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Cloud Energy Storage Based Embedded Battery Technology Architecture for Residential Users Cost Minimization

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ABSTRACT This paper presents a cloud energy storage (CES) architecture for reducing energy costs for residential microgrid users. The former of this article concentrates on identifying an appropriate battery technology from various battery technologies with the aid of a simulation study. The later part addresses the economic feasibility of the storage architecture with three different scenarios namely grid connected energy storage, distributed energy storage (DES) and CES. The performance of the proposed architecture has been evaluated by considering five residential users with suitable battery technology identified from the former part of the study. For the purpose of the analysis, PV and load profiles including seasonal effects and grid price were taken from IIT Mumbai, India and IEX portal, respectively. In addition, this article also examines the impact of increased number of users with CES. The value of this study is that the proposed CES architecture is capable of reducing the cost of electricity experienced by the user by 11.37% as compared to DES. With this, CES operator's revenue can be increased by 6.70% in summer and 16.97% in winter in the case of fixed number of users. Finally, based on the analysis and simulation results, this paper recommends CES with Li-ion battery technology for residential application.

INDEX TERMS Cloud energy storage, distributed energy storage, lead-acid battery, lithium-ion battery, sodium–sulfur battery, redox flow battery.

NOMENCLATURE

A. SUBSCRIPT

i	User index
I	Total number of users
t	Time Index
T	Set of time intervals

B. FUNCTION

EC_i^{grid}	The electricity consumption per day of the i^{th} user (Rs/day)
EC_i^{DES}	Daily electricity cost of i^{th} prosumer with DES $(Rs/year)$
EC_t^{CES}	The final cost experinced by the i^{th} prosumer with the use of CES with PV generation $(Rs/year)$
O_i^{DES}	The operation cost of the distributed energy storage (Rs/day)
O^{CES}	The operation cost of the cloud energy storage (Rs/day)

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C. VARIABLES

1) DISTRIBUTED ENERGY STORAGE SIDE VARIABLES

$P_{i,t}^C$	The amount of charged power to the storage by the i^{th} user for a time interval of delta t (kW)

$P_{i,t}^{D}$ The amount of discharged power to the storage by the i^{th} user for a time interval of delta t (kW)

2) CLOUD ENERGY STORAGE SIDE VARIABLES

P_{t}^{C} The amount of charge power of the cloud energy storage at time (t) in (kW)

P_{t}^{D} The amount of discharge power of the cloud energy storage at time (t) in (kW)

D. PARAMETERS

θ_t The price of sold electricity from the extra PV power generation that is fed to the power grid at time (t) in (Rs/kWh)

λ_t The price for purchaing electricity from the power grid at time (t) in (Rs/kWh)

λ_D Discharging threshold price at t time (Rs/kWh)

λ_C Charging threshold price from grid at t time (Rs/kWh)

Δt The time interval

r The discount rate $(\%)$)

y The life of the system System (number of years)

$d_{i,t}$ The demand of user i at time t measured in t (kW)

$P_{i,t}^{pv}$ The amount of power generated by the PV user i at time t measured in (kW)

G_t The cost of purchasing power from the power grid (Rs/kW)

SoC^{min} The minimum value of the state of charging

SoC^{max} The maximum value of the state of charging

1) DES SIDE PARAMETERS

I_i^{DES} The cost of investment per day for the DES of the i^{th} user (Rs/day)

P_i^{cap} The power capacity of the distributed energy storage of i user in (kW)

$c^{P,DES}$ The cost of investing in a Unit power (Rs/kW)

$c^{E,DES}$ Unit energy investment cost (Rs/kWh)

η_i^C Charging efficiency

η_i^D Discharging efficiency

2) CES SIDE PARAMETERS

I^{CES} Daily investment cost of CES users (Rs/day)

P^{cap} CES users power capacity (kW)

E^{cap} CES users energy capacity (kWh)

E^{min}/E^{max} CES minimum/maximum energy state (kWh)

$c^{E,CES}$ Per unit energy cost (Rs/kWh)

$c^{P,CES}$ Per unit power cost (Rs/kW)

I. INTRODUCTION

Residential photovoltaic system combined with battery storage systems can limit the reliance on grid supply and minimize electricity consumption cost [1]–[3]. However, these residential grids are facing various challenges, which encourages researchers and energy experts to focus towards the energy storage direction. The challenges which are associated with the residential grids are the modulation in frequency, voltage regulation, power quality, bidirectional power flow, peak shaving, load demand shifting, emergency services and the reliability of supply system with the integration of high penetration of RE [4]–[7]. The storage technologies have potential to offer assistance to these types of uncertainties [8], [9]. In spite of this, the economic feasibility of this system is subject to successful utilization of battery energy storage architecture to store surplus renewable generation at a residential scale. In addition, it supports the increasing of RE penetration rate at residential grid. Nowadays, the battery technology is dramatically developing, and batteries are being associated with houses to maximum utilization of onsite PV generation. The installation of battery technology architecture i.e.distributed energy storage (DES) and cloud energy storage (CES) play a significant role in reduction in electricity cost [10]–[13].

