Energy Proceedings
ISSN 2004-2965
Vol 33, 2023

# Optimal operation of multiple shared energy storage systems for load peak shaving

Huqing Zhang[1], Xiaoling Song [1*]

1 Department of Management Science and Engineering, Nanjing University of Science and Technology, Nanjing 210094, China

(*Corresponding Author: songxiaoling@njust.edu.cn)

**ABSTRACT**

High penetration of renewable energy presents great challenges in the operation of a distribution grid, and load peak shaving and power smoothing cannot be ignored. The application of multiple shared energy storage systems is a promising solution to this problem. Therefore, in order to analyze the capability of multiple shared energy storage systems to smooth the aggregators' total load curve, this paper proposes a day-ahead peak shaving model to optimize the coordinated operation strategy of energy storage and PV distributed generation systems. This model aims to minimize the residual load peak-to-valley difference, and comparative analyses are conducted. The results show that the proposed model can provide peak shaving effectively, and the application of multiple shared energy storage systems can enhance the stability of the combined net load.

**Keywords:** Shared energy storage systems, optimal operation, peak shaving, load smoothing, linear programming

## 1. INTRODUCTION

With the rapid economic development and the accelerated urbanization pace in recent decades, energy consumption, especially residential energy demand, has grown very rapidly [1]. Moreover, in order to reduce carbon emissions and achieve sustainable development goals, efforts have been made to increase distributed renewable energy generation facilities in the power system [3]. However, due to the diversity of residential customers' electricity consumption patterns and the intermittent characteristics of renewable energy sources, the stability and coordinated operation of the power system are challenged [5]. In particular, the uncertainty of the peak-to-valley difference in the power system is increasingly prominent [6]. To solve this problem, the energy storage system is considered one of the most promising technologies owing to its superiority in increasing system flexibility and improving the reliability and economy of the grid [11]. Furthermore, it can be applied to peak and valley regulation and improve the absorption capacity of renewable energy, as it can store excess energy during valley hours and release it during peak hours [12].

However, as the high cost of energy storage equipment has inhibited many investors from investing, shared energy storage is gaining more interest due to its lower price of service. The shared energy storage (SES) system has become a hot issue discussed by many scholars in recent years, and many studies have investigated problems such as pricing and capacity planning for SES services [15]. As a result of the reformed operation of the electricity market environment, the model of multiple SES operators serving many customers at the same time is gaining attention, which is also referred to as a peer-to-peer trading market mechanism. This mechanism allows electricity consumers more freedom in the way they purchase electricity and also encourages healthy competition among SES operators [17]. The scholars in [17] compare different ownership structures of different battery storage systems in an energy-sharing network to analyze the economic efficiency of the stakeholders. The researchers analyze auction mechanisms and bidding strategies in a peer-to-peer solar market to investigate changes in the economic efficiency of the market [19].

From the above literature, it can be seen that most studies on the objective of customers' participation in SES projects focus on economic benefits. Nevertheless, the above background analysis clarifies the fact that this model was originally born to alleviate the grid peak operation problem. For this reason, we introduce a fundamental question: how can the model of customer participation in the SES system bring benefits to the peak and valley operation of the grid? Although there is some literature on the internal operation and planning of shared energy storage and customers, few [20] have been conducted on the benefits of this model for the grid. For example, [20] integrates renewable energy with local electric utilities to derive integrated tariff and energy management strategies by coordinating

# This is a paper for International CCUS Conference 2023 (ICCUSC2023), April 14-15, 2023, Beijing, China.

customer electricity supply and demand. The test results show the effectiveness of the scheme in limiting peak loads. However, this study does not focus on the role of energy storage sharing. [21] It aims to investigate an energy management approach applicable to residential communities including photovoltaic (PV) systems, shared energy storage systems, and electric vehicles, with the goal of reducing energy costs and peak demand. [22] established a peer-to-peer energy trading community where a third party manages and owns the shared energy storage system. It optimizes the capacity dispatch of the energy storage system by determining market prices, and the results validate the model in terms of its effectiveness in terms of economic benefits and the benefits of reducing the negative watts fed back to the grid. However, this research is primarily concerned with effectiveness in the economy and reducing peak demand without consideration of the overall goal of minimizing load fluctuation and ignores the importance of net load peak-to-valley differences for grid stability.

