Multi-time-scale Resource Allocation Based on Long-term Contracts and Real-time Rental Business Models for Shared Energy Storage Systems

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***Abstract*—The push for renewable energy emphasizes the need for energy storage systems (ESSs) to mitigate the unpredictability and variability of these sources, yet challenges such as high investment costs, sporadic utilization, and demand mismatch hinder their broader adoption. In response, shared energy storage systems (SESSs) offer a more cohesive and efficient use of ESS, providing more accessible and cost-effective energy storage solutions to overcome these obstacles. To enhance the profitability of SESSs, this paper designs a multi-time-scale resource allocation strategy based on long-term contracts and real-time rental business models. We initially construct a life cycle cost model for SESS and introduce a method to estimate the degradation costs of multiple battery groups by cycling numbers and depth of discharge within the SESS. Subsequently, we design various long-term contracts from both capacity and energy perspectives, establishing associated models and real-time rental models. Lastly, multi-time-scale resource allocation based on the decomposition of user demand is proposed. Numerical analysis validates that the business model based on long-term contracts excels over models operating solely in the real-time market in economic viability and user satisfaction, effectively reducing battery degradation, and leveraging the aggregation effect for SESS can generate an additional increase of 10.7% in net revenue.**

***Index Terms*—Capacity allocation, long-term contracts, shared energy storage system, stochastic programming.**

Nomenclature

A. Indices

bn	Index for battery unit
i	Index for discharge events
k	Index for scenario
n	Index for user
t	Index for dispatch time

B. Parameters

α	Conversion coefficient for the maximum state of charge for real-time energy storage
β	Conversion coefficient for power constraint of shared energy storage system (SESS) for real-time energy rental
υ_{op}	Conversion parameter from variable to cost, indicating a relation to operation and maintenance
υ_{pinv}, υ_{cinv}	Conversion parameters from variable to cost, indicating a relation to investment costs
τ	Other costs related to operation and maintenance
δ	Total number of battery units
ζ	Uncertainty parameter
Φ	Conversion coefficient between energy and capacity
π_{E2G}^t, π_{G2E}^t	Prices at which SESS and power grid sell energy to power grid and SESS
λ	Regularization parameter that controls smoothness of modes
κ	Discount percentage of grid selling price
B_R	Rated charge life of battery
B_{eff}	Effective charge life of battery
C_A	Ampere-hour capacity of a battery at given discharge current
C_{binv}	Investment cost for every battery unit bn
$C_{cto}^{\min}$, $C_{cto}^{\max}$	Lower and upper bounds of total capacity leased by SESS in the first stage at long-term contract price
cm	Total capacity of SESS

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$c_n^{\min}$, $c_n^{\max}$	Lower and upper bounds on capacity that user n can lease for a long-term contract
C_R	Ampere-hour capacity of a battery at rated discharge current
d_{act}	Actual ampere-hour discharge
d_B	Actual depth of discharge (DoD) level
d_{eff}	Effective ampere-hour discharge as adjusted for DoD and cycling number
D_A	Actual discharge as a percentage of rated power capacity
D_R	Percent DoD at which rated cycle life is determined
G	Expected profit level
h_c	Contract price per unit of capacity
h_e	Contract price per unit of energy DoD
h^t_{real}	Price of real-time rental, assumed to be consistent with price at which SESS sells to power grid
j	Total number of discharge events
K	Total number of scenarios
L_{time}	Actual lifetime of battery
L_R	Cycle life at rated DoD and rated discharge current
M	Contract duration for a long-term contract
T_{life}	System operation time
u_0, u_1	Fitting parameters of life cycle curve
y	Rated lifetime of SESS
Z	Number of modes after decomposition
Z_b	Number of modes with low frequencies

C. Variables

η_{cha}, η_{dis}	Charging and discharging efficiencies
$b(t)$	Base load curve
C_{bage}	Degradation cost for every battery unit bn
C_{bom}	Operation and maintenance cost for every battery unit bn
c_{contr}	Total amount of capacity allocated to long-term contracts
C_{inv}	Initial investment cost for every battery unit bn
c_n	Long-term contract capacity allocated by SESS to user n
C_{life}	Life cycle cost at level of SESS
$c_{RT}^{\max}$	Capacity allocated to real-time rental
$\mathbb{E}[Q(x,\xi)]$	Mathematical expectation of revenue in the second stage
$E_{bn,\max}$	The maximum energy that battery unit bn can store and output
E_n	Cumulative energy value signed by user n
$fl(t)$	Fluctuation load curve
$f_{\{1,2,3\}}(x)$	Revenue collected by SESS from long-term leasing capacity or energy rentals in the first stage, and 1 represents capacity contract, 2 represents energy contract, and 3 represents multiple contracts
$f_n^{k,t}$	Fluctuation demand for user n
$op_{cha,n}^{k,t}$, $op_{dis,n}^{k,t}$	Boolean variables representing the operation status of energy storage leased to users through long-tem contracts in the second phase ($op_{cha,n}^{k,t}=1$ represents charging at time t)
$ow_{cha,n}^{k,t}$, $ow_{dis,n}^{k,t}$	Boolean variables representing the operation status of energy storage leased to users through real-time rental in the second phase ($ow_{cha,n}^{k,t}=1$ represents charging at time t)
$p_{cha,n}^{k,t}$, $p_{dis,n}^{k,t}$	Power of charging and discharging of SESS for long-term contract
$P_{bn,\max}$	The maximum power that battery unit bn can output
$r(t)$	Residual component
$r_{buy,n}^{k,t}$, $r_{sell,n}^{k,t}$	Slack variables indicating that user n buys or sells electricity to power grid through SESS
$SOC_{RT}^{k,t}$	State of charge of the portion of energy storage allocated to real-time rental
$u_n^{k,t}$	Load reduction size for user n
$u_z(t)$	The z^{th} mode component after variational mode decomposition (VMD)
$wy^{\max}$	Power constraint for real-time energy storage
$w_{cha,n}^{k,t}$, $w_{dis,n}^{k,t}$	Power of charging and discharging of SESS for real-time rental
x	All decision variables in two-stage model
$y_{buy}^{k,t}$, $y_{sell}^{k,t}$	Power for buying or selling electricity to power grid from portion of energy storage allocated to real-time rental

I. Introduction

THERE is a global consensus that the advancement and application of renewable energy, exemplified by wind and solar power, are pivotal in steering the current energy industry toward a clean and low-carbon type [1]. The increasing threat to power system security from the inherent unpredictability of renewable energy, marked by its intermittency and volatility, places a growing emphasis on the indispensable role of energy storage systems (ESSs) as key flexible regulation resources [2]. However, multiple factors currently impede the widespread adoption and development of ESS. For instance, the cost of storage devices remains prohibitively high, leading to prolonged investment recovery time, thus discouraging individual investment [3]. Additionally, user behavior in charging and discharging, often influenced by fluctuating electricity prices, results in sporadic utilization and idle storage capacity [4]. Furthermore, the limited variety of storage products and the variable and uncertain nature of user demand present challenges in aligning storage capacities effectively with needs [5].

