$$0 \le P_i^{\mathrm{RU,gout}}(t) \le \mathrm{P}_{\max}^{\mathrm{RU,gout}}\,X_i^{\mathrm{DB,g}}(t) \tag{10}$$

Eq. (1) represents the objective function (COE_i^{RU}), in which the COE of the user $i \in \boldsymbol{I}$ is minimized. $\boldsymbol{V}_i^{\mathrm{DB}}$ is the set of decision variables for the first-stage optimization, composed of Q_i^{DB}, $P_i^{\mathrm{DB,ch}}$, $P_i^{\mathrm{DB,ch}}$, S_i^{DB}, $X_i^{\mathrm{DB,cd}}$, $P_i^{\mathrm{RU,gin}}$, $P_i^{\mathrm{RU,gout}}$, and $X_i^{\mathrm{DB,g}}$. Eq. (2) indicates that the COE is calculated based on the NPC of the battery (NPC_i^{DB}), capital recovery factor (CRF), total electricity demand of the RU (E_i^{RU}), and the annual electricity bill of the user (AB_i^{RU}), as detailed below.

The constraints of the first-stage problem (optimal sizing) are expressed by (3)-(10). The capacity of the batteries is limited by $\mathrm{Q}_{\max}^{\mathrm{DB}}$ in (3). The power balance should be maintained at each time interval between demand and generation, as in (4). Herein, $P_i^{\mathrm{RU,gin}}$ and $P_i^{\mathrm{RU,gout}}$ are the net power imported/purchased from and exported/sold to the grid by the RU, respectively. The SOC is calculated based on its value in the previous time interval and the battery power change in the current time interval as shown by (5). Eq. (6) represents the SOC that should be maintained between its minimum value $\mathrm{S}_{\min}^{\mathrm{B}}$ and maximum value $\mathrm{S}_{\max}^{\mathrm{B}}$. The charging and discharging power values of DBES are limited to the capacity of the DBES multiplied by the ratio of power to energy of the battery unit ($\mathrm{R}^{\mathrm{bat}}$) as shown in (7) and (8), respectively. The binary variable $X_i^{\mathrm{DB,cd}}$ is added to avoid charging and discharging simultaneously. Eqs. (9) and (10) describe the limitations of the import/export power from/to the grid, $\mathrm{P}_{\max}^{\mathrm{RU,gin}}$ and $\mathrm{P}_{\max}^{\mathrm{RU,gout}}$, respectively, by the RUs. The binary variable $X_i^{\mathrm{DB,g}}$ avoids importing and exporting power at the same time interval.

The annual electricity bill of RUs can be calculated based on the annual supply charge (ASC) of electricity, as well as the total cost for imported and exported electricity, as follows:

$$AB_i^{\mathrm{RU}} = ASC^{\mathrm{RU}} + \sum_{t\in \boldsymbol{T}} \mathrm{C}_i^{\mathrm{RU,gin}}(t)\;P_i^{\mathrm{RU,gin}}(t)\Delta t - \sum_{t\in \boldsymbol{T}} \mathrm{C}_i^{\mathrm{RU,gout}}(t)\;P_i^{\mathrm{RU,gout}}(t)\Delta t \tag{11}$$

The annual supply charge of electricity for the RUs is calculated from the daily supply charge, which is a fixed cost for maintaining the infrastructure used to connect the RUs to their energy supply.

The NPC of the battery (NPC_i^{DB}) is calculated by taking into account the capital present cost ($\mathrm{PC}^{\mathrm{DB,c}}$), replacement present cost ($PC_i^{\mathrm{DB,r}}$), maintenance present cost ($\mathrm{PC}^{\mathrm{DB,m}}$), and salvation cost ($PC_i^{\mathrm{DB,s}}$), as follows:

$$NPC_i^{\mathrm{DB}} = Q_i^{\mathrm{DB}}\left(\mathrm{PC}^{\mathrm{DB,c}} + PC_i^{\mathrm{DB,r}} + \mathrm{PC}^{\mathrm{DB,m}} - PC_i^{\mathrm{DB,s}}\right) \tag{12}$$

The capital present cost of the battery is the initial investment at the beginning of the project.

The replacement present cost of the battery, if required, is expressed by:

$$PC_i^{\mathrm{DB,r}} = \frac{\mathrm{RC}^{\mathrm{DB,r}}}{(1+\mathrm{ir})^{Y_i^{\mathrm{DB}}}} \tag{13}$$

where $\mathrm{RC}^{\mathrm{DB,r}}$ is the replacement cost of the battery, ir is the interest rate, and Y_i^{DB} is the obtained lifetime for the battery.