In summary, to explore the role of multiple SES systems on the residential side in reducing load fluctuations and narrowing net load peak-to-valley differences of the grid, this paper develops the model of multiple SES operators serving multiple customer aggregators. First, the objective of this model is to minimize the total net load peak-to-valley difference to derive optimal strategies for shared energy storage systems and PV distributed generation systems. Second, the model is mathematically analyzed and transformed into linear programming (LP) by a linearization method. Finally, case studies with different weights verify the superiority of the proposed model in reducing the net load peak-to-valley differences of the grid.

## 2. SYSTEM DESCRIPTION

Fig. 1. shows the general architecture of the multiple SES system proposed in this paper, including the grid, multiple SES operators, and multiple customer aggregators. Next, the functions and objectives of each participant are described.

1) **Grid**: We consider a main grid, where the grid acts as a supplier that needs to provide all the demand deficits generated by electricity consumers. For the grid, it is crucial to improve grid stability by encouraging the utilization of flexible power devices such as energy storage on the customer side to regulate the load and reduce demand fluctuations. 2) **Aggregators**: We consider multiple groups of aggregators, each of which manages a fraction of the scale of electricity customers. It is worth noting that the development of distributed generation has transformed the role of end-users from traditional consumers to prosumers with the ability to produce and consume energy [23]. Therefore, electricity customers under aggregator management in this paper are prosumers who hold PV distributed generation systems. Specifically, each aggregator can purchase electricity from the grid or discharge from shared storage systems, and can also charge the shared storage system to satisfy subsequent demand at the moment when PV generation is available. In this context, aggregators will flexibly apply SES systems and renewable energy generation equipment to respond to the call of the electricity market and reduce the peak-to-valley difference in grid demand. 3) **SES operators**: We consider multiple SES operators who maintain and manage SES systems of different scales. At varying moments, they allocate optimal power to different aggregators with the goal of smoothing the net load of the grid. Therefore, each SES may allocate different amounts of power to different aggregators, which also provides an optimization space for aggregators ' charging choices.

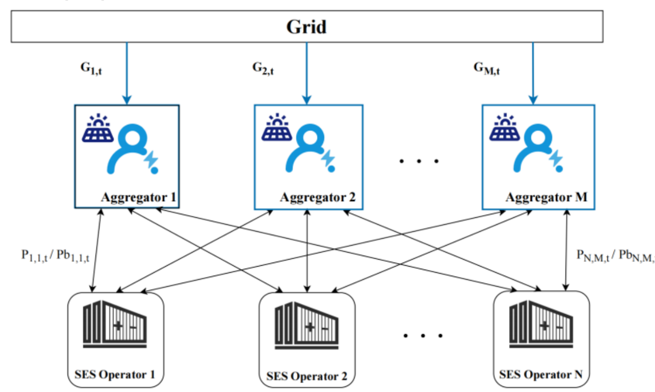


Fig. 1. Diagram of proposed multiple SES systems serving multiple aggregators model

## 3. MODEL AND METHODS

This study focuses on the grid peak shaving problems in the residential-side context. Nowadays, the SES system is widely considered a flexible tool to reduce the peak-to-valley differential. Moreover, the model of multiple SES operators serving multiple customer aggregators can achieve complementary supply with demand among customers and coordinated operation of multiple energy storage operators. Therefore, this section presents the mathematical formulation of the proposed model involving multiple SES operators and multiple aggregators.

### 3.1 Operation constraints

First, when establishing the relevant problem, the following constraints should be considered:

3.1.1 Power balance constraints

(1) $\sum_{m=1}^{M} Pb_{n,m,t} = P_{n,t}^{C}$

(2) $G_{m,t} = D_{m,t}^{R} - \sum_{n=1}^{N} P_{n,m,t} + \sum_{n=1}^{N} Pb_{n,m,t} - Pr_{m,t}$

(3) $soc_{n,t} = soc_{n,t-1} + P_{n,t}^{C} \times \eta^{c} - P_{n,t}^{D} / \eta^{d}$