The various applications of storage system include to control the power generation by distributed energy resource (DER) and on-site and off-site power generation [14]–[17]. In the high penetration RE scenario, the energy storage system can provide an ancillary services for maintaining not only the frequency but also the voltage with in specified range for reliable power supply due to their intermittency nature [18], [19]. Battery technology is one of the reliable technology among the several storage technologies due to their inherent maturity. So, it is highly used in stationary applications compared to other types of storage in different case study [20]–[22]. Battery energy storage technology also helps to develop a reliable supply system for residential grid users. A PV system with storage can store the extra power generation and can be used when there is a shortage of power for maintaining the Demand-Supply balance of the system [23]–[25]. It also enables the users to reduce their electricity bill by charging the storage at the time of low grid price and discharge the energy at time of high price [26], [27]. In addition, it supports the minimization of peak demand charges.

A. LITERATURE REVIEW

A lot of researchers are nowadays conducting the research on energy storage system and have introduced various types of battery technologies and their applications for maintaining supply-demand balance in various sectors [28], [29]. These literatures provide possible research gaps for future enhancement in the battery technology. A brief discussion on different storage technologies for stationary applications are presented in [30]. A critical review of storage technologies such as super capacitor, flywheel, superconducting magnetic and battery can be found in [31], [32] and the modeling of the energy storage was presented in [33]. The available storage technologies that can be implemented in present power system has been illustrated in [10]. A comprehensive study of PV system with and without storage has been discussed for the frequency control in [34], [35]. The above literature only addresses the fundamental principle of battery technology, that has not explored in detail. However, less literature focuses on different technologies for the application in PV connected residential grid with different storage architecture.

In the available literature on storage, DES architecture has been implemented in distribution network to overcome the challenges introduced by renewable integration [36]. Energy storage model with distributed PV system have been discussed in [37] respectively. The seasonal user demand and PV generation impact on storage size has been explained in [38]. In addition, authors also discussed storage size, which are required to balance intermittent RE generation. Further, storage application for smoothing the demand in the residential grid has been discussed in [39], [40]. In the residential grid, prosumers can install battery storage at their home to reduce electricity cost by storing excess PV generation [41]. Apart from this, storage technologies can also be used for peak demand shaving in the residential grid, as discussed in [42]. The storage can be installed in the residential grid in two manners, i.e. distributed energy storage and centralized energy storage. However, the main challenges associated with DES are the fixed size and high installation cost. To overcome these challenges in [35], [43], centralize storage has been proposed. In centralize energy storage, a single storage installed by any third party is operated by the storage system owner. Users have own PV system, they can used DES facility from centralized storage and pay rent to storage operator [44], [45].

A lot of researchers are working towards the scheduling of energy storage system with RE integration for the maximum utilization of RE generation. The authors, in [46], proposed a standalone centralized energy storage system with the help of multiagent concept the utilization various generation forecasting. The technical feasibility analysis of the centralized energy storage system for operating economic benefits is presented in [47]. The economic results have been analyzed using mixed-integer linear programming in [47]–[49] for the centralized and distributed energy storage in the day ahead electricity market. In [50] a linear programming model has been developed to reduce the operating cost of storage by optimizing the community energy. The energy storage management including charging-discharging scheduling has been explored in following studies [51]–[53]. It has also been found from the literature that various optimization techniques have been utilized for solving energy storage scheduling problems. Dynamic programming is used to minimize consumer cost, considering storage sizing and aging parameter as in [54]. The storage operation with utility operator has been reported in [55]. The multiple studies explored the scheduling algorithm. A linear programming approach is used in [56] at small scale for storage management. Sequential quadratic programming subject to real-time price constraints is used to maximize centralized storage-consumer benefits. Non-linear programming is used to design the charging and discharging controller of the storage to minimize operation cost, as in [57].