The maintenance present cost of the battery is paid yearly and, considering the project lifetime of n years, can be calculated by:

$$\mathrm{PC}^{\mathrm{DB,m}} = \frac{\mathrm{MC}^{\mathrm{DB,m}}}{\mathrm{CRF}} \tag{14}$$

$$\mathrm{CRF} = \frac{\mathrm{ir}(1+\mathrm{ir})^{\mathrm{n}}}{(1+\mathrm{ir})^{\mathrm{n}} - 1} \tag{15}$$

The salvation present cost of the battery ($PC_i^{\mathrm{DB,s}}$), which is the cost of the battery at the end of project life, is given by:

$$PC_i^{\mathrm{DB,s}} = \frac{L_i^{\mathrm{DB}}}{Y_i^{\mathrm{DB}}}\,\frac{\mathrm{PC}^{\mathrm{DB,c}}}{(1+\mathrm{ir})^{\mathrm{n}}} \tag{16}$$

where the battery lifetime Y_i^{DB} (in years) is estimated based on the total energy throughput in annual operation. Hence, the estimated battery lifetime (replacement year), which cannot exceed the battery's calendar lifetime $\mathrm{CL}^{\mathrm{DB}}$, is given by:

$$Y_i^{\mathrm{DB}} = \min\left\{\mathrm{CL}^{\mathrm{DB}}, \frac{Q_i^{\mathrm{DB}}\,\tau^{\mathrm{ref,thr}}}{E_i^{\mathrm{DB,tot}}\mathrm{Q}^{\mathrm{ref,thr}}}\mathrm{Y}^{\mathrm{ref}}\right\} \tag{17}$$

where the reference energy throughput $\tau^{\mathrm{ref,thr}}$ for $\mathrm{Y}^{\mathrm{ref}} = 1$ year of a lithium-ion battery with reference capacity $\mathrm{Q}^{\mathrm{ref,thr}} = 1$ kWh is taken from [77]. The total energy throughput in annual operation $E_i^{\mathrm{DB,tot}}$ is calculated based on the total annual charging/discharging energy of the battery. The remaining lifetime of DBES at the end of the project (L_i^{DB}) is calculated using an "if " function based on the project lifetime (n) and the obtained battery life (Y_i^{DB}) as follows:

$$\text{if}\,Y_i^{\mathrm{DB}} \le n\ \text{then}\,L_i^{\mathrm{DB}} = 0$$

$$\text{else}\,L_i^{\mathrm{DB}} = Y_i^{\mathrm{DB}} - \mathrm{n} \tag{18}$$

It is assumed that the RUs are not allowed to purchase/sell electricity from/to the grid by charging/discharging their DBESs. This is necessary to manage the interactions between RU-based DBES and cloud-based CBES consistently, as the RUs cannot participate in the market. More generally, CBES management can be one of the functions of energy community management.

4. Second stage optimization: robust feasibility analysis

The second stage optimization investigates the feasibility of the optimized battery capacity determined at the first stage from the CBES point of view. The feasibility assessment in this study is primarily conducted from the operator's perspective, focusing on system-level performance and operational viability. At the same time, the economic attractiveness for users is also assessed by applying the same DBES capacity obtained from the first stage, ensuring that the battery system remains a viable and profitable investment for residential customers.

In the second stage, the energy capacity of CBES is determined from the total energy capacity of the batteries found at the first stage:

$$Q^{\mathrm{CB}} = \sum_{i\in \boldsymbol{I}} Q_i^{\mathrm{DB}} \tag{19}$$

At the first step, the CBES operator's profit from trading energy with the electricity market is formulated as a deterministic model. Then, to model the CBES operator's profit in the worst case in the face of uncertainties, the proposed deterministic model is reformulated as a robust one. At the end, to compare the economic feasibility of CBES with that of DBES, the NPC of CBES is formulated.

4.1. Deterministic model

The objective function of the second stage is to maximize the profit of the CBES from participating in the market in the period of analysis with T hours. Considering the set $\boldsymbol{V}^{\mathrm{CB}}$ of the decision variables in the CBES optimization problem, composed of $P^{\mathrm{CB,gin}}$, $P^{\mathrm{CB,gout}}$, $P^{\mathrm{CB,ch}}$, $P^{\mathrm{CB,ds}}$, $X^{\mathrm{CB,cd}}$, S^{CB}, and $X^{\mathrm{CB,g}}$, the following objective function is maximized considering the net power of the CBES as in (22):

$$\underset{\boldsymbol{V}^{\mathrm{CB}}}{\mathrm{maximize}} PRA^{\mathrm{CB}} \tag{20}$$

$$PRA^{\mathrm{CB}} = \sum_{t\in \boldsymbol{T}} \lambda^{\mathrm{RTP}}(t) P^{\mathrm{CB,g}}(t) \quad \Delta \mathrm{t} \tag{21}$$

$$P^{\mathrm{CB,g}}(t) = P^{\mathrm{CB,gout}}(t) - P^{\mathrm{CB,gin}}(t) \tag{22}$$

where PRA^{CB} represents the CBES profit from arbitrage, calculated as the revenue from electricity sold to the grid by the CBES minus the cost of the electricity purchased by the CBES. It is also important to note that Stage 2 adopts the same time resolution as Stage 1, with a time interval (Δt) of 1 h and a full-year simulation period (8760 hours), thereby ensuring consistency in the modelling framework and comparability of results.