In response to these challenges of traditional ESS, the shared energy storage system (SESS) emerges as a potential solution, proposing a more unified and efficient method to ESS utilization, while also offering more accessible and cost-effective energy storage services [6]. The SESS concept merges traditional energy storage technology with the sharing economy model [7]. In this system, SESS provides services to multiple entities, enabling users to utilize centralized energy storage facilities according to their needs, without the necessity to construct their own ESS, paying only for the energy storage services utilized [7]. In terms of advantages, the SESS enhances the efficiency of the energy storage value chain through the complementary alignment of user demand profiles and unified coordination within the storage system [8]. This method not only improves the utilization efficiency of ESS but also, by leveraging centralized investment and economies of scale, reduces the per-unit investment cost of storage facilities [9]. Globally, several pilot projects in SESS have been initiated. For instance, in 2019, China launched demonstration projects in Qinghai [10] and Changsha, while Tesla in the United States embarked on the Connected Solutions project. Consequently, SESS offers an economically viable new solution for the large-scale application of energy storage, further diminishing the operation costs of energy storage services.

In the realm of business models, SESS managed by operators typically offers two types of services to users: ① providing energy storage capacity, and ② offering charging/discharging services [7]. The former allows users to freely manage the energy storage capacity they lease over a specified time [11]. To some extent, it can represent a long-term contract service. For the provision of the latter, SESS operators cater to the power demands of users, with charges based on actual usage patterns [12]. This arrangement can either follow predefined demand curves or adapt to real-time power demands submitted via a digital platform. Hence, these services can be structured through various contractual frameworks: they might be encompassed within long-term contracts for larger projects such as SESS at new energy generation sites, or operate under real-time leasing models, especially suitable for community-based SESS scenarios. Reference [13] presents a two-stage, price-based method for SESS: initially, operators set investment capacities and user prices for cost minimization, followed by users adjusting their purchased capacities in response to these prices. Reference [14] proposes an auction-based ES sharing model to allocate ES resources by assigning the rights of using stored energy and ES capacity to the users. In summary, the current business models for SESS exhibit several limitations: ① a lack of flexibility in leasing methods and uniformity in long-term contract types; ② a predominant focus on single-time dimension leasing strategies with limited research on balancing resources between long-term and short-term leases; ③ both the provision of capacity and power for SESS long-term services are based on the assumption of fixed contract time, without considering the impact of contract time on the economic aspects of SESS. As energy storage technology and the electricity market evolve, electricity is increasingly treated as a commodity. For SESS, on the one hand, leasing through long-term contracts ensures stable income. On the other hand, although real-time leasing may face unstable demand, it often generates higher income and efficiently utilizes idle storage resources within the platform. The combination of these two models not only guarantees stable revenue but also improves the resource utilization of SESS, making the integration of long-term and short-term leasing a potential future business trend.

Despite the scarcity of research specifically targeting multi-time-scale scheduling strategies for the allocation of long-term and short-term contract resources within SESS, the broader field of multi-time-scale resource allocation has been thoroughly investigated. Established methods such as two-stage stochastic optimization [15], [16], model predictive control, dynamic programming [17], and alternating direction method of multipliers [18] offer valuable insights and tools for complex resource allocation challenges. For instance, [19] models a multi-stage stochastic program designed to optimize the energy purchase cost for a community with distributed solar generation and an SESS. Among these methods, two-stage stochastic optimization is particularly well-aligned with the decision-making processes inherent in long-term and short-term SESS contracts. It divides decision-making into two distinct stages: the first stage involves making immediate, "here-and-now" decisions based on expected demands, while the second stage adapts to the actual outcomes of random events. This method mirrors the typical contractual decision-making in SESS, where contracts are signed based on forecasted demand, followed by real-time adjustments according to actual events. Consequently, we have adopted two-stage stochastic optimization to address the multi-time-scale scheduling problem in SESS.

Additionally, when considering operation strategies for SESS, it is crucial to recognize the extra economic costs compared with traditional storage systems [20]. SESS facilities, catering to a wide range of users with diverse service functions, often face more frequent and unpredictable dispatching, potentially leading to rapid battery degradation and increased battery replacement costs [21]. Thus, SESS operation must carefully weigh the additional operation costs of battery usage against dispatch strategies. Reference [22] proposes a novel cooperative framework for an equitable clearing mechanism in SESS, which includes ESS degradation costs in the pursuit of optimal social energy costs. However, in [22], the degradation costs are calculated by multiplying a subjectively set conversion coefficient with power, which may not accurately reflect the true degradation process during actual charging and discharging operations in SESS.

To this end, this paper designs a multi-time-scale resource allocation strategy based on long-term contracts and real-time rental business models for SESS. The main contributions are summarized as follows.

1) Various long-term contract models for centralized SESS

are provided from both capacity and energy perspectives, and corresponding mathematical models are constructed. Business models and operation processes have been developed that bridge long-term contracts with real-time rental. An economic comparison analysis of different contract models is conducted, and recommendations for contract types are proposed for different types of users.

2) A two-stage resource allocation algorithm based on the decomposition of user demands for SESS has been introduced. This algorithm exhibits significant robustness and is adept at proficiently managing the uncertainty of user demands in SESS, harmonizing the coordination between long-term contracts and real-time rental.

3) Recognizing the more frequent charging-discharging cycles of SESS versus traditional systems, battery degradation costs have been integrated into the optimization scheduling algorithm. This integration acts as a constraint on the charging-discharging behavior of SESS, promoting enhanced economic efficiency.

The remainder of this paper is organized as follows. Section II illustrate life cycle cost of SESS. Section III presents various business models for SESS. Section IV outlines the two-stage resource allocation for SESS. Experimental results are presented in Section V. Section VI concludes this paper and discusses potential directions for future studies.

II. Life Cycle Cost of SESS

SESSs serve a broad spectrum of users and provide a multitude of service functionalities, necessitating more frequent dispatches with irregular depths each time compared with traditional ESS. This irregularity and frequency can potentially accelerate battery degradation and elevate the associated costs of battery replacements, which is a phenomenon we term “degradation cost”. Therefore, compared with traditional ESS, SESS necessitates a more considerable emphasis on the additional degradation costs of batteries incurred due to dispatch strategies. In this section, we initially propose a method for calculating the degradation costs of battery in SESS, considering both the frequency of cycling and depth of discharge (DoD). Subsequently, we present a comprehensive cost calculation model for SESSs, along with the pricing assumptions applied when delivering services to users. This model is then integrated within the optimization framework of the long-term and short-term contractual business models outlined in Section III, guiding the optimized operation of SESS.

