Applied Energy 373 (2024) 123880

Contents lists available at ScienceDirect

Applied Energy

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

Energy storage sharing in residential communities with controllable loads for enhanced operational efficiency and profitability

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HIGHLIGHTS

- A consistent evaluation framework is proposed for diversified battery energy storage use scenarios.
- The operational cost of a community with various controllable loads is optimized to find the optimal storage solution.
- The sharing rate is proposed to quantify inter-user resource-sharing capability.
- The Community Energy Storage Sharing scheme outperforms other Energy Sharing paradigms profitably and efficiently.
- Optimal scheduling of storage is analyzed to provide insights into energy-sharing strategies.

ARTICLE INFO

Keywords:
Energy storage sharing
Controllable loads
Operational cost
Capital cost
Energy utilization
Sharing rate

ABSTRACT

Given the widespread adoption of renewable energy, the role of battery energy storage systems (BESs) in ensuring the reliable operation of BES-integrated power systems has become prominent. Due to the high costs of BESs, current research focuses on spreading out BES costs by energy sharing between multi-entities, emphasizing the averaged economic performance. However, BES's average economic performance does not ensure operational profitability, due to several outstanding considerations on interplays between BES use scenarios, operational costs, capital costs, storage utilization, and sharing rate. Here we show that a consistent evaluation framework across use scenarios which can optimize the BES operational efficiency and profitability, validated by representative use scenarios, i.e., Community Energy Storage Sharing (CESS), Personal Energy Storage (PES), and Personal Energy Storage Sharing (PESS). Incorporating real-world operational data, CESS stands out with the lowest operational cost at 48,063 euros, and the highest discharge capacity at 3552 kWh, facilitated by inter-user resource sharing with a sharing rate of 17.30%. CESS incurs the lowest capital cost at 518,887 euros, 32% economically efficient compared to PES and PESS, boosting immediate BES integration. By consistently evaluating heterogeneous BES use scenarios, particularly for distributed BES sharing in residential communities characterized by controllable loads, this work presents new possibilities for system operators that one can regulate inter-user sharing capability, i.e., the sharing rate, for optimized operational efficiency and profitability.

1. Introduction

Modern power systems have integrated low-carbon energy resources such as wind and solar to reduce greenhouse gas emissions and enhance sustainability. However, intermittent and unpredictable renewable energy resources pose significant challenges to power system stability [1–3]. Battery energy storage systems (BESs) have become critical in managing power fluctuations, peak shaving, and demand responses

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https://doi.org/10.1016/j.apenergy.2024.123880
Received 30 April 2024; Received in revised form 23 June 2024; Accepted 9 July 2024
Available online 18 July 2024

[4–9,66–68]. BESs are growing to improve the resilience and reliability of power infrastructure for community use [10,65]. However, the high capital cost of BES limits its widespread application [11–14]. To address these issues, the energy-sharing concept has been integrated into BESs, aiming to distribute the costs of BES across multiple entities and emphasizing average economic performance [15–21]. Numerous studies have proposed diversified BES use scenarios based on different ownership models [22], including Personal Energy Storage (PES), Personal Energy Storage Sharing (PESS), and Community Energy Storage System (CESS).

BES presents considerable variations in use scenarios, leading to different operational and capital costs. Personal Energy Storage (PES) use scenario is typically managed by individual users. However, PES economic benefits are limited due to a lack of an inter-user resource-sharing scheme. Personal Energy Storage Sharing (PESS) is viewed as an intuitive extension of PES by involving multiple individual energy practitioners, where the ownership of storage equipment remains residential [23]. PESS use scenario allows for shared BES capacity, thereby utilizing energy more efficiently and reducing costs, leading to lower operational costs and improved economic benefits [24–29]. However, individual energy practitioners can be under-motivated to share. One solution is to design policy support to boost BES efficiency and profitability. Australia's ShineHub has proposed a scheme where users who agree to join the Virtual Power Plant (VPP) initiative receive a premium payment from ShineHub, as well as the normal solar feed-in tariff, thus generating a profit and encouraging more users to participate in energy-sharing [30]. Nevertheless, in PES and PESS use scenarios, users invest in BES devices, still resulting in relatively high capital costs. Hence, the Community Energy Storage System (CESS) is adopted to establish a communal storage system [31]. By implementing large-scale BESs at the community level, CESS enhances the capacity to handle energy demand fluctuations [32–35]. Through centralized management, often integrated with incentive policies, CESS is promising to optimize energy utilization and promotes broader energy-sharing possibilities [31,36,37], by involving and managing distributed energy storage resources among multiple energy practitioners or prosumers [38,39]. The cost-saving effects of CESS will gradually cancel the high initial capital costs over the long term. The New York State Energy Research and Development Authority (NYSERDA) provides financial incentives for both commercial and residential installations of BESs [40]. The expansion of community solar projects considers the inclusion of BES as a beneficial driver for wider adoption of community solar nationwide [41]. In Australia, Ausgrid initiated a study to assess the feasibility of a community battery as an alternative to traditional network investment and found that such a project could be economically viable within 3–5 years [42]. These policies offer positive incentives for projects that have been abandoned due to the cost concerns of the CESS use scenario. Other studies have focused on additional economic performance metrics of different BES usage scenarios, such as payback period, net present value, and internal rate of return [37,43,44], originating from primary economic indicators of operational and capital costs. However, regardless of the existing economic performance metrics, the complex interplay between operational and capital costs stresses a gap for a consistent evaluation framework inclusive of diversified BES use scenarios, which is important for operational efficiency and profitability.

More importantly, a consistent evaluation framework provides comprehensive insights into the BES performance of various BES use scenarios, ensuring informed decision-making for system operators. In addition to economic metrics, efficiency considerations are critical to evaluate BES performance [44]. Many efficiency indicators focus on enhancing self-consumption, self-sufficiency, and solar utilization through energy storage systems [5,45]. However, for BES with a small penetration of renewable energy, economic indicators can be less significant. Instead, the BES utilization rate becomes a key metric for assessing efficiency performance. The sharing scheme is important in promoting the BES utilization rate by smoothing out demand fluctuations of multiple users [46]. Walker et al. found that the storage utilization rate increased by 38.98% after using sharing schemes [10]. However, the evaluation framework failed in assessing efficiency due to the simplified load modeling by directly involving actual load data from specific sites, losing general applicability [47]. Integrating controllable loads into load profile optimization significantly enhances both efficiency and accuracy [48]. Regardless of restricted load data representativeness, the sharing capacity plays an essential role in the profitability of shared BESs by reflecting the ability to integrate resource sharing among users in different BES usage scenarios. Huang et al. attempted to quantify the sharing capacity of BES using the storage sharing rate, but the metric was defined on peak power, thereby missing the off-peak energy patterns [28]. However, a metric that can consistenly reflect sharing characteristics and load patterns throughout the day is urgent to evaluate the resource-sharing capacity. The summary of current studies and their evaluation metrics are detailed in Table 1 for the formulation of a consistent BES evaluation framework across use scenarios. A consistent evaluation framework that considers heterogeneous BES use scenarios with controllable loads, including operational costs, capital costs, storage utilization, and sharing rates, is crucial for achieving more profitable and efficient management of shared BESs. (See Table 2.)

This study presents a consistent evaluation framework across different usage scenarios that optimizes the operational efficiency and profitability of BESs. The framework is validated through representative BES use scenarios such as PES, PESS, and CESS. By integrating real-world load data from 300 households, including non-controllable loads and solar generation, a model is developed to characterize the community's load profile, incorporating deferrable loads, uninterruptible loads, thermal loads, and energy storage as controllable elements [48]. To maintain a consistent baseline across scenarios, the total storage ca- pacity available for sharing within the community is standardized. Within this energy-efficient community composed of controllable loads, a mathematical optimization model is employed to minimize total operational costs, ensuring efficient energy management and optimal operational scheduling. The mathematical optimization model uses the mixed integer linear programming (MILP) algorithm, which excels in accuracy and solving large-scale problems [49]. Subsequently, the proposed consistent evaluation framework is applied to assess heterogeneous BES usage scenarios in residential communities by analyzing the interactions between total operational costs, capital costs, storage utilization, and sharing rate. This work aims to provide new possibilities for system operators to optimize op- erational efficiency and profitability by adjusting the resource-sharing capability, i.e., the sharing rate, among multiple energy practitioners.

The structure of the rest of this paper is organized as follows: Section 2 outlines the consistent evaluation framework across use scenarios. Section 3 details the formulas used in each scenario, with a special focus on different types of residential loads. Section 4 offers case simulations, results, and discussions, culminating in a conclusion presented in Section 5.

2. System configuration

Fig. 1 presents the consistent evaluation framework across use scenarios. Stage 1 shows schematic diagrams of three scenarios: (a) Personal Energy Storage (PES), (b) Community Energy Storage Sharing (CESS), and (c) Personal Energy Storage Sharing (PESS), illustrating their differences. In PES, the energy storage (ES) system is powered by both solar (PV) and grid sources, encompassing all household devices within a dashed box. Energy is not discharged back to the grid, but sharing is facilitated by regulating the energy flow from the grid, thus, the energy flow arrows between ES and the grid are bidirectional. PESS is similar but includes arrows between residences indicating shared energy capacity. Conversely, CESS involves a communal energy storage system, omitting individual household storage.

In Stage 2, we optimize the operational costs for the community

Table 1
Analysis of use scenarios, controllable loads and effectiveness validation in existing literature.

Literature	Involved Scenarios	Controllable Loads	Evaluation matrices			Limitations
			Economic Metrics	Technical Metrics	Sharing Capabilities	
[5]	CESS	ES	electricity cost	self-consumption, self-sufficiency	/	Lack of diverse scenario validation
[37]	CESS	ES	payback period, net present value, internal rate of return	self-consumption	/	Lack of diverse scenario validation
[11]	PES , CESS	ES	electricity cost	energy storage and solar utilization	/	Simplistic load modeling
[16]	CESS	ES, fixed load, deferrable load, reducible load	electricity cost	/	/	Limited by a sole focus on economic metrics
[31]	CESS	ES, uninterruptible load, thermal load	operational cost, capital cost	equipment utilization rate	/	Lack of analysis on sharing capabilities
[28]	PESS	ES	electricity cost	Self-sufficiency	Energy sharing ratio	Ignores off-peak sharing dynamics

Personal Energy Storage(PES) Personal Energy Storage Sharing(PESS)
Community Energy Storage Sharing(CESS)

across each use scenario. During the modeling of the community, real-world baseline load data and solar energy data were employed, along with controllable load modeling. The energy storage configurations differ across the three use scenarios, but to ensure consistency, the total energy storage capacity is kept the same for all scenarios.