Eq. (23) is used to model the power balance constraint of the CBES in net form, where the difference between the purchased power from the market and the charging power of the CBES is equal to the difference between the sold power to the market and the discharging power of the CBES, plus the net power exchange with the RUs.

$$P^{\mathrm{CB,gin}}(t) - P^{\mathrm{CB,ch}}(t) = P^{\mathrm{CB,gout}}(t) - P^{\mathrm{CB,ds}}(t) + P^{\mathrm{RU,net}}(t) \tag{23}$$

Eqs. (24) and (25) are used to model the maximum power limitation of the CBES to trade power with the main grid. The binary variable $X^{\mathrm{CB,g}}(t)$ is equal to unity when there is an input to the grid.

$$0 \le P^{\mathrm{CB,gin}}(t) \le \mathrm{P}_{\mathrm{g,max}}^{\mathrm{CB}} \; X^{\mathrm{CB,g}}(t) \tag{24}$$

$$0 \le P^{\mathrm{CB,gout}}(t) \le \mathrm{P}_{\mathrm{g,max}}^{\mathrm{CB}} \; \left(1 - X^{\mathrm{CB,g}}(t)\right) \tag{25}$$

The maximum charging/discharging power limitation of the CBES is modeled as (26) and (27), respectively. The effect of charging/discharging power of the CBES on its SOC is modeled in (28). The minimum and maximum limitations of the stored energy in the CBES are modeled in (29).

$$0 \le P^{\mathrm{CB,ch}}(t) \le Q^{\mathrm{CB}} \, \mathrm{R}^{\mathrm{bat}} \; X^{\mathrm{CB,cd}}(t) \tag{26}$$

$$0 \le P^{\mathrm{CB,ds}}(t) \le Q^{\mathrm{CB}} \, \mathrm{R}^{\mathrm{bat}} \left(1 - X^{\mathrm{CB,cd}}(t)\right) \tag{27}$$

$$S^{\mathrm{CB}}(t) = S^{\mathrm{CB}}(t-\Delta t) + \frac{\left(P^{\mathrm{CB,ch}}(t)\eta_{\mathrm{ch}} - P^{\mathrm{CB,ds}}(t)/\eta_{\mathrm{ds}}\right)\Delta t}{Q^{\mathrm{CB}}} \tag{28}$$

$$\mathrm{S}_{\mathrm{min}}^{\mathrm{B}} \le S^{\mathrm{CB}}(\mathrm{t}) \le \mathrm{S}_{\mathrm{max}}^{\mathrm{B}} \tag{29}$$

Since the capacity of the CBES is determined in the first-stage optimization problem, in this stage, the total annual energy throughput of the CBES is considered as a limitation for the power charging/discharging of the CBES. The total annual energy throughput of the CBES is calculated based on the CBES capacity multiplied by the reference energy throughput $\tau^{\mathrm{ref,thr}}$ for one year of a lithium-ion battery with reference capacity $\mathrm{Q}^{\mathrm{ref,thr}} = 1$ kWh [14].

$$\sum_{t\in \boldsymbol{T}} \left(P^{\mathrm{CB,ch}}(t) + P^{\mathrm{CB,ds}}(t)\right)\Delta \mathrm{t} \le \frac{Q^{\mathrm{CB}} \; \tau^{\mathrm{ref,thr}}}{\mathrm{Q}^{\mathrm{ref,thr}}} \tag{30}$$

In the proposed framework, the contract cost paid by users is based on their equivalent NPC, which is derived from the optimal DBES sizing in Stage 1 that minimizes their COE. This ensures that users achieve the lowest possible energy cost compared to alternative options (e.g., without storage or with individually owned storage). Therefore, the users' benefit is inherently guaranteed through COE minimization. The operator's profit in Stage 2 is generated through coordinated operation and market participation of the aggregated CBES, which enables additional value streams (e.g., arbitrage) that are not accessible at the individual user level. As such, the framework is designed to be mutually beneficial, where users reduce their energy costs while the operator captures value from aggregation and optimized operation, rather than extracting surplus at the expense of users.

4.2. Robust Model

The price of electricity market and the net power trading with the RUs are considered as two uncertain parameters in the decision-making problem of the CBES operator. To protect the CBES operator's decisions against these uncertainties, the proposed model in the previous subsection is reformulated as a robust optimization model as (31)-(36). Details of this reformulation are described in the Appendix.

$$PRA_{\mathrm{robust}}^{\mathrm{CB}} = \sum_{t\in \boldsymbol{T}} \lambda^{\mathrm{RTP}}(t) P^{\mathrm{CB,g}}(t) \quad \Delta \mathrm{t} + \sum_{t\in \boldsymbol{T}} q^{\mathrm{RTP}}(t) + \Gamma^{\mathrm{RTP}} z^{\mathrm{RTP}} \tag{31}$$

$$q^{\mathrm{RTP}}(t) + z^{\mathrm{RTP}} \ge \alpha^{\mathrm{RTP}} \lambda^{\mathrm{RTP}}(t) y^{\mathrm{RTP}}(t) \; \Delta \mathrm{t} \tag{32}$$

$$-y^{\mathrm{RTP}}(t) \le P^{\mathrm{CB,g}}(t) \le y^{\mathrm{RTP}}(t) \tag{33}$$

$$\begin{aligned} P^{\mathrm{CB,gin}}(t) - P^{\mathrm{CB,ch}}(t) &= P^{\mathrm{CB,gout}}(t) - P^{\mathrm{CB,ds}}(t) + P^{\mathrm{RU,net}}(t) + q^{\mathrm{RU}}(t) \\ &\quad + \left(\Gamma^{\mathrm{RU}}(t)\right)^2 Z^{\mathrm{RU}}(t) \end{aligned} \tag{34}$$