A. Degradation Cost

The battery life cycle is key in assessing the state of health of SESS. Degradation, mainly due to charging and discharging, is influenced by two-factor categories: non-operational (ambient conditions and calendar aging) and operational (cycle depth, overcharging/discharging, and average state of charge). Our study focuses on operation elements for capacity allocation and dispatching in SESS. This is due to the known nature of these factors in the dispatch strategy, making analysis more feasible, and the non-operational factors, which are typically uncertain and unrelated to dispatch strategies, are beyond the scope of this study. Hence, we propose a method for approximating lifetime estimation, based on cycling numbers and DoD. The findings of research imply that each battery possesses a finite number of life cycles, quantified by the aggregate of effective ampere-hours throughput at the rated DoD and rated discharging rate throughout its operation life. Any specific discharging event can be translated to an equivalently effective ampere-hour discharging, contingent on the actual DoD in comparison to the rated DoD. When the cumulative ampere-hour aligns with the rated charging life of BESS, the system ceases to function. The rated charging life B_R is represented as:

$$B_R = L_R D_R C_R \tag{1}$$

The functional relationship between the number of BESS life cycle L_B and the battery DoD d_B can be expressed as:

$$L_B\left(d_B\right) = L_R\left(\frac{D_R}{D_A}\right)^{u_0} \mathrm{e}^{u_1\left(1-\frac{D_A}{D_R}\right)} \tag{2}$$

The actual life cycle can be calculated as a function of the DoD at which it is cycled as:

$$d_{eff} = \left(\frac{D_A}{D_R}\right)^{u_0} \mathrm{e}^{u_1\left(\frac{D_A}{D_R}-1\right)} \frac{C_R}{C_A} d_{act} \tag{3}$$

Combining (2) and (3), the actual lifetime of the battery L_{time} under a specific usage pattern containing j discharging events in system operation time T_{life} can be calculated as:

$$L_{time} = \frac{B_R}{B_{eff}/T_{life}} = \frac{L_R D_R C_R}{\sum\limits_{i=1}^{j} d_{eff}(i)} T_{life} \tag{4}$$

Battery degradation cost C_{bage} is calculated as:

$$C_{bage} = \frac{C_{binv}}{B_R} \sum_{T_{life}} B_{eff}(t) \tag{5}$$

B. Life Cycle Cost

In alignment with conventional ESS, the comprehensive life cycle cost model for SESS encapsulates initial investment cost, auxiliary facility cost, operation and maintenance cost, replacement cost, disposal cost, and residual value. We condense the aforementioned diverse cost categories into a cost model based on investment costs, operation and maintenance costs, and degradation costs, which are most pertinent to the dispatch model articulated as:

$$C_{life} = \sum_{bn} C_{binv} + \sum_{bn} C_{bom} + \sum_{bn} C_{bage} \tag{6}$$

The initial investment cost refers to the fixed capital investment made during the initial stage of equipment construction. It is simplified to consist of the rated power capacity cost and energy capacity cost, considering the discount rate, as shown in (7). The operation and maintenance costs are mainly influenced by the rated power of SESS and the number of charging/discharging cycles, as stated in (8).

$$C_{binv} = \upsilon_{pinv} P_{bn,\max} + \upsilon_{cinv} E_{bn,\max} \tag{7}$$

$$C_{bom} = \upsilon_{op} P_{bn,\max} + \tau \tag{8}$$

C. Cost-based Pricing Scheme

Two business models are considered: long-term contracts and real-time rental, where the long-term contracts further contemplate two forms, namely capacity contracts and energy contracts. Therefore, it is necessary to provide SESS rental prices separately for capacity contracts, energy contracts, and real-time rental. The SESS can represent the state of charge at each moment during its actual operation as an equivalent average state of charge for the entire day. Based on this average state of charge, the rated operation lifetime, and the profitability factor, the service unit price for the energy contract can be computed as:

$$h_c=(1+G)\frac{\sum_{bn}C_{binv}+\sum_{bn}C_{bom}}{T_{life}\delta\sum_{bn}E_{bn,\max}y} \tag{9}$$

For varying users and different scales of leased capacities, SESS can theoretically establish diverse pricing standards for capacity contracts. However, since the pricing strategy is not the focal point of this paper, we will simplify and assume that the price of the capacity contract is directly proportional to the capacity and is unrelated to the types of users. The service unit price for the capacity contract can be expressed as:

$$h_e=(1+G)\varPhi\frac{\sum_{bn}C_{binv}+\sum_{bn}C_{bom}}{T_{life}\delta\sum_{bn}E_{bn,\max}y} \tag{10}$$

Considering that the discharging duration of most ESSs is currently 4 hours, this paper assumes the value of the conversion coefficient $\varPhi$ to be 8.

For real-time rental, we assume that the service price is a discount on the forecasted electricity price. Note that this price fluctuates within a day, distinguishing it from the fixed price of long-term contracts. The price of real-time rental is assumed to be consistent with the price at which SESS sells to the power grid.

$$h_{real}^t=\pi_{E2G}^t=\kappa\pi_{G2E}^t \tag{11}$$

III. Business Models of SESS

The business model of SESS significantly impacts the operation strategies, operation profits, and mechanisms of interaction between users and the SESS, which are key factors constraining the profitability of SESS. With the continuous development of energy storage technology, the business models of SESS will become more diversified and mature. In the future, we anticipate the emergence of an SESS business model that combines long-term contracts with real-time rental. SESS offers users long-term contracts to ensure their foundational needs over a certain period, while also providing a short-term method of real-time leasing to meet occasional and stochastic demands of users for power.

The effective implementation of the economics of SESS operation is inseparable from the design of the business process. SESS operators need standardized business processes to help the platform operate efficiently when providing services. Figure 1 illustrates the business process of business model that bridges long-term contracts and real-time rental, which is divided into five phases ①-⑤. The processes marked in yellow are related to long-term contracts, and those in purple are related to real-time rental. In this section, a business model for SESS is designed that integrates both long-term contracts and real-time rental.

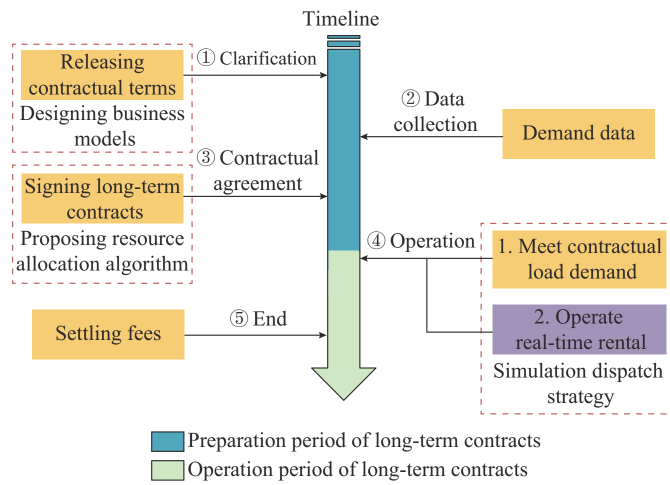

Fig. 1. Business process of business model.

We propose two long-term service methods for SESSs, namely contracting by capacity and by energy. Among them, the energy contract is further subdivided into two types: daily accumulation and total contract duration accumulation of energy. Additionally, the SESS can also dispatch energy to the real-time market, selling it in a fragmented, instantaneous manner to users to meet their immediate needs, thereby earning revenue from real-time rental. The specific definitions are shown in Table I.