We Analyze the outcomes of the consistent evaluation framework in stage 3. The optimization conducted in Stage 2 resulted in the optimal operation of BESs, leading to reduced operational costs, enhanced energy storage utilization, and a detailed characterization of sharing rates. Additionally, the investment costs for each scenario were calculated. These metrics form the basis of our consistent evaluation framework across use scenarios.

3. Mathematical formulation

Fig. 2a displays all the models related to the three use scenarios in Section 3, represented in a loop. The outer three rings represent the three use scenarios, with the mathematical components encompassed by each use scenario contained within their respective rings. Fig. 2b illustrates the entire simulation process using MILP. The workflow involves loading solar generation and load data for R residences (where r in the diagram represents the r-th residential property, and the variable R denotes the total number of residential properties within the system), simulating various mathematical models for each part, and finally conducting objective optimization.

3.1. Residential Loads

This section outlines the mathematical models used in the optimization system. The analysis operates over a 24- h period, represented as T = {0, …, 23}, with hourly intervals ($\Delta T = 1$). This interval aligns with typical patterns of household energy consumption, providing sufficient resolution to capture the dynamics of energy usage and storage behaviors in households. The subscript d denotes the d-th household appliance. Residential loads are categorized into Uninterruptible, Deferrable, and Thermal types. In the PES and PESS use scenarios, households have individual energy storage systems, whereas in community energy storage, residential units share a communal energy storage system.

3.1.1. Uninterruptible Loads

This section details the formulas for Uninterruptible loads, which include essential residential appliances like washing machines and dishwashers that cannot be stopped once started. This detailed modeling allows for better planning and allocation of resources, ensuring that these kinds of appliances continue to function without disruption during their usage time.

$$P_{d,t} = \sum_{k=0}^{L-1} u_{d,t-k} \widetilde{P}_{d,k} \qquad \forall t \in T \tag{1}$$

$$\sum_{t=0}^{T-L} u_{d,t} = 1 \qquad \forall t \in T\# \tag{2}$$

$$u_{d,t} \in \{0,1\} \qquad \forall t \in T \tag{3}$$

Eq. (1) calculates the power consumption, $P_{d,t}$, of all uninterruptible loads. Eqs. (2)and (3) ensure that once these loads are activated, they operate continuously for their designated period, with $u_{d,t}$ being a binary indicator showing whether the load is active (1) or not (0).

3.1.2. Deferrable Loads

Deferrable loads, such as electric vehicles (EVs), can be postponed or rescheduled, offering flexibility to adjust their operation times during peak electricity demand and allowing for interruptions if needed. Considering EVs is essential due to their significant increase in number in recent years and their continuous growth trend, making them an indispensable component of future community loads.

$$S_{ev_{d,t+1}} = S_{ev_{d,t}} + P_{d,t}\Delta T \qquad \forall t \in T \tag{4}$$

$$p_{dod} S_{ev_{max}} \le S_{ev_{d,t}} \le S_{ev_{max}} \qquad \forall t \in T \tag{5}$$

$$e_{d,t} P_{ev_{min}} \le P_{d,t} \le e_{d,t} P_{ev_{max}} \qquad \forall t \in T \tag{6}$$

$$e_{d,t} \in \{0,1\} \qquad \forall t \in T \tag{7}$$

$$S_{ev_{d,19}} \le p_{st} S_{ev_{max}} \qquad \forall t \in T \tag{8}$$

$$S_{ev_{d,7}} \ge p_{ed} S_{ev_{max}} \qquad \forall t \in T \tag{9}$$

Eq. (4) calculates the energy level $S_{ev_{d,t}}$ of electric vehicles (EVs) based on hourly charging power. Eq. (5) enforces charging constraints, and Eq. (6) limits the charging power. The variable $e_{d,t}$ indicates whether the EV is actively charging. Eqs. (8) and (9) mandate that EVs be charged between 19:00 and 7:00, providing flexibility to adjust charging times and amounts during off-peak hours.

3.1.3. Thermal Loads

Thermal loads refer to household appliances such as central air conditioning or heaters that are responsible for regulating indoor temperature. These loads are indispensable in modern households and consume significant amounts of energy. We aim to coordinate the control of these loads to meet residents' needs while minimizing power consumption as much as possible. The thermal conduction formula used

Table 2
Notation.

Nomenclature	
Acronyms	
PES	Personal Energy Storage
PESS	Personal Energy Storage Sharing
CESS	Community Energy Storage Sharing
Sets	
R	Set of households
D	Set of household devices
C	Set of community energy storages
R_1	Set of sharing households
Parameters	
T	
ΔT	
$\widetilde{P}_{d,k}$	
$S_{ev_{max}}$	Maximum battery state of charge of deferrable load (kWh)
p_{dod}	Depth of discharge
$P_{ev_{min}}, P_{ev_{max}}$	Minimum and maximum charging power limitation of deferrable load (kW)
$S_{ev_{d,7}}, S_{ev_{d,19}}$	Initial and final battery state of charge of deferrable load (kWh)
p_{st}, p_{ed}	Initial and final percentages of deferrable load
$\vartheta^{env}_{d,t}$	Ambient temperature ($^{\circ}$ C)
R_d	Thermal resistance of thermal load ($^{\circ}C/kW$)
C_d	Thermal capacitance of thermal load ($kW/^{\circ}C$)
$\eta_{tran}, P^{tran}_{d,t}$	Performance coefficient and transfer efficiency (kW)
$\vartheta^{min}_d, \vartheta^{max}_d$	Minimum and maximum power capacity limitation of thermal load (kW)
$P^{ch,min}_d, P^{ch,max}_d$	Minimum and maximum charging power limitation of personal energy storage (kW)
$P^{dis,min}_d, P^{dis,max}_d$	Minimum and maximum discharging power limitation of personal energy storage (kW)
$P^{ch,min}_c, P^{ch,max}_c$	Minimum and maximum charging power limitation of community energy storage (kW)
$P^{dis,min}_c, P^{dis,max}_c$	Minimum and maximum discharging power limitation of community energy storage (kW)
S^{min}_d, S^{max}_d	Minimum and maximum battery state of charge of personal energy storage (kWh)
S^{min}_c, S^{max}_c	Minimum and maximum battery state of charge of community energy storage (kWh)
$\eta^e_{ch}, \eta^e_{dis}$	Charging and discharging efficiency of energy storage (%)
$G_{d,t}$	Power generation of PV system d at time t (kW)
$C_{d,t}$	Power consumption of basic load d at time t (kW)
P^{min}_{sh}	Minimum power limitation of sharing energy (kW)
P^{min}_r, P^{max}_r	Minimum and maximum power capacity limitation of household r (kW)
P^{min}, P^{max}	Minimum and maximum power capacity limitation of community (kW)
Π_t	Price of electricity at time t ($€/kW$)
Variables	
$P_{d,t}$	Power consumption of household devices d at time t (kW)
$u_{d,t}$	Binary status indices of uninterruptable load d at time t
$S_{ev_{d,t}}$	Battery state of charge of deferrable load (kWh)
$e_{d,t}$	Binary status indices of deferrable load d at time t
$S_{d,t}, S_{c,t}$	Battery state of charge of personal and community energy storage (kWh)
s^{ch}_t, s^{dis}_t	Binary status indices of energy storage on charging and discharging mode at time t
$P^{in}_{r,t}, P^{out}_{r,t}$	Power received and delivered of household r at time t (kW)
s^{in}_t, s^{out}_t	Binary status indices of energy sharing on receiving and giving modes at time t

in this study is derived from Mathieu's [50] paper.

$$\vartheta_{d,t+1} = a_d \vartheta_{d,t} + (1 - a_d)\left(\vartheta^{env}_{d,t} - \vartheta^m_{d,t}\right) \qquad \forall t \in T \tag{10}$$

$$a_d = e^{-\frac{\Delta T}{C_d R_d}} \tag{11}$$

$$\vartheta^m_{d,t} = R_d P^{tran}_{d,t} \qquad \forall t \in T \tag{12}$$

$$P_{d,t} = \frac{\left|P^{tran}_{d,t}\right|}{\eta_{tran}} \qquad \forall t \in T \tag{13}$$

$$m_{d,t} P^{min}_d \le P_{d,t} \le m_{d,t} P^{max}_d \qquad \forall t \in T \tag{14}$$

$$m_{d,t} \in \{0, 1\} \qquad \forall t \in T \tag{15}$$

$$\vartheta^{min}_d \le \vartheta_{d,t} \le \vartheta^{max}_d \qquad \forall t \in T \tag{16}$$

Eq. (10) models temperature control, with $\vartheta_{d,t}$ indicating indoor temperature, constrained by Eq. (16). Constants a_d, thermal resistance R_d, and capacitance C_d are set in Eq. (11). Eq. (12) defines $\vartheta^m_{d,t}$ as the thermal gain, and $P^{tran}_{d,t}$ as the transfer efficiency. The performance coefficient η_{tran} is specified in Eq. (13), while $P_{d,t}$ in Eq. (14) denotes power used for temperature regulation, controlled by $m_{d,t}$.

3.2. Energy storage

In the PES and PESS use scenarios, each residence is equipped with individual energy storage devices. In contrast, the CESS use scenario features centralized storage within the community. This stored energy is used during high demand or power outages, helping to reduce costs and enhance reliability.

$$S_{d,t+1} = S_{d,t} + \left(\eta^e_{ch} P^{ch}_{d,t} - \frac{P^{dis}_{d,t}}{\eta^e_{dis}}\right)\Delta T \qquad \forall t \in T \tag{17}$$

$$S^{min}_d \le S_{d,t} \le S^{max}_d \qquad \forall t \in T \tag{18}$$

$$P_{d,t} = P^{ch}_{d,t} - P^{dis}_{d,t} \qquad \forall t \in T \tag{19}$$

$$s^{ch}_t P^{ch,min}_d \le P^{ch}_{d,t} \le s^{ch}_t P^{ch,max}_d \qquad \forall t \in T \tag{20}$$

$$s^{dis}_t P^{dis,min}_d \le P^{dis}_{d,t} \le s^{dis}_t P^{dis,max}_d \qquad \forall t \in T \tag{21}$$

$$s^{ch}_t + s^{dis}_t \le 1 \qquad \forall t \in T \tag{22}$$

$$s^{ch}_t, s^{dis}_t \in \{01\} \qquad \forall t \in T \tag{23}$$

$$S_{d,23} = \eta_s S^{max}_d \tag{24}$$

Eq. (17) models the battery state of charge at time t, denoted as $S_{d,t}$. In the CESS use scenario, the subscript 'd' is replaced with 'C' to reflect communal storage ownership. The charging and discharging efficiencies are represented by η^e_{ch} and η^e_{dis}, respectively, while $P^{ch}_{d,t}$ and $P^{dis}_{d,t}$ indicate the respective power levels. Eqs. (18), (20) and (21) define the operational ranges for these variables. Eq. (19) calculates the net power derived from energy storage by residences. To prevent simultaneous charging and discharging, constraints are set in Eqs. (22) and (23). Lastly, Eq. (24) specifies the required state of charge at the end of the day to begin the next day's cycle efficiently.