$$q^{\mathrm{RU}}(t) + z^{\mathrm{RU}}(t) \ge \alpha_{\mathrm{net}}^{\mathrm{RU}} \, P^{\mathrm{RU,net}}(t) \, y^{\mathrm{RU}}(t) \tag{35}$$

$$y^{\mathrm{RU}}(t) \ge 1 \tag{36}$$

4.3. NPC of the CBES

To compare the cost of installing the CBES with the DBES, it is necessary to calculate the NPC of the CBES as (37). The first term is the present capital cost of the CBES, which is a portion of the present capital cost for the total DBES as (38), where α is a coefficient in per cent that represents the reduction in CBES costs due to economies of scale. The second, the third, and the fourth terms are used to model the replacement, the maintenance, and the salvation present costs of the CBES, which can be calculated similarly to the equations presented for the DBES. The present operation cost of the CBES is the opposite of the profit the CBES earns from participating in the market over the CRF. Since the operation cost is calculated annually, its present cost is obtained using the CRF as the last term in (37).

$$NPC^{CB} = Q^{CB}\left(PC^{CB,c} + PC^{CB,r} + PC^{CB,m} - PC^{CB,s}\right) - \frac{PRA^{CB}}{CRF} \tag{37}$$

$$PC^{CB,c} = \alpha\, PC^{DB,c} \tag{38}$$

5. Case study and results

The case study and results for the first and second stages are evaluated in this section. The time interval is $\Delta t = 1$ h.

5.1. Case study

A residential community in South Australia is considered as the case study. It is assumed that 500 end users are available at the residential community. Noting that 50% of South Australian houses have already installed rooftop PV [78], it is considered that 250 houses (of the 500 houses) in the residential community are equipped with a PV system. Since only the houses with rooftop PV can contribute to the CBES application, those 250 houses with PV can purchase battery capacity from the CBES. It is also assumed that 150 houses (PV-equipped) use flat electricity rates, and the remaining 100 houses use a TOU electricity tariff. The RUs are not allowed to use RTP for the electricity tariff. The houses considered have installed a range of PV capacities of 3 kW, 5 kW, 7 kW, and 9 kW. The PV generation profile is scaled according to the assigned capacity for each household, while a representative residential load profile is adopted. This synthetic aggregation approach enables a realistic representation of community-level diversity while maintaining computational tractability. The solar PV generation profile and load profile for a residential household were adopted from [14]. Fig. 3 illustrates the actual data on the total output power of PV and the total electricity demand of the users contributing to the CBES.

Table 2 lists the flat and TOU electricity prices for the RUs [77]. It is shown that in the flat tariff, the electricity price remains constant throughout the day. However, the TOU tariff changes the electricity price for off-peak, shoulder, and peak periods. The RTP data for the electricity market in 2020 was obtained from the Australian Energy Market Operator (AEMO) website [79]. The project lifetime is 10 years, and the interest rate is assumed as 8%. The grid export limit is set at 5 kW for residential solar PV installations in Australia [80]; therefore, the same export limit has been applied uniformly across all households,

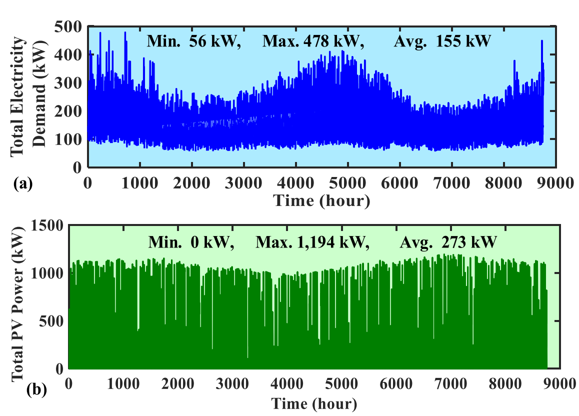

Fig. 3. (a) Total electricity demand of the users, and (b) Total PV output power for the users.

Table 2
Electricity prices for users [15].

Tariff*	Time (hour)	Rate for import from the grid	Rate for export to the grid
Flat (¢/kWh)	All day hours	48	17
TOU (¢/kWh)	Peak (6 pm - 11 pm)	60	18
	Shoulder (8 am - 6 pm)	40	10
	Off-peak (11 pm - 8 am)	25	5

*The users can only use Flat or TOU pricing tariffs and cannot use RTP for energy trading because of grid limitations for small-scale consumers.

regardless of their PV capacities. Similarly, the import limit is assumed to be 5 kW for all households.

Currently, the price of distributed residential battery storage, Lithium-ion type, is around $1000 per kWh, including installation costs and GST (goods and services tax) in Australia [81]. The battery's calendar lifetime is assumed to be 20 years [77]. Table 3 summarizes the technical characteristics of BES. The maintenance costs of DBES and CBES are assumed to be $10/kWh and $5/kWh, respectively. It is noted in [18] that the price of a battery for CBES is 65% of the price of a battery for DBES. Table 4 lists the economic assumptions of the project. The initial SOC represents the battery condition at the beginning of the simulation horizon. No explicit terminal SOC constraint is imposed in the current model. However, given the long simulation horizon (e.g., 8760 hours), the impact of the end SOC on the overall results is minimal and does not significantly affect the operational strategy.