(4) $\sum_{m=1}^{M} P_{n,m,t} = P_{n,t}^{D}$

where $n \in [1, N]$ n represents the set of shared storage operators, $m \in [1, M]$ represents the set of aggregators, and $t \in [1, T]$ represents the set of time. $Pb_{n,m,t}/P_{n,m,t}$ represents the power of the SES system charged/discharged by the $m$th aggregator to the $n$th at time slot $t$, and $P_{n,t}^{C}$ /$P_{n,t}^{D}$ represents the total power $n$th shared storage charged/discharged. Eq. (1) and (4) represent the charge/discharge balance of each shared energy storage. $G_{m,t}$ is the power purchased from the grid by each aggregator, and $Pr_{m,t}$ is the power produced by the prosumers under the management of $m$th aggregator at time $t$. Eq. (2) shows the calculation of the net load on the grid on the basis of each aggregator's participation in SES systems. $soc_{n,t}$ represents the state of charge (SOC) of the $n$th SES at time $t$, and $\eta^{c}/\eta^{d}$ denotes the charging and discharging efficiency, Eq. (3) shows the calculation of the SOC of SES systems.

3.1.2 Variable Limits

(5) $\sum_{m=1}^{M} Pb_{n,m,t}/\eta^{d} \le P_{n}^{SES}$

(6) $\sum_{n=1}^{M} P_{n,m,t} \times \eta^{c} \le P_{n}^{SES}$

(7) $\sum_{n=1}^{N} Pb_{n,m,t} \le Pr_{m,t}$

(8) $Pb_{n,m,t} \ge 0$

(9) $0 \le P_{n,m,t} \le P_{n,t}$

(10) $\sum_{n=1}^{N} P_{n,m,t} \le D_{m,t}$

(11) $\mathrm{soc}_{n}^{\min} \le \mathrm{soc}_{n,t} \le \mathrm{soc}_{n}^{\max}$

where Eqs. (5) and (6) represent SES charging and discharging power limits. Eqs. (7) and (8) denote aggregator charging capacity limits, where Eqs. (7) restricts that each group of aggregators should charge within the generation capacity. Eqs. (9) and (10) show the power constraints assigned to aggregators by SES operators, where each aggregator is assigned no more than the total allocation, and each aggregator is assigned no more than its demand. Eqs. (11) represents the SOC constraint of the SES system.

### *3.2 Optimal model based on linearization method*

3.2.1 The proposed model

According to the analysis in [22], the purpose of peak regulation for the grid is to obtain a smooth residual compliance sequence. And the residual load can be obtained from the original load and the power allocated to it during the participation in the optimization process as well as from its own power production. From the idea of [26], we take the peak-to-valley difference as the objective function as an alternative to smooth net load, and the smaller the peak-to-valley difference the better the objective value. That is to say, SES operators should try to allocate more power at the peak and the aggregator should generate more power at the peak to reduce the peak-to-valley difference and achieve the purpose of smoothing the net load of the grid, which is expressed below:

(12) $f_m = \min\{\max_{1\le t\le T}\{G_{m\cdot t}\} - \min_{1\le t\le T}\{G_{m,t}\}\}$

where $f_m$ denotes the peak-to-valley difference in residual load for $m$th aggregator. However, due to the difficulty of solving the above objective function, we introduce two auxiliary variables as follow:

(13) $\bar{P}_m = \max_{1\le t\le T}\{G_{m,t}\}$

(14) $\underline{P}_m = \min_{1\le t\le T}\{G_{m,t}\}$

where the following constraints are also introduced to ensure the validity of the auxiliary variables.

(15) $0 \le \bar{P}_m \le \bar{D}_m$

(16) $0 \le \underline{P}_m \le \bar{D}_m$

(17) $\underline{P}_m \le G_{m,t} \le \bar{P}_m$

where Eqs. (15) and (16) limit the maximum limit of the two auxiliary variables, and $\bar{D}_m$ represents the maximum value of the initial load of the $m$th aggregator.

3.2.2 Standardization of model

However, it can be seen that the objective function is still a multi-objective optimization problem.

(18) $f_m = \bar{P}_m - \underline{P}_m$

We introduce weight values $w_m$ to transform it into a single-objective problem to truly give the optimized net load range, and to simplify the calculation, it is normalized.