3.3. Sharing Formulation

$$\sum_{r \in R_1} P^{out}_{r,t} = \sum_{r \in R_1} P^{in}_{r,t} \quad \forall t \in T \tag{25}$$

$$P^{out}_{r,t} = max\{P_{dis} + G_{d,t} - C_{d,t} 0\} \tag{26}$$

$$s^{in}_t P^{min}_{sh} \le P^{in}_{r,t} \le s^{in}_t M \tag{27}$$

$$s^{out}_t P^{min}_{sh} \le P^{out}_{r,t} \le s^{out}_t M \tag{28}$$

$$s^{in}_t + s^{out}_t \le 1 \qquad \forall t \in T \tag{29}$$

$$s^{in}_t, s^{out}_t \in \{01\} \qquad \forall t \in T \tag{30}$$

This section outlines capacity sharing formulas unique to the PESS

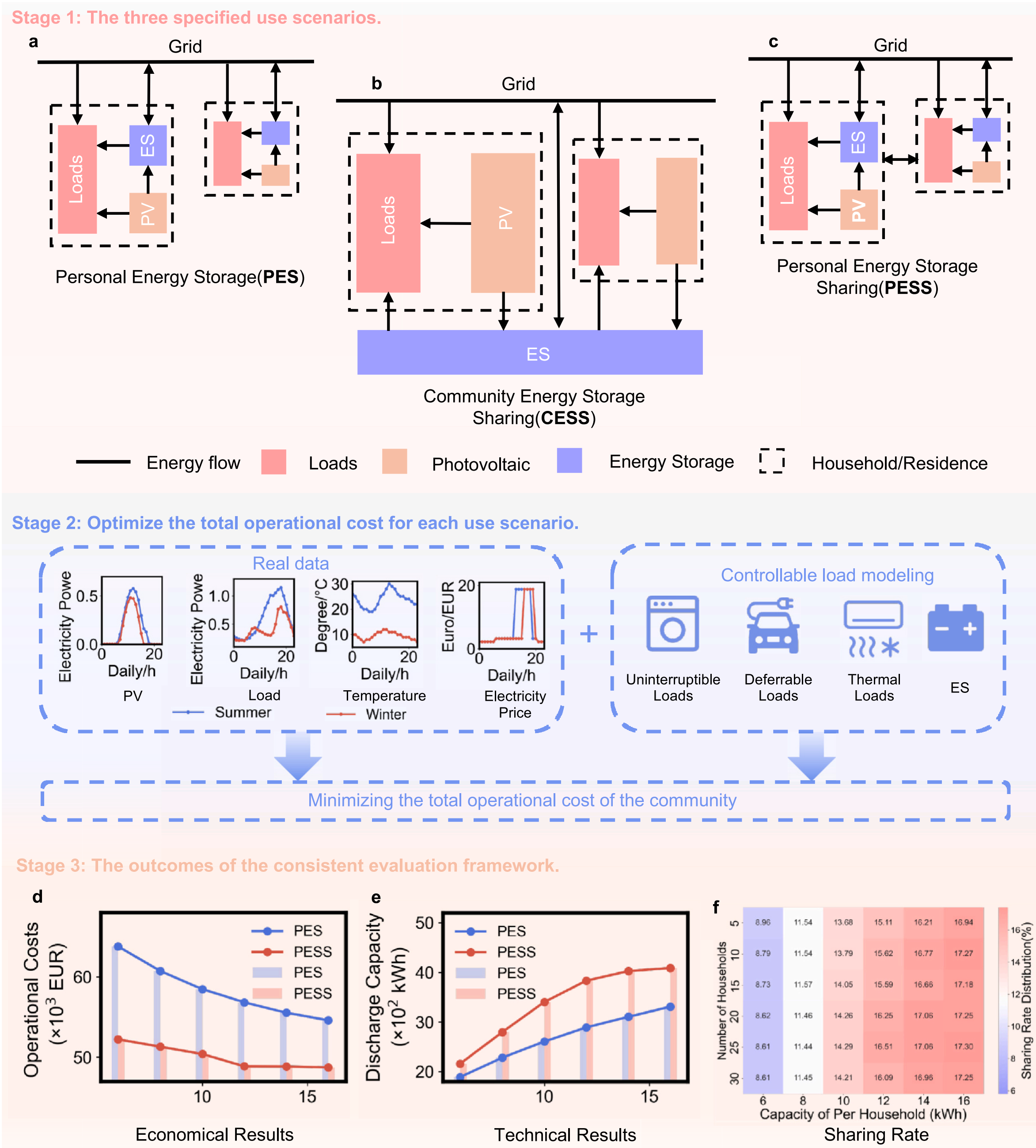

Fig. 1. Consistent Evaluation Framework Across Use Scenarios. (Propose a consistent evaluation framework based on economical and technical metrics across use scenarios (**a.** PES: households have energy storage but do not share it; **b.** CESS: shared community energy storage; and **c.** PESS: households have energy storage and share it) and analyze the results.)

use scenario. Formula (25) sets the basic constraint for capacity sharing among participating households, represented by R_1. According to Formula (26), a household can share excess energy. Formulas (27) and (28) specify the permissible range of shared energy, using a large constant M. Formulas (29) and (30) prevent simultaneous energy sharing and receiving.

3.4. Household Power Constrain

$$P_{r,t} = \sum_{d \in D} P_{d,t} - G_{d,t} + C_{d,t} \qquad \forall t \in T \tag{31}$$

$$P_r^{min} \le P_{r,t} \le P_r^{max} \tag{32}$$

Each residential property faces power limitations due to physical constraints, as specified in the formulas specific to the PES use scenario. The energy consumption $P_{r,t}$ of a property includes the total power consumption of all household appliances (denoted by subscript r for the r-th property), the base load $C_{d,t}$, and solar power generation $G_{d,t}$. These sources are all subject to an upper limit set by the property's physical capacity.

$$P_{r,t} = \sum_{d \in D} P_{d,t} - P_r^{in} + P_r^{out} - G_{d,t} + C_{d,t} \qquad \forall t \in T \tag{33}$$

$$P_r^{min} \le P_{r,t} \le P_r^{max} \tag{34}$$

The formulation presented above represents the power constraints specific to the PESS use scenario, highlighting the distinguishing

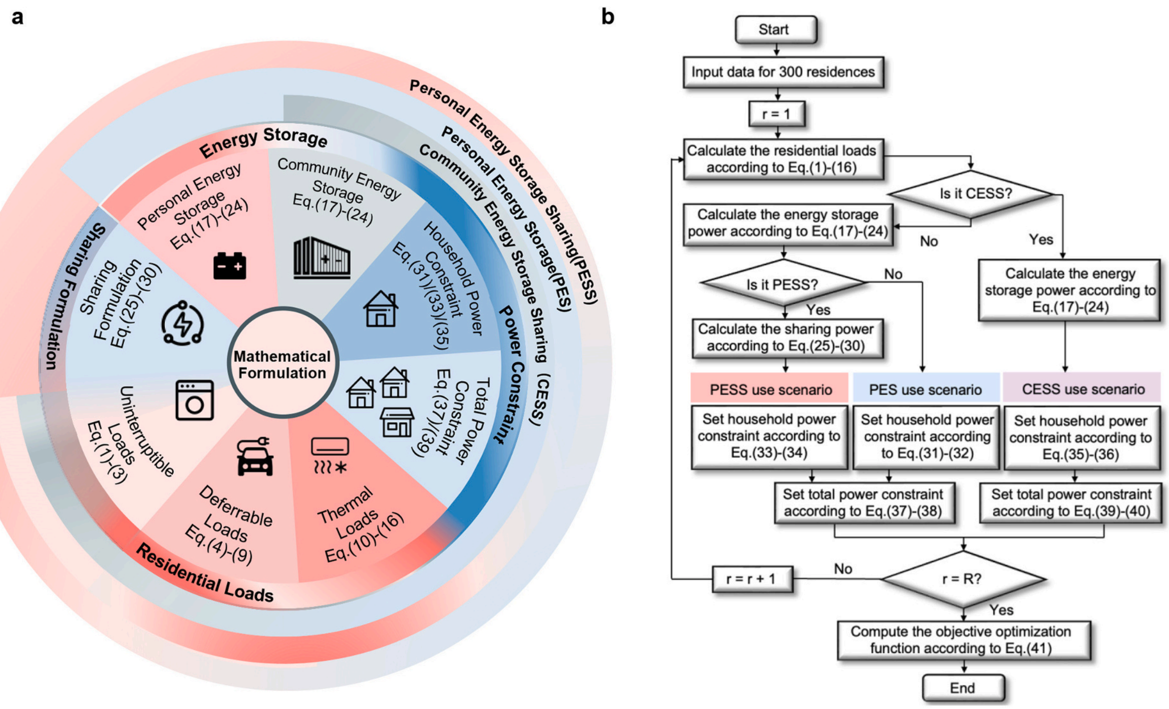

Fig. 2. Mathematical Models Utilizing Loops and Workflow Diagram. (**a.** Mathematical models adopted in each use scenario, distinguished by different colors, with reference to the classification of each use scenario below Eq. (45) for a comprehensive view. **b.** Mixed Integer Linear Programming(MILP) Algorithm Simulation Workflow.)

features compared to other use scenarios.

$$P_{r,t} = \sum_{d \in D} P_{d,t} - G_{d,t} + C_{d,t} \qquad \forall t \in T \tag{35}$$

$$P_r^{min} \le P_{r,t} \le P_r^{max} \tag{36}$$

In the CESS use scenario, similar to PES, there is a power constraint, but $P_{d,t}$ excludes power from individual energy storage, reflecting that storage devices are communally owned, not by individual households.