The proposed optimization model is implemented in the General Algebraic Modelling System (GAMS). The problem is formulated as a mixed-integer linear programming model and is solved using CPLEX as a standard commercial solver available within GAMS. Default solver settings are adopted unless otherwise specified.

5.2. First-stage results

The optimization model resulted in zero DBES capacity for the RUs based on the current battery price ($1000/kWh). Hence, the optimization is repeated by reducing the battery price in steps of $10 to obtain an affordable price of DBES for the

users. The affordable price is defined as the maximum battery cost, but still below the market price of a residential battery, at which the residential user can adopt the DBES while minimizing the COE, ensuring the most economically efficient system configuration. Table 5 lists the optimal sizing results for DBES in the houses considered in the residential community. As shown in the table, the affordable battery price ranges from 510 $/kWh to 610 $/kWh across different users. The optimized capacity of DBES is the lowest, 2 kWh, for the users with a flat electricity rate and 3 kW rooftop PV. However, the highest DBES capacity is 8 kWh for users on a flat electricity tariff with 7 kW and 9 kW rooftop PV. For the users with TOU tariff, the optimized battery capacity is obtained from 4 kWh to 7 kWh. The NPC of DBES increases with battery capacity. As shown, the COE is decreased significantly for the RUs with flat and TOU tariffs.

The optimized capacity of DBES, affordable battery price, NPC, and

Table 3
Battery energy storage characteristics.

Characteristic	Symbol	Value
Unit size	E^{DB}/P^{DB}	1 kWh/0.4 kW
Initial SOC	-	70%
Maximum SOC	S^{B}_{max}	100%
Minimum SOC	S^{B}_{min}	20%
Input/output efficiency	η_{ch}/η_{ds}	95%

Table 4
Economic assumptions for the project.

Parameter	Value
Project lifetime	10 years
Interest rate	8%
Battery market price for DBES	$1000/kWh
Battery market price for CBES	$650/kWh
Maintenance cost of DBES	$10/kWh
Maintenance cost of CBES	$5/kWh

Table 5
Optimal sizing results for DBES in the types of houses considered in the residential community.

Type of house	DBES capacity (kWh)	Affordable price* ($/kWh)	NPC of DBES ($)	COE (¢/kWh)	Number of houses
Flat with 3 kW PV	2	510	953	30.13	25
Flat with 5 kW PV	5	520	2509	20.97	50
Flat with 7 kW PV	8	550	4254	12.81	50
Flat with 9 kW PV	8	570	4414	7.52	25
TOU with 3 kW PV	4	610	2426	26.34	15
TOU with 5 kW PV	6	610	3730	19.79	35
TOU with 7 kW PV	7	610	4142	15.19	35
TOU with 9 kW PV	7	610	4142	9.67	15
Total	1520	-	846,365	-	250

*This is the affordable price of DBES for economic investment by the users after reducing the current price of the battery. It is notable that the current price of DBES is $1000/kWh.

charging/discharging pattern of DBES are extracted to be used in the next stage. Fig. 4 shows the charging/discharging pattern of the users to

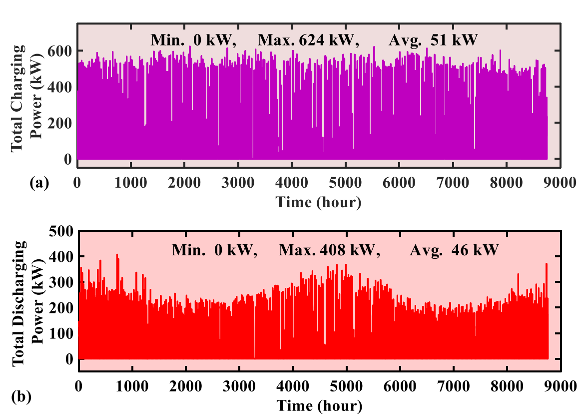

Fig. 4. (a) Total charging power of the DBESs, and (b) Total discharging power of the DBESs.

be met by the CBES in the second stage.

After terminating the optimal sizing of the first stage, the total NPC for the DBES investment in the residential community is calculated as follows:

$$NPC_{\mathrm{tot}}^{\mathrm{DB}} = \sum_{i \in \boldsymbol{I}} NPC_i^{\mathrm{DB}} \tag{39}$$

where NPC_i^{DB} is the NPC of the battery for user i.

Based on (39) and the results reported in Table 5, the total NPC of DBES for all users is obtained as $846,365.

5.3. Second-stage results

The economics of the CBES problem are given in Table 6. The energy capacity of the CBES is 1520 kWh, its capital and annual maintenance costs are $988,000 and $7600, respectively. Also, the annual CBES profit is $49,965. Therefore, the NPC of the CBES is $703,727, which is lower than the NPC obtained in the first-stage problem for the DBES for the RUs, i.e., $846,365. This is a clear confirmation of the effectiveness of introducing and exploiting CBES in the system.