TABLE I
Definition of Various Leasing Methods

Type	Definition
Capacity contract	During the contract term, SESS provides energy services based on power demand of users within leased capacity boundary
Full contract duration cumulative energy contract (FCDC-energy contract)	The contract specifies a flexible energy accumulation and consumption model over the entire contract period
Daily cummulative energy contract (DC-energy contract)	Users have a daily energy limit, measured daily with no carry-over of unused energy to the next day
Real-time rental	Users can purchase capacity and energy as per actual needs at any time, billed at a fixed unit cost

A. Capacity Contract Model

The decision variables in the first phase are the allocated long-term capacity for user n, and the objective function is:

$$f_1(x)=\sum_n h_c c_n \tag{12}$$

In order to plan the allocation of long-term leasing capacity and signing contracts, it is necessary to ensure that the total contract capacity is less than the storage capacity. At the same time, to leave sufficient flexibility support for intra-day operation, we set boundaries for the contract capacity:

$$c_{cto}^{\min} \le c_{contr} \le c_{cto}^{\max} \tag{13}$$

$$c_{contr} = \sum_n c_n \tag{14}$$

The SESS reserves a portion of the capacity for intra-day flexible power support. Therefore, it is ensured that $c_{cto}^{\max} \le cm$. For practical purposes and to simplify the model, we set the default value of $c_{cto}^{\min}$ to be 0 and $c_{cto}^{\max} = 0.5cm$.

Furthermore, to restrict users from engaging in speculative behaviors such as leasing excessive SESS for energy arbitrage, and to ensure the reasonable utilization of SESS by each user, limitations are imposed on the long-term contract capacity that each user can sign.

$$c_n^{\min} \le c_n \le c_n^{\max} \tag{15}$$

In this paper, $c_n^{\min}$ is set to be 0, and the default value of $c_n^{\max}$ is set to be $c_{cto}^{\max}/N$. In more complex scenarios, $c_n^{\max}$ could be linked to factors such as the scale of the user operation and the equity relationship with the SESS, e.g., whether the user n is an investor or operator of the SESS. However, in this paper, we do not focus on these complex scenarios.

The charging and discharging behaviors of battery modules in SESS are subject to two kinds of constraints. Firstly, the charging and discharging rates are limited and cannot exceed the rated values of the modules, which ensure safe and efficient charging and discharging processes. Secondly, there is a relationship between the charging/discharging power and the energy storage capacity. The charging/discharging power is limited by the available energy storage capacity.

$$\begin{aligned} &op_{cha,n}^{k,t} \cdot op_{dis,n}^{k,t} = 0 \\ &op_{cha,n}^{k,t} + op_{dis,n}^{k,t} = 1 \end{aligned} \tag{16}$$

$$0 \le r_{buy,n}^{k,t} + p_{cha,n}^{k,t} \le p_n^{\max} \quad \forall n, \forall t, \forall k \tag{17}$$

$$0 \le r_{sell,n}^{k,t} + p_{dis,n}^{k,t} \le p_n^{\max} \quad \forall n, \forall t, \forall k \tag{18}$$

$$r_{buy,n}^{k,t}, p_{cha,n}^{k,t}, r_{sell,n}^{k,t}, p_{dis,n}^{k,t} \ge 0 \quad \forall n, \forall t, \forall k \tag{19}$$

$r_{buy,n}^{k,t}$ and $r_{sell,n}^{k,t}$ indicate that the base load demand of users (see Section IV for details) can be met by buying ($r_{buy,n}^{k,t}$) or selling ($r_{sell,n}^{k,t}$) electricity to the power grid through SESS.

B. Energy Contract Model

For users with high demand uncertainty and users with low demand uncertainty, we divide the energy contracts into two types: FCDC-energy contract and DC-energy contract.

For the energy contract, the contract revenue in the first phase can be calculated as:

$$f_2(x) = \sum_n h_e E_n \tag{20}$$

$$c_{contr} = \frac{\sum_n E_n}{\Phi} \tag{21}$$

1) FCDC-energy contract. This type of energy contract allows users to accumulate and consume a certain amount of energy over a fixed duration. The energy consumption is not limited to a specific daily amount but is summed up over the entire contract period. Users with high demand uncertainty can benefit from this type of contract as it provides flexibility in energy consumption and allows them to adjust their usage based on their varying needs throughout the contract duration.

$$\sum_k \sum_t \left(\left| p_{cha,n}^{k,t} \right| + \left| p_{dis,n}^{k,t} \right| \right) \le E_n \tag{22}$$

2) DC-energy contract. In this type of energy contract, users have a daily cumulative energy limit. The energy consumed by the user is measured daily, and any unused energy from a specific day does not carry over to the next day. This contract type is suitable for users with low demand uncertainty who have a relatively stable energy consumption pattern. It provides a predictable daily energy allocation and allows users to plan their energy usage accordingly.

$$\sum_t \left(\left| p_{cha,n}^{k,t} \right| + \left| p_{dis,n}^{k,t} \right| \right) \le E_n \tag{23}$$

By offering these two types of energy contracts, SESS can cater to different needs and demand patterns of users with varying levels of demand uncertainty. It allows for more customized and flexible energy services, enhancing the overall user experience and optimizing the utilization of SESS resources. In addition, constraints (13) and (16)-(19) are used to ensure the normal operation of SESS.

C. Coexistence Model of Multiple Contracts

Furthermore, we allow users to sign different contracts. In this case, the objective function for the first phase can be expressed as:

$$f_3(x) = \sum_n (h_c c_n + h_e E_n) \tag{24}$$

Apart from that, the remaining constraint conditions remain unchanged.

D. Real-time Rental Model

For real-time leased energy storage, its capacity is related to the total contracted capacity as:

$$c_{RT}^{\max} = cm - \sum_n c_n \tag{25}$$

The charging and discharging rates of real-time leased energy storage need to adhere to the rated limits of the energy storage module. This is done to ensure the safety and performance of the ESS and prevent exceeding the rated charging and discharging rates of the module.

$$\begin{cases} ow_{cha,n}^{k,t} \cdot ow_{dis,n}^{k,t} = 0 \\ ow_{cha,n}^{k,t} + ow_{dis,n}^{k,t} = 1 \end{cases} \tag{26}$$

Real-time leased energy storage needs to satisfy the state of charge constraints, which ensure that the ESS can handle the required energy exchange during the leasing period without exceeding its storage limitations, as shown in (27) and (28). By managing the energy storage capacity effectively, it can provide sufficient energy to meet the user demand while maintaining the integrity and operation stability of the system.

$$\begin{aligned} SOC_{RT}^{k,t} = SOC_{RT}^{k,t-1} + \eta_{cha}\left(y_{buy}^{k,t} + \sum_n ow_{cha,n}^{k,t} \cdot w_{cha,n}^{k,t} \right) - \\ \eta_{dis}\left(y_{sell}^{k,t} + \sum_n ow_{cha,n}^{k,t} \cdot w_{dis,n}^{k,t} \right) \end{aligned} \tag{27}$$

$$0 \leq SOC_{RT}^{k,t} \leq \alpha c_{RT}^{\max} \tag{28}$$

The energy storage engaged in real-time rental operates under specific power constraints during both the charging and discharging processes. These constraints are pivotal in ensuring that the ESS neither receives nor releases power beyond established thresholds, maintaining the safety and efficiency of the system. Adherence to these constraints allows the system to control the pace of its energy intake and release, operating within its designated power limits and averting potential complications or risks stemming from excessive power transitions. This adherence is crucial for sustaining the stability and reliability of the system while meeting the demands of real-time energy rental.