3.5. Total Power Constraint

$$\begin{cases} \text{Personal Energy Storage(PES)}: & \text{s.t.}1-24, 31-32, 37-38 \\ \text{Personal Energy Storage Sharing(PESS)}: & \text{s.t.}1-30, 33-34, 37-38 \\ \text{Community Energy Storage Sharing(CESS)}: & \text{s.t.}1-24, 35-36, 39-40 \end{cases}$$

$$P_t = \sum_{r \in R} P_{r,t} \qquad \forall t \in T \tag{37}$$

$$P^{min} \le P_t \le P^{max} \qquad \forall t \in T \tag{38}$$

The power constraints for the entire community in both the PES and PESS use scenarios are depicted in the preceding formulas. Eq. (37) defines P_t as the total system power, summing the consumption from all residential properties, represented by "R". It is essential that this total power adheres to the constraints outlined in Eq. (38).

$$P_t = \sum_{r \in R} P_{r,t} + \sum_{c \in C} P_{c,t} \qquad \forall t \in T \tag{39}$$

$$P^{min} \le P_t \le P^{max} \qquad \forall t \in T \tag{40}$$

The power constraint for the CESS use scenario includes power from the community energy storage system ($P_{c,t}$), which is integral to the total community power (P_t). Unlike PESS, where sharing equations are explicit, CESS incorporates sharing through the inclusion of $P_{c,t}$, effectively facilitating the sharing mechanism.

3.6. Objective Optimization Function

$$min \sum_{t \in T} \Pi_t \Delta TP_t \tag{41}$$

The optimization objective across all use scenarios is to minimize the system's operational cost, determined by the time-of-use electricity price(Π_t) Specific formulas for each use scenario are detailed under Eq. (41) and further illustrated in Fig. 2.

4. Case study

4.1. Parameters Setting

This section outlines the data sources and parameter settings for the study. Data were obtained from Ausgrid [51], the Australian electricity grid operator, including load and solar power generation data from 300

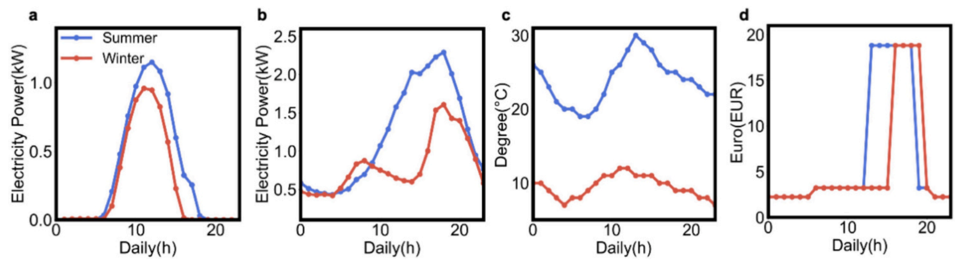

Fig. 3. Daily Parameters. (**a.** Power generation of PV System. **b.** Power consumption of base loads. **c.** Ambient temperature. **d.** Electricity price.)

residential properties. For this research, data from a typical summer day (January 18) and winter day (July 15) during 2012–2013 were selected, covering all 300 residential users.

Fig. 3a and b display average solar power generation and user load data for summer and winter, respectively. Solar power peaks from 6:00–18:00 in summer and 6:00–16:00 in winter, with higher output in summer. User loads vary distinctly between seasons, as shown in Fig. 3b. Weather data from the Australian Bureau of Meteorology (BoM) [52] is presented in Fig. 3c.

For uninterruptible loads, the BOSCH WAW28420AU washing machine model [53], consuming 0.74 kW per hour over a typical 2-h cycle, and the BOSCH SMP66MX04A dishwasher model [54], using 0.66 kW for the first 2 h and 0.99 kW in the last hour of a 3-h cycle, were selected based on CHOICE [55] guidelines.

The Tesla Model 3 [56] was selected as the electric vehicle for this study, with a maximum charger power of 11.5 kW (P_{ev}^{max}) and a battery capacity of 75 kWh (S_{ev}^{max}). Recharging is assumed necessary when the battery level drops to 10% (p_{dod}).

Private energy storage data were obtained from Tesla Powerwall [57]. The parameter S_d^{max} will be explained separately in the private energy storage section. The charging and discharging efficiency(η_{ch}^e,η_{dis}^e) was set to 0.975, and the maximum charging ($P_d^{ch,max}$) and discharging ($P_d^{dis,max}$) powers were set to 5 kW.

Thermal parameters based on Methieu's work [50] set η_{tran} at 2.5, R_d at 2 °C/kW, C_d at 2 kWh/°C, and $P_{d,t}^{tran}$ at 14 kW. Recommended temperatures from the Australian website Your Home [58] are 18–20 °C in winter and 25–27 °C in summer.

Time-of-use electricity prices (Π_t), sourced from Ausgrid [59], are expressed in euros. The price data is shown in Fig. 3d.

Energy storage sharing necessitates a range of communication devices to ensure the communication and control of the community, which are crucial components that play a significant role in decision-making processes. Therefore, when investing in an energy-sharing community, the cost of communication equipment must be considered. We propose the use of HPE Aruba Networking 560 Series Wi-Fi 6 Access Points [60], each radio of which can support up to 256 connected clients (totaling 512 clients). In practical use scenarios, the maximum recommended client density depends on environmental conditions. To ensure reliability, we plan to deploy four APs to cover the entire community, with each AP costing €466. The central controller requires only one unit, selected as the HPE Aruba Networking 7000 Series Mobility Controller and Gateway [61], which integrates a router and is priced at €3300. For switches, we choose the HPE Aruba Networking 2930F Series [62], each priced at €2325. In this project, the cost of installing communication equipment is considered negligible. In contrast, in non-sharing communities, there is no cost associated with communication equipment.

To incentivize the VPP initiative, ShineHub has introduced a policy that compensates users at a rate of €0.51 per kilowatt-hour when they use their personal BES to support VPP operations [30]. Although this work is not based on the VPP framework, it involves the sharing of BES devices within a PESS use scenario. Consequently, a similar incentive policy is applied in this context: users who participate in the sharing scheme will receive a discount of €0.51 per kilowatt-hour for the portion of their BES that is shared, in addition to the standard electricity rate, to encourage participation in the sharing initiative. For the CESS use scenario, a similar discount of €0.51 per kilowatt-hour is applied to the shared energy, which not only increases the profitability beyond peak-valley arbitrage but also aims to attract more third-party operators to participate in the construction of community batteries.

Table 3
All parameters considered in this paper.

Category	*Parameters*	*Category*	*Parameters*
Time period	$\Delta T = 1, \lvert T \rvert = 24$	*Temperature* ϑ_d	$summer: [25, 27]$, $winter: [18, 20]$
Washing machine	$\widetilde{P}_{1,2} = [0.74, 0.74]$	*Dish washer*	$\widetilde{P}_{1,3} = [0.66, 0.66, 0.99]$
EVs	$P_{dod} = 10\%$, $S_{ev}^{max} = 74kWh$ $P_{st} = 20\%, P_{ed} = 95\%$ $P_{ev}^{max} = 11.5kW$	*Thermal*	$C_d = 2kW^{\circ}C^{-1}, R_d = 2^{\circ}CkW^{-1}$, $\eta_{tran} = 2.5, P_{d,t}^{tran} = 14kW$
PES storage	$\eta_{ch}^e, \eta_{dis}^e = 97.5\%$ $S_d^{min} = 5kW$, $P_d^{max} = 5kW$ $P_d^{min} = 0, \eta_s = 40\%$	*CESS storage*	$P_d^{max} = 5kW, P_d^{min} = 0$ $S_d^{max} = 6 - 16kWh$ $S_c^{max} = 30 - 480kWh$ $P_c^{max} = 500kW, P_c^{min} = 0$
PES	$P_r^{max} = 10kW$, $P_r^{min} = 0$	*CESS*	$P^{max} = 10kW \times 300$, $P^{min} = 0$
PESS	$P_{sh}^{min} = 0, M = 10000$ $R_1 = 30$	*Capital Cost*	$Cost_{inv} = €1271.2$, $rate_c = 0.5$ $Cost_{cell} = €211.9/\text{kWh}$
Communication devices	$Cost_{AP} = €466$ $Cost_{Con} = €3300$	*Communication devices*	$Cost_{Swi} = €2325$ $Cost_{om} = €93$

Personal Energy Storage(PES) Personal Energy Storage Sharing(PESS)
Community Energy Storage Sharing(CESS)

All parameters used in the study are summarized in Table 3 for quick reference.

4.2. Optimization Results

4.2.1. Personal Energy Storage(PES)

This section analyzes the PES use scenario using solar generation and user load data from 300 residential users, with temperature and price data sourced from Fig. 3. The selection of energy storage capacities S_d^{max} is based on commonly used values, namely 6 kWh, 8 kWh, 10 kWh, 12 kWh, 14 kWh, and 16 kWh. Simulation results are presented in Fig. 4, where six graphs illustrate average charging and discharging profiles and Depth of discharge (DOD) curves for these capacities, split between summer and winter seasons.

In the summer case(Figs. 4a-c), energy storage systems predominantly charge during the off-peak electricity pricing period from 21:00 to 5:00. This strategy takes advantage of lower electricity costs. Conversely, they discharge during the peak period from 12:00 to 17:00 to supply energy when demand and prices are higher. The DOD curves in Fig. 4c reflect the usage of the battery, increasing during the night and decreasing in the early morning and the afternoon, indicating efficient usage aligned with cost-saving strategies.