It should be noted that the second-stage problem is solved over a *one-year period* (8760 hours), considering the decisions of the RUs shown in Fig. 4. However, to discuss the details of the optimal decisions of the CBES operator, some illustrative results are presented here for a typical day. For this purpose, the electricity market price for this typical day is shown in Fig. 5. The optimal decisions of the operator to charge/discharge the CBES and to trade energy with the market are shown in Fig. 6. The CBES operator's decisions depend on two main parameters, that is, the net power trading with Rus (obtained in the previous step) and the electricity market price. As shown in Fig. 6, the net power trading with users RUs in hours 1–8 is zero. Therefore, the behavior of the operator in these hours only depends on the market price. The CBES is charged through purchasing energy from the market in hours 1, 5, and 6, where the market price is low, as shown in Fig. 5. Then, the CBES is discharged in hours 2, 3, 7, and 8 to sell energy to the market due to the high electricity market price in these hours. In hours 9–14 and 17, the net power trading with the RUs is negative, meaning that the users need to receive power from the grid. For this purpose, the CBES operator purchases power from the grid to meet the demand of RUs. Also, the CBES is charged at hours 10, 12, and 13 due to the low market price in those hours. The net power traded with the users is positive in hours 16 and 18–24, meaning that the users have excess energy to deliver to the grid. Therefore, the CBES operator sells this extra energy to the market at these hours. Also, the CBES is discharged in hours 19 and 20 to sell energy to the market due to the high market price at these hours.

5.4. Sensitivity analysis

The sensitivity of the percentage of increasing the NPC to the robust parameters of price and net power trading with RUs is investigated. For this purpose, the uncertainty budget related to the electricity market price changes from 4 to 24 and the uncertainty deviation changes from 5 per cent to 15 per cent. Also, the uncertainty budget for the net power trading with the RUs changes from 0.2 to 1 and its deviation changes from 5 per cent to 20 per cent.

Table 6
Economics of the CBES problem.

Terms	Value ($)
Capital cost	988,000
Annual profit	49,965
Present profit	335,269
Annual maintenance cost	7600
Present maintenance cost	50,967
NPC	703,727

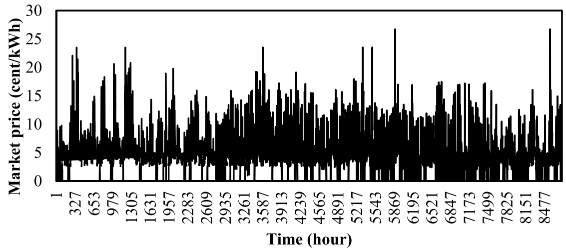

Fig. 5. The annual energy market price.

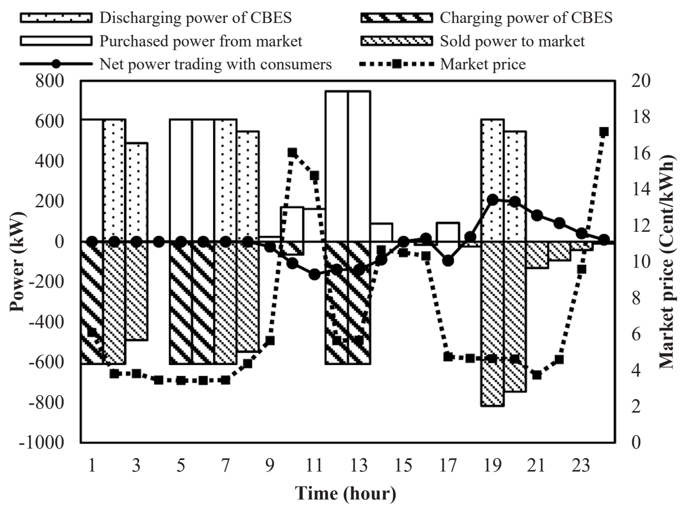

Fig. 6. The results of the energy balance of the CBES for a typical day.

Table 7 presents the percentage increase in the NPC due to uncertainties in energy market prices. The maximum percentage of NPC increase is 5.7% when the uncertainty budget and the deviation related to the electricity market price are at their highest values. In addition, when the budget and the deviation of the market price are the lowest, the minimum percentage of NPC increase is obtained.

Table 8 presents the percentage increase in the NPC due to uncertainties in energy market prices and net power trading with RUs, respectively. When the uncertainty budget of net power (Γ_t^{RU}) is 1 and its deviation is 20 per cent, the percentage of NPC increase reaches 3.12 per cent. Therefore, it can be concluded that the uncertainty of the market price has a greater effect on the CBES operator's cost in comparison with the net power trading with the RUs. It should be noted that the amount of the NPC in the worst case (when $\Gamma^{\mathrm{RTP}} = 24$, $\Gamma_t^{\mathrm{RU}} = 1$, $\alpha^{\mathrm{RTP}} = 15\%$, $\alpha_{\mathrm{net}}^{\mathrm{RU}} = 20\%$), is equal to \$765,804, which is still lower than the NPC obtained in the first-stage problem.

The sensitivity of the results is evaluated with respect to variations in the battery price for CBES. Fig. 7 shows the sensitivity of the NPC of the CBES to variations in the battery price. Moreover, this cost is compared with the NPC of the DBES, i.e., \$846,365. As shown in Fig. 7, when the battery price of CBES is \$743.84, the NPC of both the DBES and CBES are equal. In fact, for battery prices below this value, using the CBES leads to a lower NPC than using the DBES.