$$0 \leq y_{buy}^{k,t} + \sum_{n} ow_{cha,n}^{k,t} \cdot w_{cha,n}^{k,t} \leq wy^{\max} \tag{29}$$

$$0 \leq y_{sell}^{k,t} + \sum_{n} ow_{cha,n}^{k,t} \cdot w_{dis,n}^{k,t} \leq wy^{\max} \tag{30}$$

$$y_{buy}^{k,t}, y_{sell}^{k,t}, w_{dis,n}^{k,t}, w_{cha,n}^{k,t} \geq 0 \quad \forall n, \forall t, \forall k \tag{31}$$

$$wy^{\max} = \beta c_{RT}^{\max} \tag{32}$$

Real-time leased energy storage needs to meet the fluctuating load demands of users. This means that the ESS should be capable of providing the necessary power output to accommodate the varying electricity consumption patterns of the users. By effectively managing the charging and discharging of the energy storage, it can help stabilize the power grid and ensure a reliable and continuous power supply to meet the load requirements of the users.

$$ow_{cha,n}^{k,t} \cdot w_{n}^{k,t} - ow_{cha,n}^{k,t} w_{n}^{k,t} + u_{n}^{k,t} = f_{n}^{k,t} \quad \forall n, \forall t, \forall k \tag{33}$$

IV. Two-stage Resource Allocation for SESS

This section primarily addresses the two-stage resource allocation issues in the third and fourth phases of the business process of business model for the SESS that bridges long-term contracts and real-time rental, as shown in Fig. 1. Given that the proposed business model encompasses transactions across two time scales, the scale of long-term contracts allocated to users by the SESS in the third phase directly impacts the operation strategies in the fourth phase. Therefore, it is crucial to simulate the operation strategies of the fourth phase during the contracting process in the third phase to attain optimal resource allocation. This ensures a harmonious capacity and energy allocation within the SESS. Figure 2 presents the schematic diagram of topology and power flow between shared energy storage, power grid, and various users. The interaction between SESS and users is orchestrated by the two-stage resource allocation algorithm. In the first stage, SESS allocates capacity and signs long-term contracts with users. In the second stage, SESS provides energy services to users according to the contents of the contracts, and any user demands that surpass the long-term contract are fulfilled through a real-time rental model.

A. Decomposition Method of Demand

During the process of contractual agreement in the third phase, resource allocation is based on the historical demand data submitted by the users. We utilize the variational mode decomposition (VMD) to decompose user demand into demand components at different time scales, namely the base load component and the fluctuating load component. The base load represents a more stable and consistent demand, and we formulate long-term contracts based on the base load, ensuring that the resource allocated to long-term contracts is not wasted. The fluctuating load signifies demands that are transient and characterized by high randomness and volatility. The fluctuating load is accommodated through the transaction model of real-time rental.

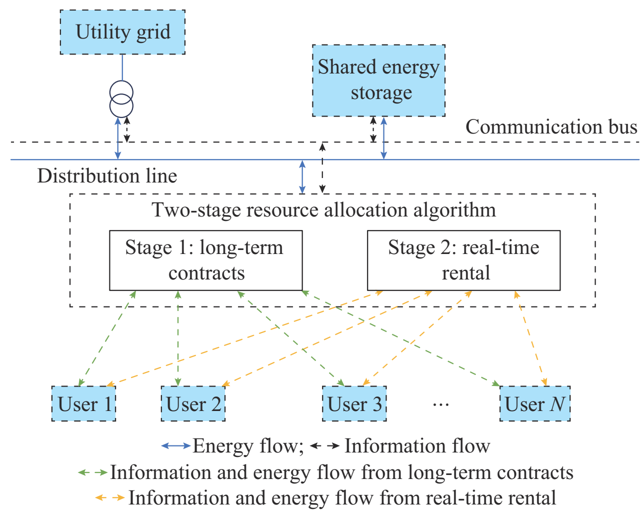

Fig. 2. Schematic diagram of topology and power flow between shared energy storage, power grid, and various users.

Given a demand curve $x(t)$, the VMD algorithm decomposes it into z modes $u_z(t)$ and a residual component $r(t)$:

$$x(t) = \sum_{z=1}^{Z} u_z(t) + r(t) \tag{34}$$

$u_z(t)$ is obtained by minimizing the following constrained optimization problem as:

$$\min_{u_z} \left[\sum_{t=1}^{T} \left(x(t) - \sum_{z=1}^{Z} u_z(t) \right)^2 + \lambda \sum_{z=1}^{Z} \left(|u_z|^2 - 1 \right) \right] \tag{35}$$

The optimization problem is solved using an iterative algorithm that alternates between updating the modes and updating the weights.

The base load curve $b(t)$ is obtained by summing the modes with low frequencies:

$$b(t) = \sum_{z=1}^{Z_b} u_z(t) \tag{36}$$

The fluctuation load curve $fl(t)$ is obtained by summing the modes with high frequencies:

$$fl(t) = \sum_{k=Z_b+1}^{Z} u_k(t) \tag{37}$$

The noise component $n(t)$ is obtained as the residual after the decomposition:

$$n(t) = r(t) \tag{38}$$

The decomposition results in the demand curve being expressed as the sum of the base load curve, the fluctuation load curve, and the noise component:

$$x(t)=b(t)+fl(t)+n(t) \tag{39}$$

B. Two-stage Resource Allocation Algorithm Based on Scenario Sets

We employ a two-stage resource allocation algorithm to elucidate and address the issue of coordinating SESS capacity allocation between long-term contracts and real-time rental markets in the presence of demand uncertainty. Figure 3 illustrates the objectives, constraints, and decision for each stage. The sample average approximation method is employed to formulate scenarios and their corresponding probabilities. Our primary goal is to optimize the revenue for the operators of SESS, which hinges on the revenue derived from long-term contracts in the first stage and the income and operation costs associated with real-time rental during intraday operations.

$$\max\left\{f_{\{1,2,3\}}(x)+\mathbb{E}[Q(x,\xi)]\right\} \tag{40}$$

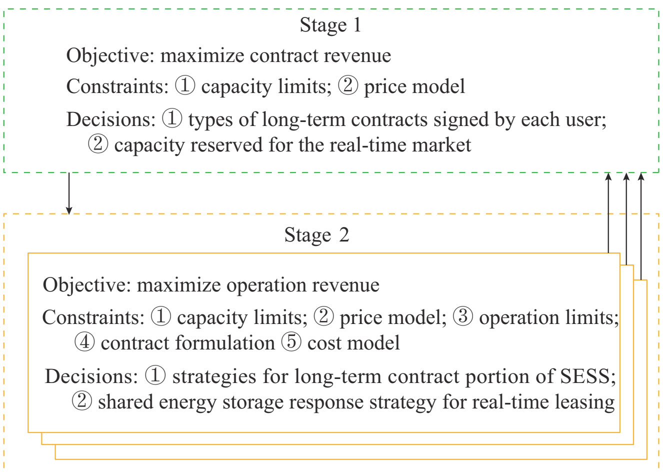

Fig. 3. Operation framework of shared energy storage plant.