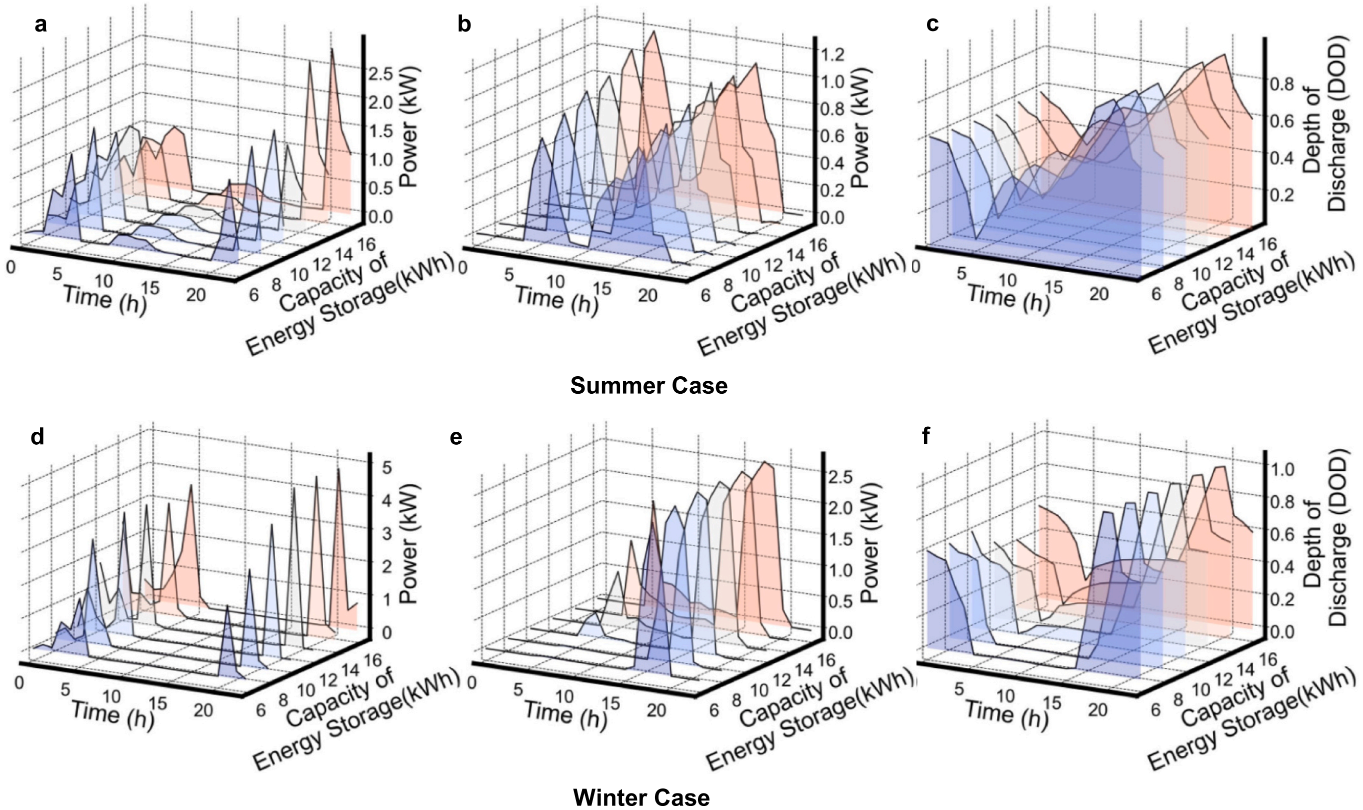

Fig. 4. Operation Results of Personal Energy Storage(PES). (**a.** Charging power in summer. **b.** Discharging power in summer. **c.** Depth of discharge in summer. **d.** Charging power in winter. **e.** Discharging power in winter. **f.** Depth of discharge in winter.)

Moving to the winter case (Figs. 4d-f), the charging curve shows several peaks between 0:00 and 5:00. This pattern arises from increased heating demands due to lower temperatures, causing more frequent charging sessions. Despite this heightened demand, the systems still primarily charge during the early morning hours. The average DOD curve in winter shows greater variation compared to summer, indicating more intense charging and discharging cycles, especially with smaller storage capacities. This increased depth of discharge suggests higher strain on the batteries, potentially reducing their lifespan due to more frequent and intense usage. Therefore, in regions with prolonged winters, it is crucial to choose energy storage systems with higher capacity.

By comparing these seasonal differences, we can infer that winter

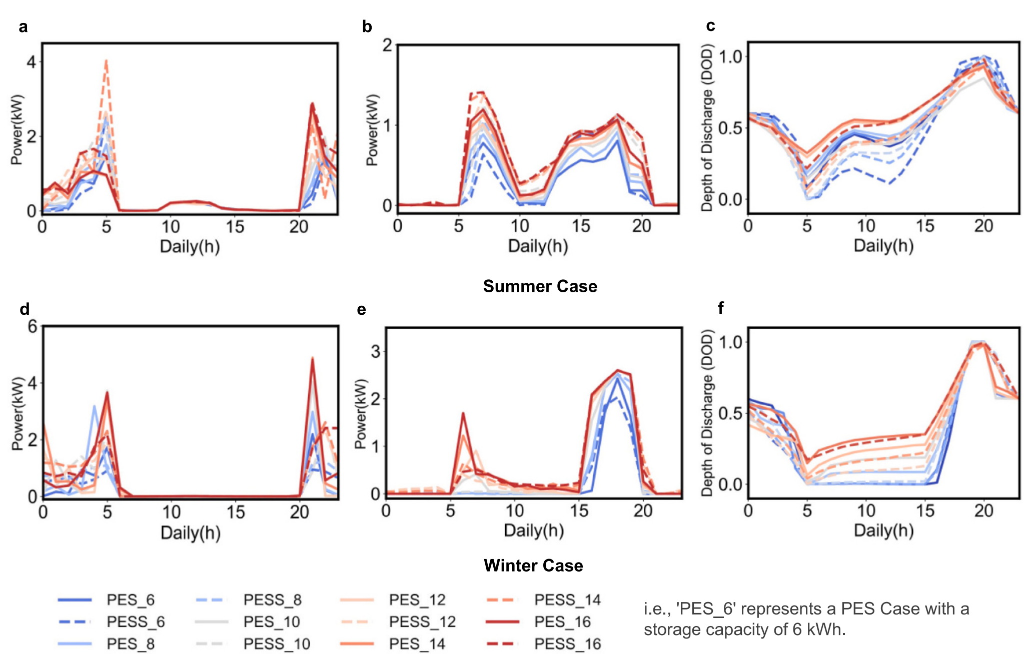

Fig. 5. Comparison of Personal Energy Storage (PES) and Personal Energy Storage Sharing (PESS). (**a.** Charging power in summer. **b.** Discharging power in summer. **c.** Depth of discharge in summer. **d.** Charging power in winter. **e.** Discharging power in winter. **f.** Depth of discharge in winter.)

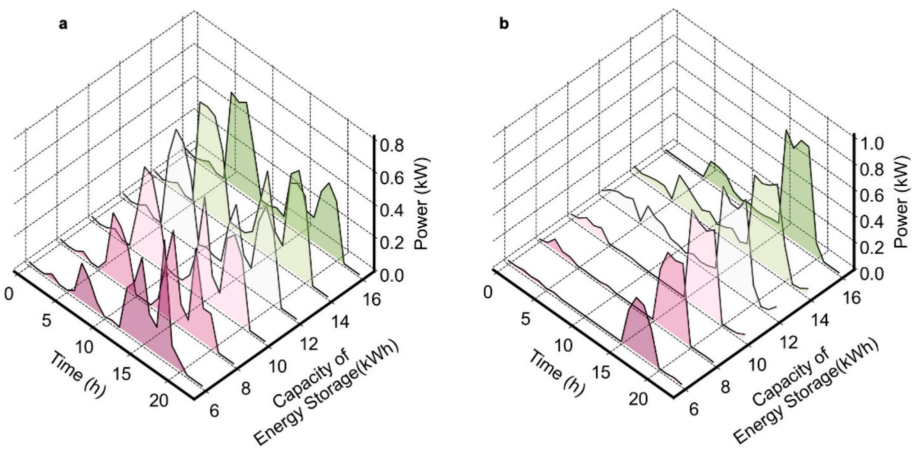

Fig. 6. Personal Energy Storage Sharing (PESS) Operation Results. (**a.** Summer case. **b.** Winter case.)

conditions, with their higher energy demands for heating, impose greater stress on energy storage systems. This seasonal variation in operational patterns is crucial for designing and managing energy storage solutions to ensure longevity and efficiency.

4.2.2. Personal Energy Storage Sharing(PESS)

The PESS use scenario, which allows users to exchange storage capacity, offers distinct advantages over PES use scenario. The simulation results are shown in Figs. 5 and 6. Figures5 illustrate solid lines representing the PES use scenario, while dashed lines represent the PESS use scenario. Upon examining the top figure in Fig. 5, which illustrates the summer case, it's noticeable that at higher capacities, the discharging curves for PESS generally exceed those in the PES use scenario, while the DOD curves are lower than those in the PES use scenario. However, this trend isn't as clear at lower capacities. In terms of charging curves, PESS does not always surpass PES·In the winter figures, both use scenarios discharge more during peak pricing and less during off-peak hours. The DOD differences between PESS and PES are marginal, with PESS slightly outperforming PES at times. However, PESS shows slightly lower performance than PES in the early morning hours (5:00–7:00), indicating less effective energy storage utilization during winter. During the summer, the DOD curve rarely approaches zero, but during the winter, particularly when the storage capacity is low, this phenomenon becomes quite common.

Figs. 6 illustrate the shared energy exchange curves for PESS across summer and winter seasons. During the summer, Fig. 6a shows higher shared energy between 5:00–10:00 and 13:00–20:00, corresponding with increased storage discharge. A noticeable dip occurs between 15:00–17:00, a peak in base load demand, as energy is predominantly used to meet user demands, reducing the shared energy. As storage capacity increases, the volume of shared energy also grows due to more available surplus energy.In winter, Fig. 6b depicts a lower overall shared energy trend, especially noticeable in the 5:00–10:00 interval, where discharging significantly drops compared to summer.

The PESS use scenario shows potential for improved energy utilization, particularly at higher capacities and during peak demand periods in summer. However, in winter, the benefits of PESS are less pronounced, and early morning performance lags behind PES, indicating a need for optimization in colder months.