Table 7
Percentage of NPC increase regarding the uncertainty of energy market price.

Uncertainty deviation [5%–15%]	Uncertainty budget [4–24]					
	4	8	12	16	20	24
5%	0.48	0.89	1.26	1.61	1.95	2.28
10%	0.89	1.61	2.28	2.91	3.51	4.09
15%	1.26	2.28	3.22	4.08	4.91	5.70

Table 8
Percentage of NPC increase regarding the uncertainty of net power trading with RU.

Uncertainty deviation [5%–20%]	Uncertainty budget [0.2–1]				
	0.2	0.4	0.6	0.8	1
5%	0.03	0.12	0.28	0.50	0.78
10%	0.06	0.25	0.56	1.00	1.56
15%	0.09	0.37	0.84	1.50	2.34
20%	0.12	0.50	1.12	2.00	3.12

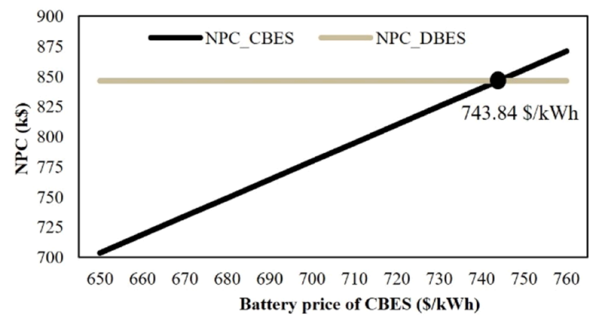

Fig. 7. Sensitivity of the NPC of the CBES to battery price.

5.5. Deeper penetration levels of PV

In this scenario, it is assumed that more end users will install distributed rooftop PV panels. Hence, a scenario analysis is conducted assuming higher PV unit diffusion in the residential community. To this end, the increased number of PVs is uniformly distributed across the RUs in Table 5. Fig. 8 shows the NPC of DBES and CBES as the penetration level of PV in the residential community increases. As shown, when the penetration level of PV increases, the NPCs of DBES and CBES increase uniformly. Hence, increasing the penetration level of PV cannot add greater benefits to the CBES option, but CBES remains a more attractive option for the residential community.

5.6. Aggregator for DBESs

In the base case, it is considered that the RUs cannot trade energy with the grid through RTP. Accordingly, to encourage RUs to install the DBES, the battery price was reduced to make the battery more affordable to purchase. In this sub-section, a use case is considered in which RUs are aggregated into a residential community using their DBESs and hence allowed to participate in the energy market to use the RTP through an aggregator. In this case, because the battery participates in the energy market, the price reduction is relaxed, and hence the base value for purchasing the battery, \$1000/kWh, is considered. In addition, consumers must pay a share of their revenues from trading energy with the market to the aggregator (e.g., 16%–24%, as mentioned in [82,83],

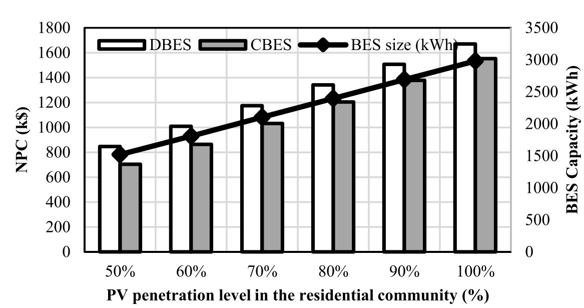

Fig. 8. NPC of DBES and CBES by increasing the penetration level of PV in the residential community.

which is neglected in this study (to obtain conservative results). The NPC of the DBES in this case is $1235,727, excluding payments to an aggregator. Nevertheless, the NPC of the CBES framework is still lower than that of the DBES, even with the DBES participating in the wholesale market. It should be noted that, although using an aggregator solves the participation problem of the DBES in the market, in the CBES framework, the CBES operator already has the function of an aggregator, so that:

- In the CBES framework, a lower cost is paid for purchasing the battery due to its large capacity; while in the DBES framework, a higher cost is paid for the battery due to low capacity, and the aggregator cannot reduce the battery price for consumers.
- In the CBES framework, only one operator is needed for energy management of the CBES, considering participation in the market. Therefore, no further aggregator is needed for CBES management.

6. Conclusion and future work

This study has investigated the optimal sizing and feasibility analysis of cloud battery energy storage (CBES) for a residential community. A two-stage optimization framework has been developed for the CBES. The proposed optimal CBES has been examined in a case study in Australia based on real data. It has been found that the current price of distributed battery energy storage (DBES), which is 1000 $/kWh, is not cost-effective for the economic integration of individual batteries by residential users (RUs). The results show that the DBES price should be reduced to at least 610 $/kWh to be economic. However, with the CBES concept, it was shown that the CBES battery price (650 $/kWh) is economic for the CBES operator and RUs. The robust optimization has illustrated that the CBES is still economic for the worst case of variations of electricity market price and the net power trading with the RUs. The sensitivity analysis of the CBES battery price indicates that the CBES would remain economically feasible for a maximum battery price of 743.84 $/kWh. Since the expected trend is towards a reduction in battery prices, the deployment of CBES emerges as an effective prospect for distribution networks and microgrids.