Then, the sample mean approximation method is employed to handle uncertain demands by generating a large number of typical daily user demand scenarios K through Monte Carlo sampling. Each scenario is treated as an independent sub-problem, enabling the discretization of uncertainty and ensuring solvability without significant loss of information fidelity.

$$\max\left\{f_{\{1,2,3\}}(x)+M\frac{1}{K}\sum_{k}Q_k(x,\xi)\right\} \tag{41}$$

The objective function of SESS in the second stage is to maximize the profit-making capability of SESS. This includes the charging and discharging costs related to contract fulfillment, real-time rental income, and costs as well as operation and maintenance costs.

$$\begin{aligned}Q_k(x,\xi)=\max\sum_t\Bigg[&-\frac{C_{life}M}{T_{life}}-\pi^t_{E2G}y^{k,t}_{buy}+\pi^t_{G2E}y^{k,t}_{sell}+\\&\sum_n(-\pi^t_{E2G}r^{k,t}_{buy,n}+\pi^t_{G2E}r^{k,t}_{sell,n})+\\&\sum_n\pi^t_n(ow^{k,t}_{cha,n}\cdot w^{k,t}_{cha,n}+ow^{k,t}_{cha,n}\cdot w^{k,t}_{dis,n})\Bigg]\end{aligned} \tag{42}$$

Figure 4 illustrates the specific process of the two-stage resource allocation algorithm, guiding how different constraints and objectives are incorporated into this algorithm based on the transaction mode.

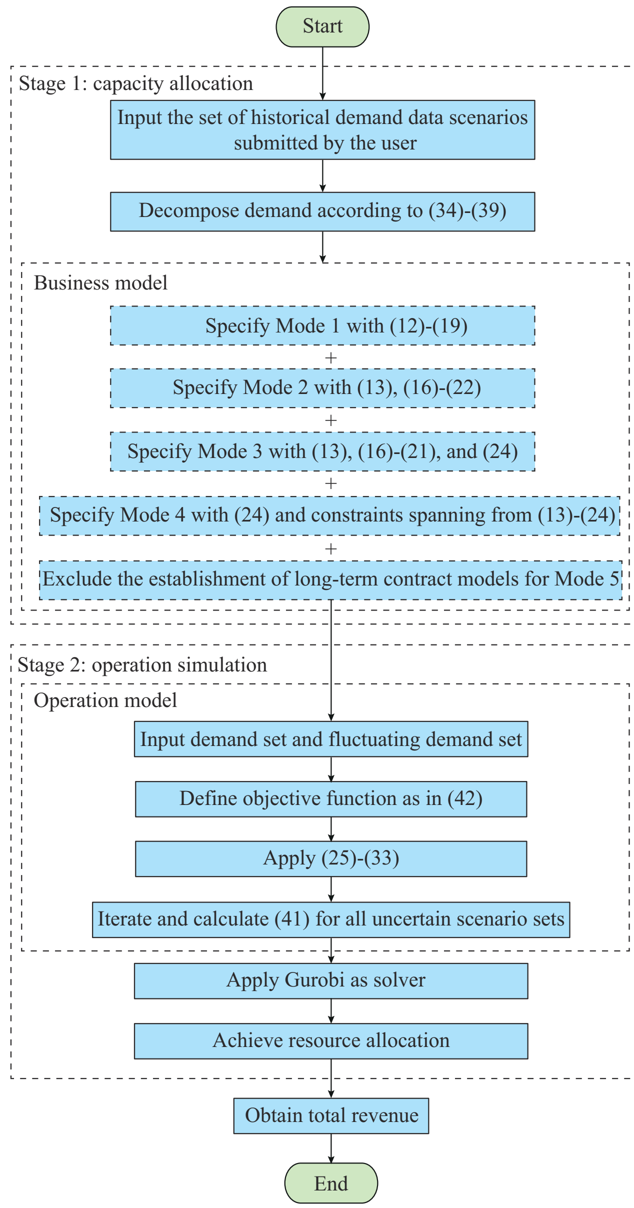

Fig. 4. Two-stage resource allocation algorithm.

V. Case Studies

In this section, the two-stage resource allocation algorithm for SESS is tested and validated in Python3.7 on a personal computer with Intel Core i5-11400F (2.60 GHz) processors and 8 GB RAM. The optimization problems are solved by Gurobi 9.0.3, with a convergence threshold set at 0.001%. The data for the renewable energy systems are derived from the Belgian grid data, where we select one year of data as the training set for the scenario collection, with time intervals of 15 min, resulting in 96 dispatch points each day. The parameter settings for SESS operation modes can be found in Table II.

TABLE II
PARAMETER SETTINGS FOR SESS OPERATION MODES

Parameter	Value
cm	100 MWh
η_{cha}	0.95
η_{dis}	0.95
t	96
M	One week, one month, three months, one year
D_R	95%
L_R	10000

We employ five modes to represent the diverse leasing strategies provided by the SESS operator to the users. As shown in Table III, the five modes essentially encompass the combinations of long-term contracts and real-time rental discussed in this paper. Modes 1, 2, and 3 represent that all users sign one of the three types of long-term contracts and utilize the real-time rental service of SESS. Mode 4 represents that different users can opt to sign different long-term contracts while also using the real-time rental service of SESS. Mode 5 represents that users solely rely on real-time rental to meet their individual needs.

TABLE III
SESS OPERATION MODES FOR USERS

Mode	Long-term contract	Short-term contract
1	Capacity contract	Real-time rental
2	FCDC-energy contract	Real-time rental
3	DC-energy contract	Real-time rental
4	Coexistence model of multiple contracts	Real-time rental
5	None	Real-time rental

A. Analysis of Different Rental Modes

This subsection presents an in-depth economic analysis of the five modes for SESS operation, the relative results are displayed in Table IV. In Table IV, the four numbers enclosed in brackets correspond sequentially to the results for contract durations of one week, one month, three months, and one year. After conducting a comprehensive analysis of the SESS operating in five different modes with four contract durations, several trends and correlations emerge.

TABLE IV
ECONOMIC ANALYSIS OF SESS OPERATION MODES

Mode	Long-term contract capacity (MWh)	Real-time rental capacity (MWh)	Contract revenue (10^4 CNY)	Real-time rental revenue (10^4 CNY)	Total revenue (10^4 CNY)	Grid electricity cost (10^4 CNY)	Daily SESS cost (10^4 CNY)	Average daily net revenue (10^4 CNY)
1	[67, 64, 59, 58]	[33, 36, 41, 42]	[12.3, 50.2, 139.9, 556.2]	[5.3, 25.2, 84.9, 354.3]	[17.7, 75.4, 224.8, 910.5]	[5.8, 25.7, 85.5, 346.6]	[0.117, 0.110, 0.122, 0.115]	[1.57, 1.54, 1.43, 1.43]
2	[54, 52, 48, 50]	[46, 48, 52, 50]	[13.4, 55.8, 152.4, 642.9]	[6.1, 27.2, 89.8, 351.0]	[19.6, 83.1, 242.2, 993.8]	[5.4, 24.6, 70.4, 322.2]	[0.108, 0.105, 0.112, 0.108]	[1.91, 1.84, 1.80, 1.73]
3	[53, 49, 45, 45]	[47, 51, 55, 55]	[14.2, 56.7, 156.4, 628.1]	[4.2, 19.6, 63.2, 258.6]	[18.5, 76.2, 219.7, 886.7]	[5.3, 22.9, 69.4, 314.5]	[0.106, 0.097, 0.107, 0.098]	[1.77, 1.68, 1.56, 1.47]
4	[61, 60, 61, 62]	[39, 40, 39, 38]	[13.1, 55.1, 168.7, 691.0]	[6.0, 26.4, 76.8, 306.4]	[19.1, 81.5, 245.4, 997.4]	[5.7, 24.8, 77.3, 337.0]	[0.110, 0.114, 0.114, 0.117]	[1.81, 1.78, 1.76, 1.69]
5	[0, 0, 0, 0]	[100, 100, 100, 100]	[0, 0, 0, 0]	[19.6, 84.1, 252.4, 1023.6]	[19.6, 84.1, 252.4, 1023.6]	[8.8, 42.9, 134.5, 522.5]	[0.176, 0.176, 0.178, 0.179]	[1.37, 1.20, 1.13, 1.19]