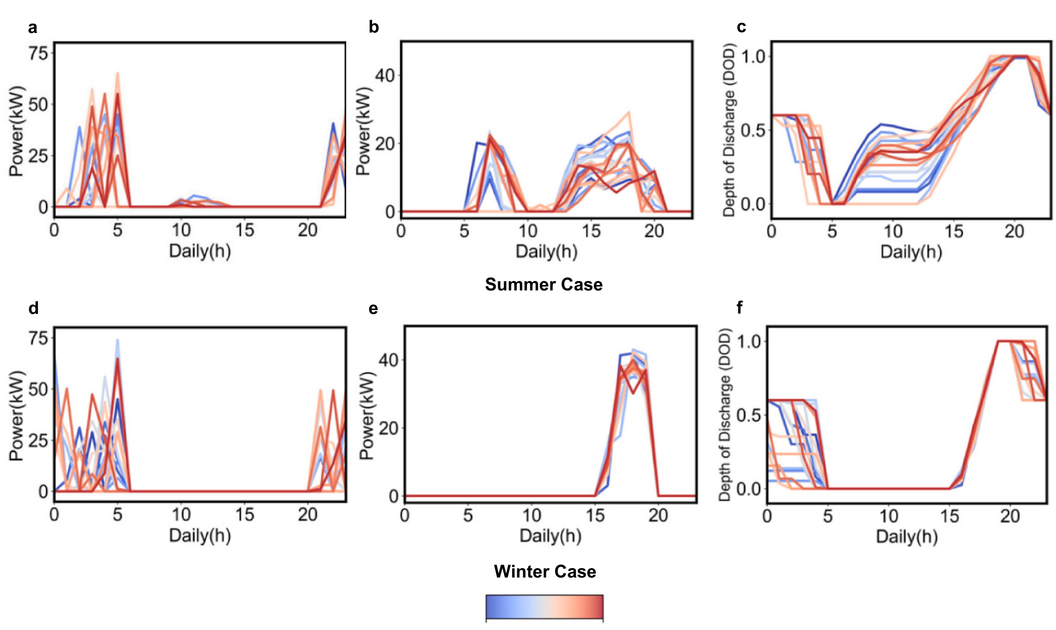

Fig. 7. 15 Households Share a 120 kWh Energy Storage System. (i.e., 300 users sharing 20 storage units) (**a.** Charging power in summer. **b.** Discharging power in summer. **c.** Depth of discharge in summer. **d.** Charging power in winter. **e.** Discharging power in winter. **f.** Depth of discharge in winter.)

4.2.3. Communityl Energy Storage Sharing(CESS)

In this section, we investigate the CESS use scenario within a community consisting of 300 users. To ensure consistency and enable comparison with the PES case, we allocate the energy storage capacity to each user proportionally based on their individual energy storage capacities, specifically 6 kWh, 8 kWh, 10 kWh, 12 kWh, 14 kWh, and 16 kWh. The 300 users are grouped into various sharing configurations consisting of 5 households, 10 households, 15 households, 20 households, 25 households, and 30 households per shared energy storage device. These six energy storage capacities and six household allocation numbers correspond to each other, forming 36 distinct configurations.

For instance, when considering a configuration of 15 households, each household is allocated an 8 kWh capacity, resulting in the aggregation of 120 kWh as a shared community energy storage resource. Among the 300 users, a total of 20 such large-scale energy storage systems are present. To provide a comprehensive overview, Fig. 7 illustrates the charging, discharging, and DOD characteristics of the specific use scenario. It is noteworthy that the charging and discharging patterns observed in these 20 storage devices closely resemble those encountered in the PES cases. These behaviors are significantly influenced by various factors, including electricity pricing, seasonal variations in solar power generation, and fluctuations in user loads. The CESS use scenario shows a strong resemblance to the PES cases but allows for more flexibility and potentially better utilization of storage resources due to shared capacity. A detailed comparative analysis between the energy storage conditions observed in CESS and PES is provided in subsequent subsections.

4.3. Economical Metrics

In this section, we present the economic metrics of three use scenarios, encompassing operational and capital costs as previously mentioned. Lower operational costs indicate good economic efficiency in the daily operation of each use scenario, while capital cost represents the initial investment. A lower capital cost implies fewer financial barriers for real-world implementation.

4.3.1. Operational cost

Table 4 presents the operational cost results and comparisons between the PES and PESS use scenarios. Observing solely the PES use scenario, it is noticeable that with an increase in energy storage capacity, there is a trend of decreasing operational costs. Compared to summer, the operational costs in winter are higher, attributed to reduced solar power generation and increased thermal load demands. Observing the PESS use scenario, similar patterns are observed. Comparing the operational costs of PES and PESS use scenarios reveals a reduction in the operational costs of PESS, particularly in summer, with a notable decrease of up to 18.09% at 6 kWh. This reduction rate is linked to the high operational costs in the PES use scenario and also highlights the substantial economic potential of PESS. The data in this table are also depicted in Fig. 8 through bar graphs and line charts, offering a clear visual representation of the operational cost differences between these two use scenarios. The data indicates that the PESS use scenario offers substantial operational cost savings over the PES use scenario. This cost efficiency makes PESS a viable and attractive option for implementation.

Table 4
The operational costs of PES and PESS.

Date	PES	PESS	Decrease Ratio (%)	Household Capacity (kWh)
Summer	63,772.71	52,237.58	18.09	6
	60,728.91	51,316.54	15.50	8
	58,476.89	50,401.66	13.81	10
	56,839.28	48,872.57	14.02	12
	55,534.55	48,855.93	12.03	14
	54,594.47	48,742.04	10.72	16
Winter	87,904.11	84,829.54	3.50	6
	80,789.97	75,596.21	6.43	8
	77,303.70	71,907.43	6.98	10
	75,750.93	71,095.83	6.15	12
	75,141.07	70,503.02	6.17	14
	74,974.15	70,287.32	6.25	16

Personal Energy Storage(PES) Personal Energy Storage Sharing(PESS)

In the CESS use scenario, the operational costs associated with different capacity levels and the corresponding number of households are visualized in Fig. 9a. The upper heatmap illustrates the variations in operational costs during the winter season, while the lower heatmap represents the summer season. The operational costs in summer are generally lower compared to winter, with the lowest operational cost occurring when 25 users share a 400kWh storage capacity (16kWh allocated per household), amounting to 48,063.86 euros. In winter, the operational costs are higher, with the highest cost at 6kWh, reaching up to 83,343.77 euros.

Fig. 9b delineates the operational cost reduction rates of CESS compared to PES at matched capacity levels, calculated via Eq. 42. Notably, cost savings are consistently realized in CESS versus PES. In the summer, the reduction is more pronounced at lower capacities, with a diminishing trend as capacity rises. The winter data exhibit an anomaly where a 6 kWh system has a lower reduction rate than an 8 kWh system. The graph indicates that optimal savings, up to 20.80%, occur with 30 households each utilizing 6 kWh, surpassing the PESS's maximum savings of 18.09%. When comparing CESS to PES and PESS use scenarios, CESS demonstrates relatively lower operational costs, which can be attributed to higher energy utilization. These substantial cost savings make CESS an attractive alternative for communities looking to implement efficient and cost-effective energy storage solutions.

$$ReductionRate = \frac{Cost_{PES} - Cost_{CESS}}{Cost_{PES}} \times 100\% \tag{42}$$

4.3.2. Capital cost

The capital cost of energy storage refers to the one-time investment cost. The calculation formula for the capital cost is provided by Eq. (43), as cited from [31]. The formula consists of two parts: the cost of the battery cells and the cost of the inverter, which together constitute the capital cost. Since PES and PESS utilize the same household energy storage systems, their capital costs are essentially identical. However, the communication equipment costs for PES and PESS are different. In PES, users independently use their own energy storage without needing to communicate with other community users. In contrast, PESS requires a range of communication devices, including four APs, one central controller, and switches. Additionally, the cost of the battery should also consider maintenance costs. The formula for the first-year maintenance cost is shown in Eq. (44), as cited from [64], and the maintenance cost increases by 2% each year. The parameters used in Eq. (43), (44) and the communication equipment costs are listed in Table 3. The capital cost, first-year maintenance cost, and communication equipment costs are all presented in Table 5. It can be observed that as the energy storage capacity increases, both the investment cost and maintenance cost gradually grow.

$$Cost_{capital} = Cost_{cell} \times S^{max} + Cost_{inv} \times \left(\frac{rate_c \times S^{max}}{3}\right)^{0.7} \tag{43}$$

$$Cost_{main} = Cost_{om} \times \left(\frac{rate_c \times S^{max}}{10}\right)^{0.6} \tag{44}$$

The CESS use scenario is more complex, as it is subdivided into 36 different cases based on varying numbers of sharing users and shared capacities. To better represent the capital cost of CESS and compare it with the capital costs of the other two use scenarios, we have created a heatmap. The y-axis represents the number of users in the shared community energy storage, while the x-axis shows the allocated capacity.

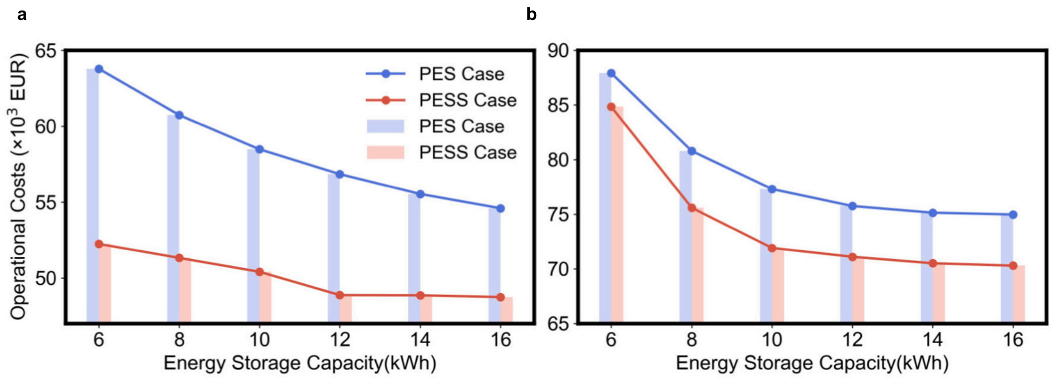

Fig. 8. The Comparison of Operational Costs Between Personal Energy Storage (PES) and Personal Energy Storage Sharing (PESS). (**a.** Summer case. **b.** Winter case.)

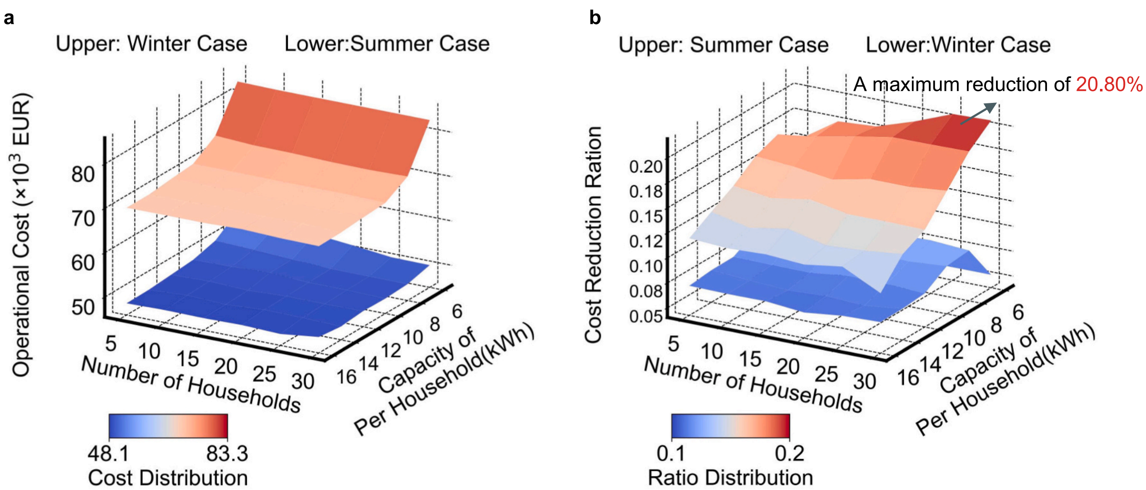

Fig. 9. Community Energy Storage Sharing (CESS) Operation Results. (**a.** Operational cost. **b.** Cost reduction ration compared to Personal Energy Storage (PES).)