B. RESEARCH CONTRIBUTION

It has been inferred from the above discussion that the energy storage technologies and their architectures are facing various challenges at the distribution level of the grid. Battery technology plays a significant role for residential users' to minimize the purchased electricity cost using by storing the extra PV power generation. In the literature [35], [35], [43], [58] DES and community energy storage architecture are described. DES architecture increases the residential grid network complexity when the number of DES installed at individual prosumer houses. Thus, distribution operators are facing some issues to manage the residential grid system. In addition, distributed energy storage have a fixed capacity storage and hence, difficult to completely store excess PV generation. The centralized storage system is a sharing based energy storage, which is installed in a residential community. In this system, users can use fixed amount of capacity according to what they need and consider paying the operator of the storage the fee of this provided service. Here, the user cannot take a decision based on the day ahead generation and demand in the real-time situation. In existing literature, the user has no option to sell unused storage space once allotted by the storage operator.Thus, the unused space is getting wasted and operators are facing some challenge to manage other user's demand. These are the main drawbacks of this type of architecture. To mitigate these challenges, this study proposes a cloud based energy storage architecture.It is managed by a centralized operator, similar to community energy storage. The price-driven theory has been used to manage the charging/discharging strategies of CES. The users' are taken decision based on their real-time demand and PV generation. They can update storage space based on collected information of a previous day. This system known as cloud energy storage system (CES). The economic scale also support this type of architecture to reduce the user's electricity cost compared to DES architecture. Thus, many studies are mandated to streamline the deployment of DES concepts in the current available system. Therefore, this study attempts to address DES challenge and introduce the CES concepts in residential microgrid. The first part of this study includes the literature gaps addressed by different battery technologies and determines the suitable battery technology for for residential application with the aid of of simulation. Further, it also addresses the advantages of DES over CES with the help of suitable case studies. The contributions of this article are illustrated as follows:

1) Calculating one-day electricity cost for individual battery technology with DES and CES architecture, and suggest suitable battery technology. A five residential users' data set profile was collected from IIT Mumbai, India for tthe purpose of analysis.
2) The performance of the proposed model has been analyzed by considering seasonal PV profile, load profiles, and grid price with a selected battery storage technologies for understanding the economic viability of the architecture. Moreover, the analysis has

been performed under three scenarios: a) grid connected supply mode (b) Distributed energy storage (c) Cloud energy storage and recommended suitable storage architecture.

3) An analysis is performed to identify the impact of the increased number of users with CES without altering the of battery capacity.
4) Evaluating CES operator revenue with the increased number of users with CES.

C. ARTICLE ORGANIZATION

This article work is structured as follows: Section II explains the existing battery technologies in the literature and their comparison; Section III discusses the energy storage architecture; Section IV presents the mathematical expression of the system model considering different scenarios; Section V presents the case study; Section VI illustrates the results and discussion part of the article and recommends the best with the best battery technology and architecture that are suitable for residential users. Section VII concludes the paper.

II. BATTERY TECHNOLOGIES

Batteries convert electrochemical energy into electrical energy or vice-versa. Mainly used battery technologies are lead-acid battery, Li-ion battery, nickel-cadmium battery, sodium sulfur and redox flow battery [16]. The applications of the batteries varies according to energy density, discharging cycle and self-discharge rate. One of the main drawback of the battery technology is the high installation, operation and maintenance costs. The battery Life depends on the battery chemistry, number of cycles, operating temperature and usage pattern [59], [60]. The different types of the battery technology used for power system and other applications are illustrated in [8], [61]–[63]. The four battery technologies are described as follows:

A. LEAD-ACID (PB-A) TECHNOLOGY

The Pb-A is an early stage of battery technology, hence it is easily available in the market [64], [65]. The different types of Lead-acid technology are discussed in [66]. The battery cell consists of an anode of lead dioxide while a cathode of sponge lead which are divergent using a microporous material. These electrodes buried in an aqueous sulfuric acid electrolyte. The electrochemistry process [67] of batteries are shown in (1) and (2).