Firstly, regarding profitability, Mode 2 consistently achieves higher average daily net revenue across all contract lengths, reflecting its advantage in balancing the revenues and costs between long-term contracts and real-time rental. In contrast, Mode 5, which operates without the support of long-term contracts, tends to incur higher overall costs in the long run, especially during periods of significant energy market price volatility, despite generating high income through real-time rental.

Delving into cost analysis reveals that as contract lengths increase, particularly for the one-year long-term contract, all modes experience an uptrend in total costs. However, Mode 2 exhibits more effective overall cost control. Despite the increase in costs, its net revenue growth remains significant, which is an essential factor in long-term operation planning since the stability offered by long-term contracts in revenue and cost forecasting is crucial for operators.

When selecting an operation mode, operators must carefully weigh the implications of contract duration, cost control, and sensitivity to market price fluctuations. While real-time rental offers substantial flexibility in the short term, hybrid modes such as Mode 2 and Mode 4 may better suit operators seeking stable long-term revenue, providing the necessary flexibility to respond to market changes.

B. Impact of Battery Degradation Costs

Upon examining the data from the Table V and Table VI, the optimization algorithm that considers DoD and discharge frequency demonstrates its effectiveness across all five modes for varying contract durations. This algorithm tends to increase the average DoD, which suggests that the battery is utilized more effectively, accessing a larger portion of its capacity within each cycle.

Concurrently, there is a noticeable reduction in the average daily discharge number when using the algorithm that accounts for DoD and discharge frequency. Fewer discharge cycles can lead to a slower rate of battery degradation, which in turn, may diminish the extra costs associated with battery wear and tear. Specifically, the equivalent degraded battery cost is lower when employing the optimization algorithm that includes DoD and discharging frequency, underscoring the potential for cost savings in long-term battery maintenance and replacement.

TABLE V
RESULTS OF OPTIMIZATION ALGORITHM CONSIDERING DOD AND DISCHARGE FREQUENCY

Mode	Average DoD (%)	Average daily discharge number	Equivalent degraded battery cost (CNY)
1	[34, 32, 36, 35]	[1225, 1234, 1125, 1265]	[613, 656, 531, 614]
2	[56, 53, 60, 59]	[752, 858, 854, 958]	[228, 274, 242, 276]
3	[48, 45, 50, 54]	[977, 1002, 1126, 1024]	[346, 378, 383, 322]
4	[39, 40, 48, 40]	[1035, 1025, 1325, 1136]	[451, 434, 469, 483]
5	[32, 32, 30, 38]	[1337, 1348, 1420, 1251]	[710, 716, 805, 560]

TABLE VI
RESULTS OF OPTIMIZATION ALGORITHM WITHOUT CONSIDERING DOD OR DISCHARGING FREQUENCY

Mode	Average DoD (%)	Average daily discharge number	Equivalent degraded battery cost (CNY)
1	[31, 29, 34, 32]	[1562, 1556, 1502, 1530]	[857, 912, 751, 813]
2	[44, 42, 41, 42]	[952, 920, 938, 1005]	[368, 372, 389, 407]
3	[40, 42, 45, 48]	[1085, 1021, 1003, 1024]	[461, 413, 379, 363]
4	[30, 32, 45, 39]	[1264, 1352, 1398, 1284]	[716, 718, 528, 560]
5	[30, 30, 30, 35]	[1588, 1459, 1432, 1354]	[900, 827, 811, 658]

For instance, in the one-week contract duration in Mode 2, when the DoD and discharging frequency is considered, the equivalent degraded battery cost is significantly lower compared with the condition when these factors are not considered. This pattern holds true across the various modes and contract durations, suggesting a consistent advantage in terms of reducing the cost implications of battery degradation. Thus, the implementation of an optimization algorithm that accounts for DoD and discharging frequency can be a strategic method to enhance the economic viability of SESS operation modes.

C. Analysis of Different Rental Modes for Users

When evaluating the leasing modes offered by SESS, notable financial considerations for both solar photovoltaic (SP) and wind power (WP) users have been identified, with comprehensive details outlined in Table VII. Considering the seasonal variations inherent to both SP and WP energy production, and given that the three-month contract duration yielded favorable outcomes in Section V-A and V-B, the analysis here is predicated on a three-month contractual setting. Calculations for other contract durations have also been executed, and the conclusions drawn remain consistent across these different timeframes.

Upon analyzing the data from Table VII for the economic implications of different SESS rental modes, it becomes evident that Mode 5, which exclusively relies on real-time rental, incurs the highest costs for both SP and WP users. This is substantiated by the highest real-time rental costs and total expenditures displayed for both user types in this mode.

TABLE VII
ECONOMIC ANALYSIS OF DIFFERENT RENTAL MODES FOR USERS

Mode	Contract cost (10^4 CNY)		Real-time rental cost (10^4 CNY)		Total expenditure cost (10^4 CNY)	
	SP	WP	SP	WP	SP	WP
1	1616	2536	577	879	2194	3415
2	1773	2395	677	677	2450	3072
3	1889	2461	468	735	2356	3195
5	0	0	2536	4047	2536	4047

For SP users, whose energy demands are relatively stable, a mode that combines reasonable contract costs with lower total expenditure is preferable. Mode 1 emerges as the optimal choice for SP users, offering the lowest total expenditure among the available options.

Conversely, WP users often experience significant variability and irregularity in their energy demands. Therefore, a mode that balances stability with moderate reliance on real-time rental costs would be more beneficial. Modes 2 and 3 present a middle ground with moderate total expenditures, making them suitable for WP users who need to navigate fluctuating energy requirements. These modes offer a cost-effective compromise between the predictability of a long-term contract and the flexibility of real-time rental expenses.

D. Analysis of Aggregation Effect and Incremental Revenue

In Modes 2 and 3, which involve the SESS entering into long-term contracts with users, we observe a significant user utilization rate. However, the utilization of energy storage modules dedicated to these long-term contracts is not as high as expected, as illustrated in Figs. 5 and 6, and detailed in Table VIII. Figures 5 and 6 specifically depict the utilization rates of two distinct types of contracts: the DC-energy contract and the FCDC-energy contract. The one-week contract duration is used as a representative example for clarity and simplicity, given the voluminous data from other contract lengths. It should be noted that this trend of moderate utilization rates for both contract types persists across all contract durations based on our comprehensive analysis, with the one-week duration serving as an illustrative case.