Table 5
The investment costs of PES and PESS.

Personal Energy Storage(PES) Personal Energy Storage Sharing(PESS)							
Scenario	Capacity (kWh)	6	8	10	12	14	16
PES& PESS	Capital costs (€)	762,780	974,996	1,180,992	1,382,361	1,580,091	1,774,848
PES& PESS	Maintenance cost (€)	13,548	16,100	18,407	20,535	22,524	24,403
PESS	Communication device cost (€)			7489			

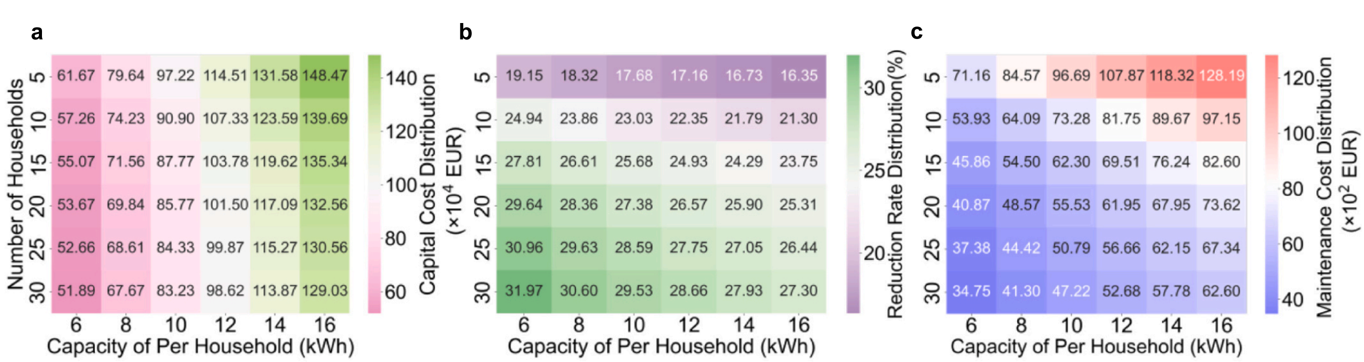

Fig. 10. Community Energy Storage Sharing (CESS) Investment Cost Results. (**a.** Capital cost. **b.** Capital cost reduction ration compared to Personal Energy Storage (PES) and Personal Energy Storage Sharing (PESS). **c.** Maintenance cost.)

The capital costs, capital cost reduction rate and maintenance cost are depicted using different color distributions, as illustrated in Fig. 10.

Fig. 10a shows the capital cost of CESS, revealing that it increases with the growth of capacity but decreases with the rising number of sharing users. In comparison to the previously mentioned use scenarios, it is evident that CESS's capital cost is lower. Therefore, Fig. 10b depicts the reduction rate of CESS's capital cost. The maximum reduction rate, at 31.97%, occurs when 30 users share 180 kWh of energy storage (with each user allocated 6 kWh of storage). Fig. 10c shows the maintenance cost of CESS, and when compared to the PES and PESS use scenarios with the same capacity as shown in Table 5, it is evident that CESS has lower maintenance costs. This is attributed to the larger scale of CESS, making it easier to maintain. From these three heatmaps, it is clear that CESS has a significant advantage in terms of one-time investment and lower long-term maintenance cost. It can be stated that CESS almost universally offers economic advantages, both in the short term (capital cost) and long term (operational cost and maintenance cost). It is important to note that because the community scale is consistent and energy sharing in both the PESS and CESS use scenarios is centrally controlled, the communication costs are identical, amounting to €7489 as shown in Table 5.

4.4. Technical metrics

The technical metrics employ energy storage discharge as an indicative measure, aptly reflecting the efficacy of energy storage systems.

4.4.1. Energy storage discharge

Fig. 11 presents the discharge capacity of PESS and PES, while Table 6 shows the increase rate in discharge capacity for PESS compared to PES. In most cases, PESS demonstrates a higher discharge capacity than PES. Particularly in summer, as shown in Fig. 11a, PESS significantly outperforms PES in terms of discharge capacity, particularly at 12 kWh, where the increase rate reaches 24.61%. This indicates that PESS is more efficient in managing energy discharge during peak demand periods. However, in winter, the increase in discharge capacity for PESS compared to PES is less pronounced. Notably, at 16 kWh, PESS's discharge capacity is slightly lower than PES, decreasing by 3.29%. Despite this reduction in winter, as highlighted in Table 4, PESS still maintains lower operational costs compared to PES. This is attributed to PESS's ability to better manage the timing of energy storage charging and discharging, leveraging the shared energy storage system to optimize cost savings. A cross-comparison with Fig. 5e reveals that at 16 kWh, although PESS's discharge volume decreases, this occurs during lower electricity pricing periods (5:00–8:00), effectively reducing operational costs.

Fig. 12 utilizes heatmaps to encapsulate CESS's discharge capacities across diverse cases. Panel a depicts summer, while panel b illustrates winter conditions. In Fig. 12a, higher discharge capacities are observed, especially in the range of 10 kWh to 16 kWh per household. The number of users sharing the storage has a minimal impact on the discharge capacity. The winter analysis reveals that higher household capacities (10kWh-16kWh) correlate with increased discharges, a trend inverted at lower capacities (6kWh-8kWh) when contrasted with summer, indicating a seasonal dependency on discharge efficiency.

Table 6
The Increased Rate of Energy Storage Discharge in PESS Compared to PES.

		Personal Energy Storage(PES) Personal Energy Storage Sharing (PESS)					
Capacity /kWh		6	8	10	12	14	16
Increase Rate(%)	Sum	12.49	18.44	23.43	**24.61**	22.88	19.03
	Win	1.09	1.96	3.37	5.76	1.78	−3.29

Fig. 13 contrasts the growth in discharge capacity of CESS with PES. CESS outperforms PES in the 8kWh-16kWh range, peaking at a 14.74% increase rate for 25 users sharing 300kWh. Despite this, PESS maintains a superior increase rate, indicating that while CESS has a lower discharge, it yields higher economic benefits due to reduced operational costs. Conversely, in winter and at 6kWh in summer, CESS underperforms in discharge growth relative to PES. Despite lower discharge capacities in certain conditions, CESS consistently demonstrates lower operational costs, making it an economically efficient option for integrating energy storage. This efficiency is particularly evident in the summer, where higher discharge capacities align with reduced costs.

4.5. Inter-user resource sharing

Having previously examined the optimization outcomes and hybrid indicators of the three use scenarios, it has been observed that CESS consistently performs well. CESS achieves the lowest operational costs and the highest increase rate in discharge capacity. In this section, we will delve into the reasons behind CESS's advantages, attributing them to effective integration of energy storage resources and enhanced inter-user resource sharing. To explore these advantages further, a precise metric is needed.

To explore these advantages further, a precise metric is needed. In this research, we define the 'sharing rate' as a metric to quantify inter-user resource sharing. Specifically, it represents the ratio of total shared capacity to overall energy consumption within a community. For the PESS use scenario, this rate is calculated as $P_{r,t}^{out}$ divided by the combined energy consumption $P_{d,t} + C_{d,t}$. In contrast, the CESS use scenario uses$P_{d,t}^{dis}$ for this calculation, while the sharing rate in the PES use scenario remains consistently zero. This measure highlights the differences in resource sharing between PESS and CESS use scenarios. Both have equivalent total storage capacities, but PESS relies on surplus energy from individual storages for sharing, requiring these systems to meet internal demands first. Conversely, CESS utilizes communal storage discharge, indicating a broader scale of sharing and suggesting greater potential for effective resource integration in CESS.

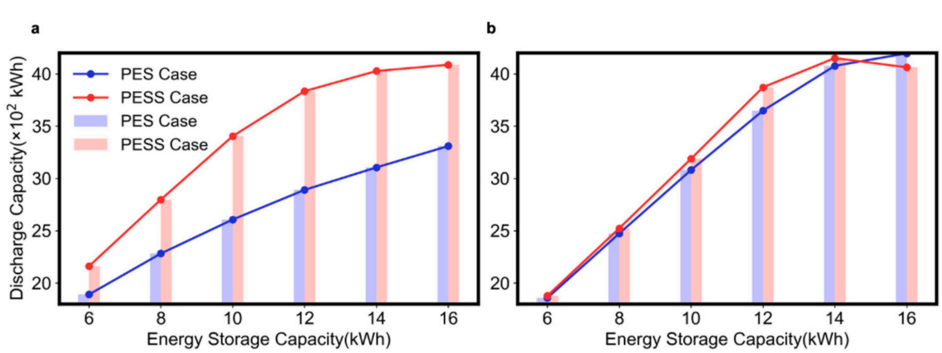

Fig. 11. The Comparison of Discharge Capacity Between Personal Energy Storage (PES) and Personal Energy Storage Sharing (PESS). (**a.** Summer case. **b.** Winter case.)

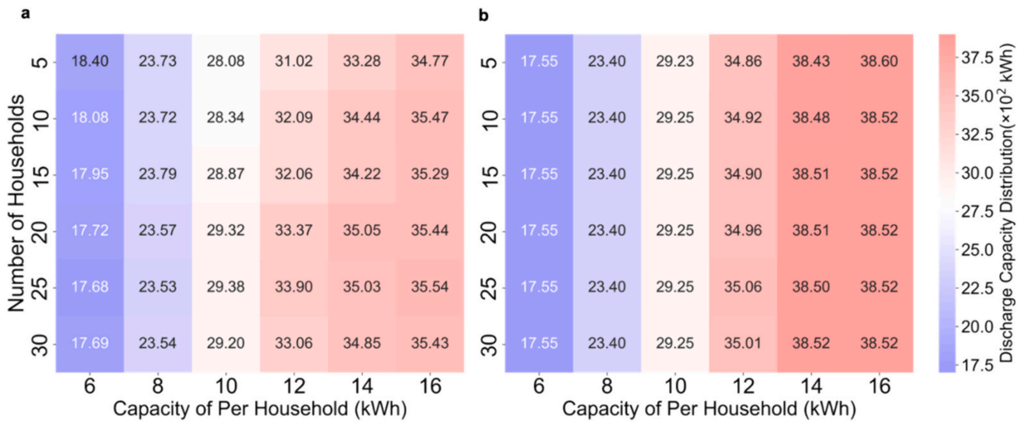

Fig. 12. The Discharge Capacity Of Community Energy Storage Sharing (CESS). (**a.** Summer case. **b.** Winter case.)