(19) $f_m^1 = f_m/\bar{D}_m$

(20) $f = \min\{\sum_{n=1}^{m}\{w_m \times f_m^1\}\}$

Based on the above analysis, the objective function is transformed into a linear programming model, which is represented by Eq. (20). In addition, the constraints consist of Eqs. (1)-(11) and (15)-(17), and the constraints are all linear functions. In this paper, we apply CPLEX 12.8 to solve the LP problem in this paper.

## *4. RESULTS AND CONCLUSION*

### *4.1 Application data and background*

The customer electricity consumption data in this section are obtained from [27] based on reports in [28] and [29]. And the generation data are derived from [30] simulations and presented in Fig. 2. In addition, Table 1 details the additional data required. We analyze the effect of different weighting factors on the optimization results to verify the validity of the model. To ensure fairness, we also set up a comparative analysis with the same weighting factors to limit the capacity used by aggregators proportionally and compare it with the initial data.

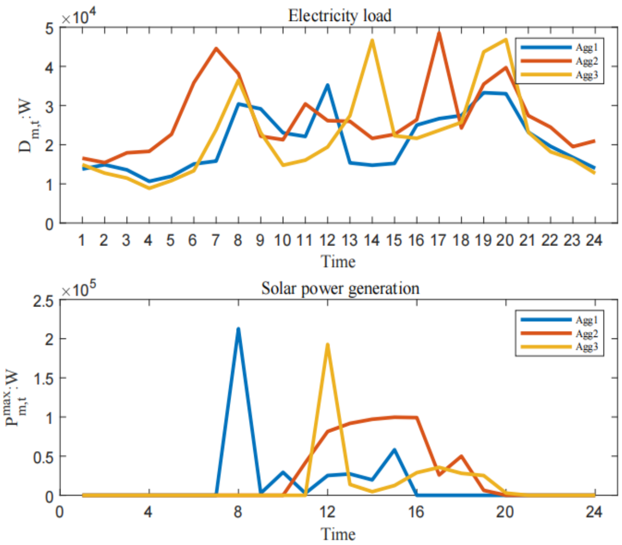


Fig. 2. Initial load and maximize power generation

Table 1. Main technological parameters

| Variable | Description | Value |
|---|---|---|
| $\eta^C/\eta^d$ | Charging and discharging efficiency of SES systems | 95% |
| $\mathbf{soc}_n^{\min}$/ $\mathbf{soc}_n^{\max}$/wh | The upper/lower bound of SOC for SES systems | [5000,7500,12500]/ [95000,142500,237500] |
| $P_n^{SES}$/w | Power capacity of SES system | [50000,75000,125000] |
| $\bar{D}_m$/w | The maximum value of the initial load | [35242.4,48544.9,46843.61] |
| $w_m$ | Weighting factor | Case 1: [0.3,0.38,0.32] |
| | | Case 2: [0.287,0.451,0.262] |

*4.2 Case study 1: Weighting factors based on demand*

In the first case study, we take the average demand data to set the target weighting factors for aggregators proportionally. Moreover, the calculation results of each aggregator's proportional restriction on the use of SES system capacity were compared under the same weighting factor. Due to the high efficiency of the calculation (which only takes about 1 second), this paper focuses on the discussion and analysis of the calculation results. Table 2 gives the peak, valley, peak-valley difference, and standard deviation of the net load of the grid calculated by our method and the capacity limitation method, respectively. The detailed hourly net loads and SES charge states of different grids are shown in Fig. 3. It is worth mentioning that in Fig. 3 (d), we indicate the optimal results below the axes for comparison purposes.