At the positive electrode,

$$Pb + SO_4^{2-} \rightleftharpoons PbSO_4 + 2e^- \tag{1}$$

At the negative electrode,

$$PbO_2 + SO_4^{2-} + 4H^+ + 2e^- \rightleftharpoons PbSO_4 + 2H_2O \tag{2}$$

B. SODIUM SULFUR (NAS) TECHNOLOGY

NaS battery technology is composed of an anode of molten sulfur and a cathode of molten sodium, which are divergent using a solid beta alumina ceramic electrode [68], [69]. The electrolyte passes only Na^+ ions and dissolves with sulfur from sodium polysulfide. The electrochemical process of NaS battery is presented in (3). In the discharging state, Na^+ ions pass via the electrolyte and negative ions would be flowing in the battery's outer circuit, thus the delivering voltage is 2V.

$$2Na + 4S \rightleftharpoons Na_2S_4 \tag{3}$$

C. LITHIUM-ION (LI-ION) TECHNOLOGY

Li-ion battery anode is graphite carbon while the cathode is a lithiated metal oxide (e.g. $LiMO_2$, $LiCoO_2$ or $LiNiO_2$) [70]–[72]. The electrolyte is made up of organic carbonates of lithium (L_ilPF_6) [73]. In the charging mode, the lithium-ion in the negative electrode becomes ions and emigrates over the positive electrode. Where it recombines with the negative ion, which are composited between carbon layers through the external circuit [74].This process is reversed at the time of discharge. The electrochemical process of this battery is presented in (4) and (5).

$$C + xLi^+xe^- \rightleftharpoons Li_xC \tag{4}$$

$$LiMO_2 \rightleftharpoons Li_{1-x}MO_2 + xLi^+ + xe^- \tag{5}$$

D. REDOX FLOW BATTERY

Energy store in redox flow batteries in the electrolyte solution. The features of electrolyte solution is opposite to electrode based conventional battery [75]–[77]. The reaction process of flow batteries is dependent on the decreasing oxidation reaction of the electrolytes. The electrolyte is oxidized at the positive electrode and discharge at the negative electrode [78], using this process electrical energy convert into chemical energy. The chemical process of the electrolyte provide the battery with the desired charging and discharging conditions. The battery's energy capacity is calculated by the stored electrolyte in the external tank. While power capacity is obtained through the active area of the cell compartment [79]. These batteries have the potential to deliver energy at a high rate,reaching a maximum of 10 hours [80]. The vanadium redox flow (VRB), Sodium Nickel Chloride polysulfide bromine (PSB), iron-chromium, and Zinc Bromine batteries comes under the category of redox flow technology.

The comparison of various battery technologies from different literature [3], [81]–[86]. Among these technologies, lead-acid technology is the oldest and full-fledged battery technology. This technology requires frequent maintenance to replace water because at the time of operation, large amount of water gets wasted. Nowadays, Li-ion and NaS technologies are becoming the leading battery technologies in the area of high-power application. Li-ion battery may be an option in this field for future development direction. The main challenges of Li-ion technology is that it is more expensive due to the high manufacture cost and special packing required due to internal overvoltage protection. The NaS technology requires heat energy management system due to the high operating temperature and these causes' reduction in overall

TABLE 1. Technical specification of various battery technologies [3], [81]–[86].

Technical Parameter	Lead-acid	NaS	Li-ion	Redox Flow
Life Span (Cycle)	1000-2000	2500	3000	10,000
Life Span (Year)	3-15 years	10-15 years	10-15 years	5-15 years
DOD (%)	70%	70%	70%	70%
Operating Temperature (°C)	5°- 40°	325°	30°- 60°	0°- 30°
Energy Density (Wh/kg)	30-55	150-230	75-190	30-50
Power Density(W/kg)	75-300	150-230	150-315	–
Selfdischarge	2-5% per-month	–	1% per-month	–
Efficiency (%)	72-78%	89%	100%	85%
Cell Voltage (V)	2.1	2	3.7	1.26
E/P ($kWhkW^{-1}$)	0.5/0.13	0.27/0.025	6	1.5

efficiency. The redox flow battery batteries are generally used when there is a requirement of of energy storage for a long duration due to its non-self discharge characteristics. In this technology, chemical production plant and pump plant are to be separately established and that will increase the operating and running cost [86].

The life cycle cost calculations of various battery storage technologies have been described in [87], [88]. The technical specification: life cycle, energy density, power density, self-discharge, efficiency and operating temperature have been presented in Table 1 based on [3], [81]–[84]. Li-ion batteries have light weight and provide more energy density, much higher compared to others. The storage efficiency is nearby 100%, so it is more appropriate for both PV energy storage and portable device.