The comparison between DBES and CBES has been carried out without considering further sources of revenue for CBES, which could arise from the larger size of the battery storage and the battery management systems for providing additional network services, such as voltage regulation. In these cases, the benefits of adopting the CBES solution would be even greater, further increasing the advantages of leveraging CBES over DBES.

Some limitations of this work stem from considering the problem formulation from the point of view of the RU and the CBES operator. In both cases, the network data are not used, also because the RU and the CBES operator generally have no information about the grid structure and parameters. For this reason, the scope of the paper does not include the generation of operational scenarios for analyzing grid-related aspects such as network losses or voltage support.

Possible extensions of the study include the incorporation of the grid structure and parameters to analyze operational scenarios in which grid-related aspects (e.g., network losses, voltage control) are addressed together with the CBES energy management in a multi-objective framework. Moreover, further extensions may consider the opportunity to participate in the provision of ancillary services as an additional viable option for CBES.

CRediT authorship contribution statement

Gianfranco Chicco: Writing – review & editing, Validation, Supervision, Investigation, Formal analysis. **Amin Mahmoudi:** Writing – review & editing, Supervision, Resources, Formal analysis. **Salah Bahramara:** Writing – original draft, Methodology, Conceptualization. **Rahmat Khezri:** Writing – original draft, Resources, Project administration, Methodology, Data curation, Conceptualization.

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

To reformulate the proposed model in (20)-(30) into a robust optimization model, firstly, the objective function of (30) is rewritten as a cost term. Then, the objective function is reformulated as a min-max function considering its related constraints as follows:

$$\text{minimize}\rho^{\text{CB}} = \sum_{t\in\boldsymbol{T}}\lambda^{\text{RTP}}(t)\ P^{\text{CB,g}}(t)\quad \Delta t$$

$$+\text{maximize}\{\alpha^{\text{RTP}}\ \lambda^{\text{RTP}}(t)\ P^{\text{CB,g}}(t)\ \ \xi^{\text{RTP}}(t)\ \Delta t\} \tag{A.1}$$

$$\sum_{t\in\boldsymbol{T}}\xi^{\text{RTP}}(t) \le \Gamma^{\text{RTP}} : \text{z}^{\text{RTP}}$$

$$\xi^{\text{RTP}}(t) \le 1 : q^{\text{RTP}}(t) \tag{A.2}$$

$$P^{\text{CB,gin}}(t) + P^{\text{CB,ds}}(t) - P^{\text{CB,gout}}(t) - P^{\text{CB,ch}}(t) \le P^{\text{RU,net}}(t) + \max\{\alpha_{\text{net}}^{\text{RU}}\ P^{\text{RU,net}}(t)\ \xi^{\text{RU}}(t)\} \tag{A.3}$$

$$\sum_{t\in\boldsymbol{T}}\xi^{\text{RU}}(t) \le \Gamma^{\text{RU}}(t) : \text{z}^{\text{RU}}(t)$$

$$\xi^{\text{RU}}(t) \le 1 : q^{\text{RU}}(t) \tag{A.4}$$

In the Equations (A.1)—(A.4), the uncertainty budget related to the price of electricity market and net power trading with the RUs are described by Γ^{RTP} and $\Gamma^{\text{RU}}(t)$, respectively. The maximum values of Γ^{RTP} and $\Gamma^{\text{RU}}(t)$ are 24 and 1, respectively. Also, α^{RTP} and $\alpha_{\text{net}}^{\text{RU}}$ are used to model the amount of the deviation of these uncertain parameters from their forecast values.

The dual form of the maximization problem in (A.1) considering its constraints in (A.2) is shown in (A.5)—(A.7).

$$\text{minimize}\Gamma^{\text{RTP}}\ \text{z}^{\text{RTP}} + \sum_{t\in\boldsymbol{T}}q^{\text{RTP}}(t) \tag{A.5}$$

$$q^{\mathrm{RTP}}(t) + \mathrm{z}^{\mathrm{RTP}} \geq \alpha^{\mathrm{RTP}}\,\lambda^{\mathrm{RTP}}(t)\,y^{\mathrm{RTP}}(t)\Delta t \tag{A.6}$$

$$-y^{\mathrm{RTP}}(t) \leq P^{\mathrm{CB},g}(t) \leq y^{\mathrm{RTP}}(t) \tag{A.7}$$

Also, equations (A.8)—(A.10) indicate the dual form of the maximization problem of (A.3) and its constraints in (A.4) [75].

$$\mathrm{minimize}(\Gamma^{\mathrm{RU}}(t))^2 \mathrm{z}^{\mathrm{RU}}(t) + q^{\mathrm{RU}}(t) \tag{A.8}$$

$$q^{\mathrm{RU}}(t) + \mathrm{z}^{\mathrm{RU}}(t) \geq \alpha^{\mathrm{RU}}_{\mathrm{net}}\,P^{\mathrm{RU,net}}(t)\,y^{\mathrm{RU}}(t) \tag{A.9}$$

$$y^{\mathrm{RU}}(t) \geq 1 \tag{A.10}$$

Data availability

The authors do not have permission to share data.

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