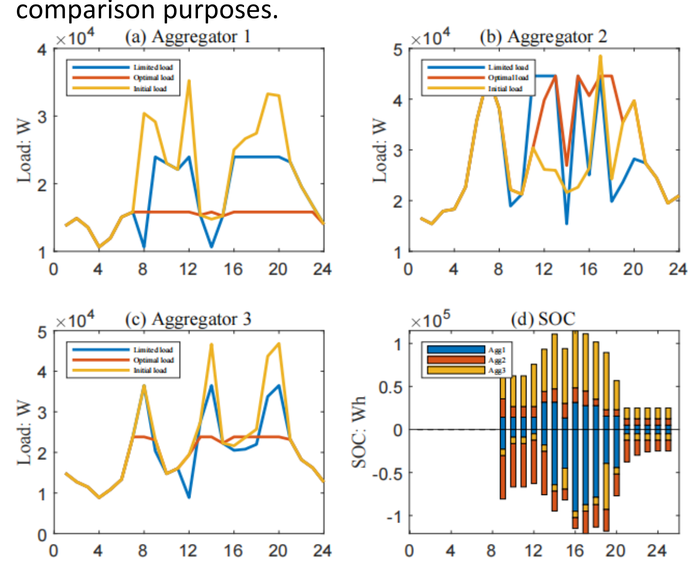


Fig. 3. Comparison of hourly net load and SOC for each aggregator, Case 1

Table 2. The results of peak, valley, peak-valley difference, and standard deviation of the net load, Case 1.

| Aggregator | Item | Peak | Valley | P-V difference | Standard deviation |
|---|---|---|---|---|---|
| Agg1 | Limited | 23964 | 19642 | 13322 | 0.37802 |
| | Optimized | 15817 | 10642 | 5175.8 | 0.14686 |
| Agg2 | Limited | 44569 | 15422 | 29148 | 0.60043 |
| | Optimized | 44569 | 15422 | 29148 | 0.60043 |
| Agg3 | Limited | 36487 | 8865.9 | 27621 | 0.58963 |
| | Optimized | 23823 | 8865.9 | 14957 | 0.3193 |
| $f_{limit} = 0.503$ $f_{optimize} = 0.374$ | | | | | |

From the data in Table 2, we can see that our proposed optimal method demonstrates the superiority of peak shaving compared to the capacity limitation method. For example, for Aggregator 1, the peak-to-valley difference is reduced by 23.1%, and for Aggregator 3 the peak-to-valley difference is reduced by 27.0%. In addition, the peaks are significantly reduced, which demonstrates the effectiveness of this method. As shown in the results in Table 2 and Fig. 3, both methods smoothed the net load throughout the sequence when compared with the initial data. However, our proposed method is more effective in reducing the peak-to-valley difference than the capacity limitation method. For example, at 8-12 hours, the Aggregator 1 peak is reduced by an average of 3504 watts. On the other hand, it can be seen from the SOC diagram that the average utilization of the SES system increases. In addition, the mismatch between Aggregator 2 generation hours and peak demand hours leads to insufficient power allocation during high-demand hours. Moreover, the low demand leads to less capacity allocated during peak generation hours, which inhibits its desire to generate electricity and thus weakens its ability to cut peaks and fill valleys. Therefore, it is concluded from the above results that our method and model are feasible and effective.

### *4.3 Case study 2: Weighting factors based on power generation*

In the second case study, the weighting factor is related to the proportion of PV power generation, and the same comparison is set to limit the capacity. To reduce space, the calculated peak, valley, peak-to-valley, and standard deviation of the net load of the grid are not shown here. The final results yield $f_{limit} = 0.520$, $f_{optimize} = 0.397$ and he detailed hourly net load and shared storage charge states for different grids are shown in Figure 4.