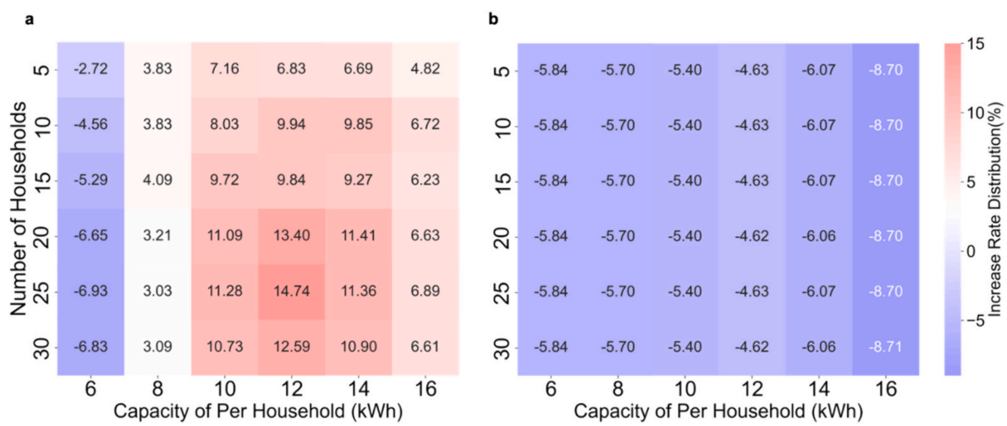

Fig. 13. The Increased Rate Of Energy Storage Discharge In Community Energy Storage Sharing (CESS) Compared To Personal Energy Storage (PES). (**a.** Summer case. **b.** Winter case.)

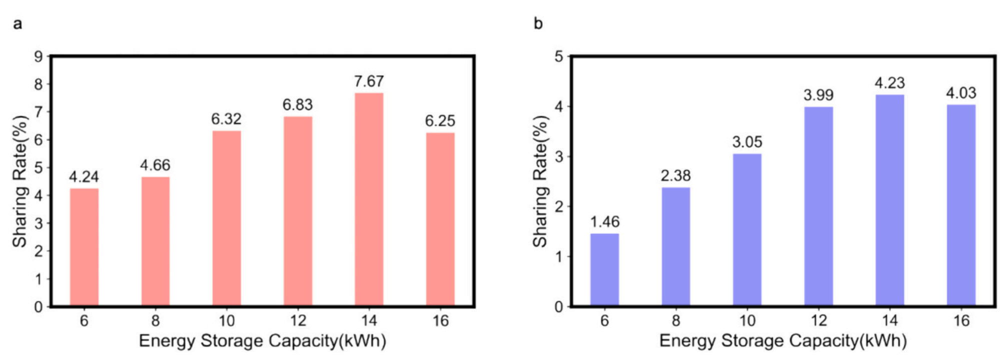

Fig. 14. The Sharing Rate of Personal Energy Storage Sharing (PESS). (**a.** Summer case. **b.** Winter case.)

Fig. 14 presents the sharing rate results for PESS, with Fig. 14a corresponding to the summer season and Fig. 14b to the winter season. The sharing rates in summer for PESS are generally higher, peaking at 7.67% at 14kWh. This higher sharing rate correlates with the lower operational costs and greater energy storage discharge capacity during this season. The sharing rates in winter are lower compared to summer, peaking at 4.23% at 14 kWh. However, since the shared capacity in PESS is available only after meeting the internal demands of users, the correlation between these factors is not direct, but the trends can still be discerned through the sharing rate.

Fig. 15 illustrates the sharing rates of CESS in both summer and winter. It is evident that CESS exhibits a higher sharing rate in summer, reaching up to 17.30%, particularly when 25 users share a 400kWh system (i.e., each user is allocated 16kWh of capacity), which corresponds to the point of lowest operational costs and the highest discharge capacity for CESS in summer. In winter, the sharing rate of CESS is slightly lower, yet still maintains a minimum of 5.95%. Compared to PES and PESS (as shown in Fig. 14), CESS exhibits much higher sharing rates, indicating its superior ability to integrate shared resources compared to the other two energy storage use scenarios. Likewise, the sharing rate of CESS is not significantly affected by the change in the number of sharing users, but it increases with larger capacities. The concept of the sharing rate is not only simple and easy to understand, but more importantly, it embodies the inherent contribution within shared energy storage use

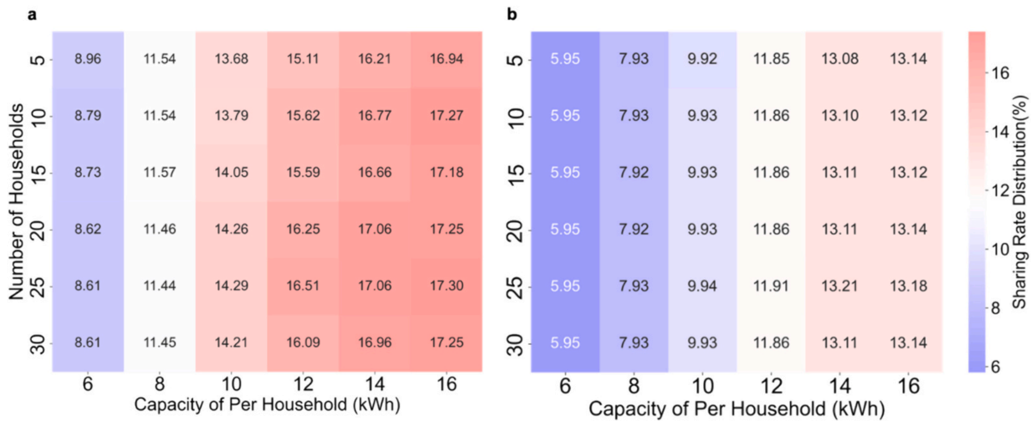

Fig. 15. **The Sharing Rate of Community Energy Storage Sharing (CESS).** (**a.** Summer case. **b.** Winter case.)

scenarios. By enhancing the capability for inter-user resource sharing, shared energy storage achieves economic and technical advantages. CESS, in particular, stands out in shared energy storage use scenarios and represents an excellent choice for sustainable communities in the future.

Sharing rate reveals disparities in resource utilization efficiency across different models. More crucially, it provides a quantifiable evaluation tool for future energy-sharing paradigms, serving as a key indicator of the success of shared energy storage initiatives. With advancements in technology and the increasing use of renewable energy sources, effective resource-sharing mechanisms can not only enhance energy efficiency but also help in reducing energy wastage, thereby supporting sustainable development goals. Looking ahead, with the evolution of smart grid technologies, the inter-user resource sharing capability is anticipated to play a pivotal role in the design and implementation of broader community and urban-level energy projects.

5. Conclusion

In this paper, a consistent framework is proposed to evaluate heterogeneous BES use scenarios, encompassing operational costs, capital costs, storage utilization, and the sharing rate. Leveraging data from 300 Australian residential customers, the framework optimizes operational scheduling under three BES use scenarios: CESS, PES, and PESS. The key conclusions drawn from this study can be summarized as follows:

1) In terms of operational costs, PESS and CESS use scenarios are significantly lower than the traditional PES use scenario. PESS achieves up to an 18.09% reduction in operational costs compared to PES, while CESS shows a maximum reduction of 20.80%. This cost efficiency is attributed to efficient energy utilization and incentive policies that promote shared BES use.
2) In terms of capital costs, CESS stands out with the lowest capital costs, up to 31.97% lower than PES and PESS. As for storage utilization, while PESS and CESS sometimes exhibit lower performance compared to PES, this does not affect their strong operational cost performance due to their superior capability in resource integration. This capability is demonstrated by inter-user resource sharing, quantified by the sharing rate. CESS, with a higher sharing rate of 17.30% compared to PESS's 7.67%, plays a critical role in integrating large-scale storage and fostering user collaboration.
3) The CESS use scenario performs optimally, effectively alleviating investors' concerns regarding the profitability of future returns adequately covering their initial investments. However, implementing the CESS use scenario typically requires investment from third-party operators rather than residents, necessitating higher financial rewards to attract investors.
4) In the policy level, both PESS and CESS can achieve significant operational profitability under incentive policies. Such policies can also encourage resident participation in shared storage, leading to faster returns on investment. Our work supports the implementation of similar policies, highlighting their potential to drive profitability and investment in shared BESs.
5) Overall, this consistent evaluation framework for heterogeneous BES use scenarios can significantly optimize operational efficiency and profitability.

Future studies should focus on assessing and optimizing the safety and sustainability of energy storage systems. This includes integrating renewable energy sources, evaluating the long-term economic and environmental impacts, and developing strategies to enhance user participation in shared energy storage initiatives. Investigating user engagement and participation rates will provide valuable insights into designing effective incentive structures and policies.

CRediT authorship contribution statement

Baligen Talihati: Writing – original draft, Software, Methodology, Conceptualization. **Shengyu Tao:** Investigation, Data curation, Writing – original draft. **Shiyi Fu:** Investigation, Data curation. **Bowen Zhang:** Investigation, Data curation. **Hongtao Fan:** Investigation, Data curation. **Qifen Li:** Investigation, Data curation. **Xiaodong Lv:** Investigation, Data curation. **Yaojie Sun:** Supervision, Project administration, Funding acquisition. **Yu Wang:** Project administration, Funding acquisition, 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.

Data availability

Data will be made available on request.

Acknowledgment

This study was supported by the 2022"Science and Technology Innovation Action Plan" Natural Science Foundation Project of Shanghai (Grant No. 22ZR1425900), Shanghai Engineering Research Center for Artificial Intelligence and Integrated Energy System (Grant No. 19DZ2252000). The authors would like to thank for the technical advice from Shanghai Electric Power University and TÜV SÜD China Co., Ltd.

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