III. STORAGE ARCHITECTURE

In this article two type of energy storage architecture are explored namely, distributed energy storage and cloud base energy storage for rooftop PV residential user. For the distributed energy storage, individual users have access to their own energy storage at their houses. While for the cloud energy storage, installed in a community and users are uses according their needs. A detailed description of the storage architecture is presented as follows:

A. DISTRIBUTED ENERGY STORAGE (DES)

DES are installed by individuals in their houses having PV units of distribution manner. This architecture supports to overcome the problems of supply and demand mismatching and voltage and frequency control [89]. The main challenge of DES that it is less efficient for residential consumer, since both generation and consumption patterns are random [88]. Moreover, it also fails to accommodate this high random behavior due to the limited storage size. Due to the high installation cost of PV with DES, the average per-unit price is significantly high. Thus, it is economically not attractive [90] and also it only offers less support to the local operator. In addition, when the number of DES devices increases, their coordination and management among each other also increases [91]. The basic architecture of DES is shown in Fig. 1.

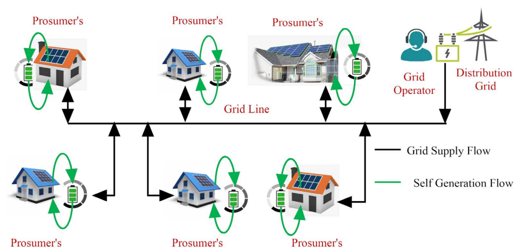


FIGURE 1. Architecture of the DES.

B. CLOUD ENERGY STORAGE (CES)

The architecture in Fig.2 has three major sections: (1) storage users, here users means that they do not have any storage at their homes, and they are interested to the join storage operator service. These users would be booking the storage space as per hid/her demand and pay rent as a storage service fee to the operator; (2) storage operator: they invest in the CES system and provide CES service on rent basis to interested users. The rate of rent is decided based on the operator's capital cost. Storage operator firstly collect users' information (e.g. Load, Prosumers PV generation) and accordingly schedule the charging/discharging mechanism. When the excess PV generation is not sufficient to meet user's demand, the storage operator can consider the direct purchase of the power from from the local power grid for such energy users. The operator would collect such a type of cost and would pay to the grid; and (3) PV units, which are installed at the user's home.

During the real-time operation, it is possible to set the instruction to charge/discharge the cloud storage battery. The charging/discharging behavior of batteries are obtained from PV generation, demand level and real-time electricity price. Further, the users gives the instruction to the storage operator that would be charging his/her cloud storage space from the power grid considering the time when the price is low. The operator collects this section of cost separately from users and paid to the local grid operator. Users can discharge their space whenever they need without paying any type of charges.

IV. PROBLEM DEVELOPMENT

The modelling of the system has been done by considering three scenarios. Scenario 1 is grid connected mode,

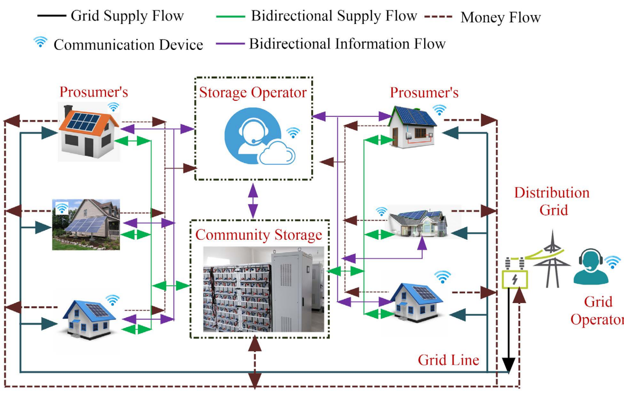


FIGURE 2. Architecture of the CES.

all user are in a direct connection with the local power grid and buy energy from the grid based on a fixed price. Scenario 2 considers the user's installed PV with storage at his/her own home, i.e. distributed energy storage system. Scenario 3 considers the CES with daily fixed capacity storage with users having their PV power generation and demand. They can charge CES booked space from the excess PV power generation and the power grid.

A. SCENARIO 1 : GRID CONNECTED MODE

All users are linked to the local grid in this scenario. They satisfy their demands from grid supplies and pay the grid for the whole cost of energy use. Aside from that, users have to pay a fixed service charge to the grid. The daily energy consumption of individual users EC_i^{grid} has been defined by (6).