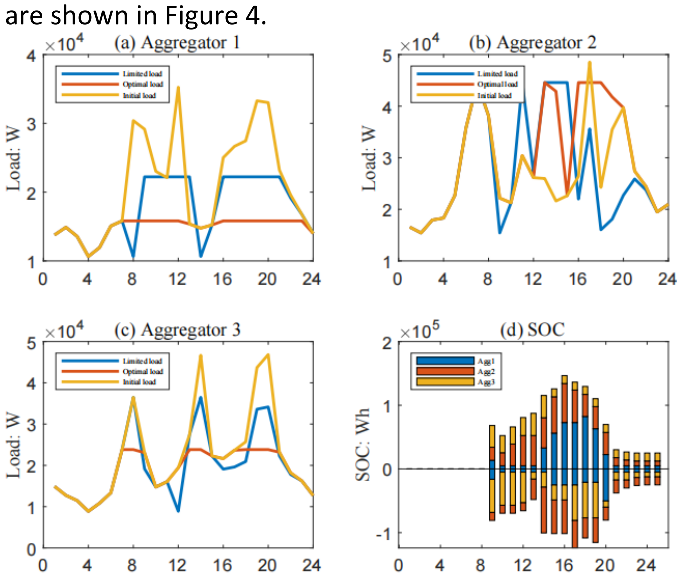


Fig. 4. Comparison of hourly net load and SOC for each aggregator, Case 2

Compared to the Case 1, the residual loads generated by the aggregators are both slightly changed due to the change in weighting factors. The change is most pronounced for Aggregator 2, which is due to the fact that Aggregator 2 has a larger average generation share and the weighting factor assigned according to the average generation has the greatest impact on Aggregator 2. Similarly, both this method and the capacity-limiting method produce better ground curves than the initial data through the rational deployment and operation of SES systems and PV distributed generation systems. From the SES system SOC diagram, we can see that the average utilization of the SES system decreases compared to the above case.

In summary, the above two cases show that the coordinated operation and operation of shared energy storage systems and renewable energy generation can flexibly relieve the pressure of peak-shaving operation and smooth the net load of the grid. Solving these problems should also take into account the characteristics of electricity consumption and the generation behavior of different customers.

## *5. CONCLUSIONS*

In recent decades, the expanding demand and the development of renewable energy sources have posed challenges to the operation stability of the power grid, especially for peak shaving operations. Coordinating multiple SES systems with residential aggregators can enhance the efficiency in smoothing the total load curve. To investigate the effect of multiple SES systems in reducing the combined net load fluctuations, this paper presents a model to coordinate the operation of multiple SES operators serving aggregators for minimizing the peak-to-valley differences of the net load. The day-ahead peak shaving model is proposed by considering operation strategies of multiple SES and PV distributed generation systems. Several case studies are constructed by varying the weight coefficients of the objective function, in which comparative analyses with different energy storage capacity limits are also established. The results demonstrate that: 1) the proposed model can smooth the total load of all aggregators effectively by taking advantage of the coordinated operation of SES systems and PV distributed generation systems; 2) the weight coefficients have different influences on aggregators with different characteristics in terms of final load, SES operating strategies, and PV generation decisions; 3) both methods of the proposed model are superior to the initial case, moreover, the proposed approach without limiting the capacity performs better in terms of reducing the load peak-to-valley differences, improving shared storage utilization, and increasing PV generation capacity.

For practical application, the model can be used in the coordinated operation of multiple SES systems in the day-ahead peak shaving plan and the appropriate weights should be selected. Further research can investigate effective interactions between grid and SES systems to enable efficient coordination of energy storage facilities with the grid.

**ACKNOWLEDGMENT**

This research was supported by the Natural Science Foundations of China under the Grant No. 71801129 and the Natural Science Foundation of Jiangsu Province of China under the Grant No. BK20180452.

**DECLARATION OF INTEREST STATEMENT**

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. All authors read and approved the final manuscript.

**REFERENCE**

[1] Lu Q, Lü S, Leng Y, et al. Optimal household energy management based on smart residential energy hub considering uncertain behaviors. Energy 2020;195:117052.

[2] Chen L, Xu L, Velasco-Fernandez R, et al. Residential energy metabolic patterns in China: a study of the urbanization process. Energy 2021;215:119021.

[3] Vecchi A, Sciacovelli A, Yan J. Long-duration thermo-mechanical energy storage – Present and future techno-economic competitiveness. Appl Energy 2023;334:120628.

[4] Henni S, Staudt P, Weinhardt C. A sharing economy for residential communities with PV-coupled battery storage: Benefits, pricing and participant matching. Appl Energy 2021;301:117351.

[5] Namilakonda S, Guduri Y. Chaotic darwinian particle swarm optimization for real-time hierarchical congestion management of power system integrated with renewable energy sources. Int J Elec Power 2021;128(1):106632.

[6] Liu Z, Zhao Y, Wang X. Long-term economic planning of combined cooling heating and power systems considering energy storage and demand response. Appl Energy 2020;279:115819.

[7] Li J, Li Y, Ma Y, et al. Research on modeling and control strategy of lithium battery energy storage system in new energy consumption. Appl Energy 2023;9:182-189.

[8] Lu R, Bai R, Huang Y, et al. Data-driven real-time price-based demand response for industrial facilities energy management. Appl Energy 2021;283:116291.