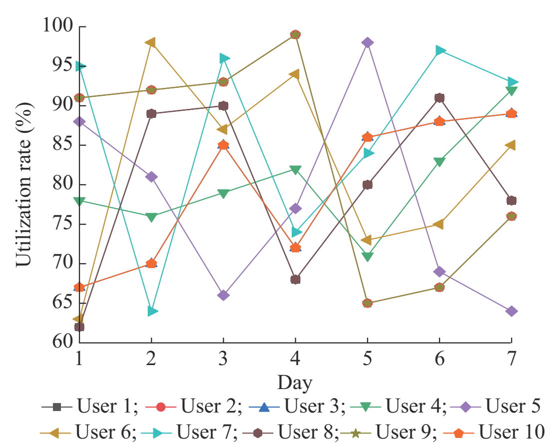

Fig. 5. Contract utilization rate for users with DC-energy contract.

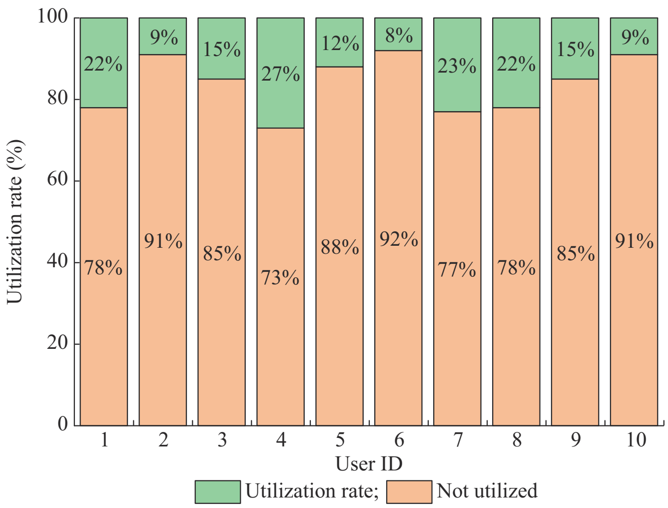

Fig. 6. Contract utilization rate for users with FCDC-energy contract.

TABLE VIII
CONTRACT UTILIZATION RATE ALLOCATED TO LONG-TERM CONTRACTS

Contract type	Utilization rate	Utilization rate after adding users	Incremental revenue (10^4 CNY)	Proportion (%)
FCDC-energy contract	[64.9, 69.4, 71.6, 62.3, 66.4, 65.2, 69.3]	[80.4, 85.5, 89.1, 78.4, 82.2, 78.9, 87.6]	2.99	15.2
DC-energy contract	67.4	89.5	1.98	10.7

Similar to the smoothing effect in wind farms, when SESS serves multiple users, there is indeed a similar effect, often referred to as the "aggregation effect". In the context of SESS, the aggregation effect refers to the potential reduction in overall demand volatility when the demands of multiple users are aggregated together. This is because the energy demands of different users might peak at different times, or have different fluctuation patterns. When these demands are combined, periods of high and low demand may offset each other, resulting in a more stable overall demand.

In the context of SESS contracts, a pivotal observation emerges regarding the utilization rates. Initially, when contracts are signed on a one-to-one basis, the aggregation effect of users is overlooked. This oversight leads to a scenario where individual contract utilization rates are commendably high, yet the overall utilization rate of SESS remains suboptimal, hovering around 60%.

Upon integrating the aggregation effect, a transformative shift is observed. The SESS that capacitates to serve an expanded user base exhibits a marked enhancement in its contract utilization rates.

For the FCDC-energy contract, the contract utilization rates, which originally fluctuated between 64.9% and 71.6%, surge to span between 80.4% and 89.1% after aggregation. This transition signifies an approximate elevation of 20% in contract utilization rate. Concurrently, the revenue trajectory also ascends, registering an increment of 29900 CNY, which translates to a 15.2% growth.

In the case of the DC-energy contract, the initial contract utilization rate stands at 67.4%. However, after aggregation, a leap to 89.5% is observed, marking a similar uptrend of around 20%. Financially, this metamorphosis yields an additional revenue of 19800 CNY, amounting to a 10.7% increase.

In conclusion, the integration of the aggregation effect undeniably amplifies both the contract utilization rates and the revenues of SESS. This underscores the imperative of considering the aggregation effect of multiple users during contract formulation to harness the maximum efficiency and profitability of SESS.

E. Calculation Time Over Extended Contract Durations

We assess the robustness of the proposed algorithm by analyzing its performance over a spectrum of scenario set sizes, spanning from 10 days to 760 days, specifically at intervals of 10, 30, 60, 120, 360, and 720 days. It is observed that the calculation time for all five rental modes exhibit convergence, as depicted in Fig. 7.

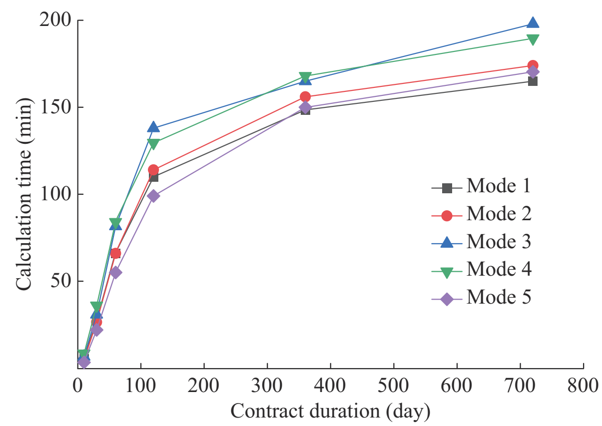

Fig. 7. Relations between contract duration and calculation time.

For all modes, there is a sharp increase in calculation time as the contract duration extends from 0 to approximately 100 days. This suggests that the complexity of the calculations for determining the optimal leasing strategy increases with the length of the contract. Beyond 100 days, the calculation time for all modes begins to converge and plateau, indicating that the complexity of the algorithm stabilizes despite increasing contract duration. Throughout the range of contract durations, Modes 1, 2, 3, and 4 show very similar calculation time with slight variations. Mode 5, while initially having a higher calculation time, converges with the other modes as the contract duration increases. Figure 7 implies that the efficiency of the algorithm, in terms of computation time, does not significantly deteriorate as the contract duration becomes longer, especially after reaching the plateau phase. This demonstrates the scalability of the algorithm in handling long-term contracts.

VI. CONCLUSION

This paper designs various long-term contracts for transaction modes between centralized SESS and users, and constructs a two-stage resource allocation algorithm for operators, guiding the sale of long-term contracts and real-time rental. Through numerical analysis, it is substantiated that the business model predicated on long-term contracts surpasses the model that solely engages in the real-time market, both in terms of economic viability and user satisfaction. Crucially, it can efficaciously mitigate battery degradation. Moreover, the numerical experiment also scrutinizes the aggregation effect for SESS and illustrates that leveraging this aggregation effect can yield an additional 10.7% of net revenue. Potential directions for future research might include investigating overselling models in SESS through user aggregation and addressing privacy problems in information exchanges by developing secure interaction algorithms and contract methods.

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