[9] Lai CS, Locatelli G. Economic and financial appraisal of novel large-scale energy storage technologies. Energy 2020;214:118954.

[10] Walker A, Kwon S. Analysis on impact of shared energy storage in residential community: individual versus shared energy storage. Appl Energy 2021; 282:116172.

[11] Curto D, Favuzza S, Franzitta V, et al. Evaluation of the optimal renewable electricity mix for Lampedusa island: the adoption of a technical and economical methodology. J Clean Prod 2020;263:121404.

[12] Le T, Nguyen T, et al. M. Optimal sizing of renewable energy storage: A techno-economic analysis of hydrogen, battery and hybrid systems considering degradation and seasonal storage. Appl Energy 2023;336:120817.

[13] Liu J, Zhang N, Kang C, et al. Cloud energy storage for residential and small commercial consumers: a business case study. Appl Energy 2017;188:226-36.

[14] Wang Z , Gu C , Li F , et al. Active Demand Response Using Shared Energy Storage for Household Energy Management. IEEE Trans Smart Grid 2013;4(4):1888-1897.

[15] Mediwaththe CP, Shaw M, Halgamuge S, et al. An incentive-compatible energy trading framework for neighborhood area networks with shared energy storage. IEEE Trans Sustain Energy 2019;11(1):467-76.

[16] Zaidi BH, Bhatti DMS, Ullah I. Combinatorial auctions for energy storage sharing amongst the households. J Energy Storage 2018;19:291-301.

[17] Rodrigues DL, Ye X, Xia X, et al. Battery energy storage sizing optimisation for different ownership structures in a peer-to-peer energy sharing community. Appl Energy 2020;262:114498.

[18] Di Silvestre ML, Gallo P, Sanseverino ER, et al. Aggregation and remuneration in demand response with a blockchain-based framework. IEEE Trans Ind Appl 2020;56(4):4248-4257.

[19] Lin J, Pipattanasomporn M, Rahman S. Comparative analysis of auction mechanisms and bidding strategies for P2P solar transactive energy markets. Appl Energy 2019;255:113687.

[20] Yanine F, Sanchez-Squella A, Parejos A, et al. Grid-tied distributed generation with energy storage to advance renewables in the residential sector: tariff analysis with energy sharing innovations; Part I. Procedia Computer Science 2019; 162:111-118.

[21] Ali M B, Akın T, P.S. J C. Cost optimization of a microgrid considering vehicle-to-grid technology and demand response. Sustain Energy Grid 2022;32:100924.

[22] Li H, Yuanzhi L, Jie Z. Peer-to-peer energy sharing with battery storage: Energy pawn in the smart grid. Appl Energy 2021;297:117129.
[23] Liu G, Jiang T, Ollis T B, et al. Resilient distribution system leveraging distributed generation and microgrids: a review. IET Energy Systems Integration 2020;2(4):289-304.
[24] Wang Z , Yu X , Mu Y , et al. Peer-to-Peer energy trading strategy for energy balance service provider (EBSP) considering market elasticity in community microgrid. Appl Energy 2021;303:117596.
[25] P!erez-Díaz JI, Chazarra M, García-Gonz!alez J, Cavazzini G, Stoppato A. Trends and challenges in the operation of pumped-storage hydropower plants. Renew Sustain Energy Rev 2015;44:767-84.
[26] Zhong-kai Feng, et al. Peak shaving operation of hydro-thermal-nuclear plants serving multiple power grids by linear programming. Energy 2017;135:210-219.
[27] M. Muratori. Impact of uncoordinated plug-in electric vehicle charging on residential power demand. Nat Energy 2018;3:193-201.
[28] M. Muratori, M. C. Roberts, R. Sioshansi, V. Marano, G. Rizzoni. A highly resolved modeling technique to simulate residential power demand. Appl Energy 2013;107:465–473.
[29] M. Muratori, V. Marano, R. Sioshansi, G. Rizzoni, Energy consumption of residential HVAC systems: A simple physically-based model. IEEE PES GM 2012:1–8.
[30] https://re.jrc.ec.europa.eu/pvg_tools/en/#PVP last accessed on May 10, 2023.