$$EC_i^{grid} = \sum_{t\in T} \lambda_t \, d_{i,t} \Delta t \tag{6}$$

B. SCENARIO 2 : PROSUMER'S WITH DISTRIBUTED ENERGY STORAGE (DES) MODE

Energy storage supports prosumers for maximum the utilization of rooftop PV. It is also helping to reduce the dependency on the grid in the duration of peak demand. In this model, prosumers have installed energy storage at their premises. In (7) represent the overall energy cost of individual prosumer's EC_i^{DES}.The electricity cost to purchase from grid when PV generation does not sufficient to meet prosumer demand is presented (9).The investment cost I_i^{DES} is present in (8). The operating cost O_i^{DES} is defined in (11) subject to the constraints represented from (12) to (17).

$$EC_i^{DES} = I_i^{DES} + O_i^{DES} + G_{i,t} \tag{7}$$

$$I_i^{DES} = \frac{1}{365} \frac{r}{1-(1+r)^{-y}} \times \left(c^{P,DES} P_i^{cap} + c^{E,DES} E_i^{cap}\right) \tag{8}$$

$$G_{i,t} = \sum_{t\in T} \lambda_t \left(d_{i,t}^{+} - P_{i,t}^{D}\right) \tag{9}$$

$$O_i^{DES} = \sum_{t\in T} \Delta t \Big[\lambda_t \big(P_{i,t}^C - P_{i,t}^D + d_{i,t} - P_{i,t}^{pv}\big)^{+} + \theta_t \big(P_{i,t}^C - P_{i,t}^D + d_{i,t} - P_{i,t}^{pv}\big)^{-}\Big] \tag{10}$$

$$P_i, t^C, P_{i,t}^D, P_{i,t}^{B,DES}(O_i^{DES}) \tag{11}$$

$$\text{Subject to } 0 \le P_{i,t}^C \le P_i^{cap} \tag{12}$$

$$0 \le P_{i,t}^D \le P_i^{cap} \tag{13}$$

$$E_i^{min} \le Et_{i,t} \le E_i^{max} \tag{14}$$

$$E_i^{min} = SoC^{min} E_i^{cap} \tag{15}$$

$$E_i^{max} = SoC^{max} E_i^{cap} \tag{16}$$

$$Et_{i,t} = Et_{i,(t-\Delta t)} + \Delta t \Big[\eta^C \big(P_{i,t}^C + P_{i,t}^{pv}\big)^{+} - \frac{P_{i,t}^D}{\eta^D}\Big] \tag{17}$$

C. SCENARIO 3 : PROSUMER'S WITH CLOUD ENERGY STORAGE (CES)

Cloud energy storage gives prosumers additional flexibility in terms of reducing demand peaks. Individual prosumers' total energy cost EC^{CES} is calculated as follows: (18). The system with a storage investment cost I^{CES} is provided by (19). All enrolled prosumers decide on the CES operating fee O^{CES}.The rental energy storage space price, which is paid to the storage operator as a service fee, includes a set cost determined by the CES operator as well as CES's running costs for scheduling the energy storage. The cost of charging CES from the grid, as well as the surplus PV revenue included in operation costs, are defined in (22) within the defined limits in (23) to (28).

$$EC_i^{CES} = I^{CES} + O^{CES} + \sum_{i\in I} G_{i,t} \tag{18}$$

$$I^{CES} = \frac{1}{365} \frac{r}{1-(1+r)^{-y}} \times \left(c^{P,CES} P^{cap} + c^{E,CES} E^{cap}\right) \tag{19}$$

$$G_{i,t} = \sum_{t\in T} \lambda_t \left(d_{i,t}^{+} - P_{i,t}^{D}\right) \tag{20}$$

$$O^{CES} = \sum_{t\in T} \Delta t \Big[\lambda_t \big(P_t^C - P_t^D + d_t - P_t^{pv}\big)^{+} + \theta_t \big(P_t^C - P_t^D + d_t - P_t^{pv}\big)^{-}\Big] \tag{21}$$

$$P_t^C, P_t^D, P_t^{B,CESO_p}(O^{CES}) \tag{22}$$

$$\text{subject to } 0 \le P_t^C \le P^{cap} \tag{23}$$

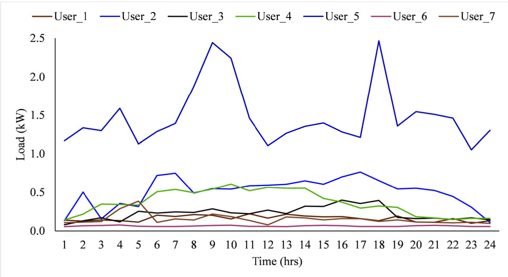
$$0 \le P_t^D \le P^{cap} \tag{24}$$

$$E^{min} \le Et_t \le E^{max} \tag{25}$$

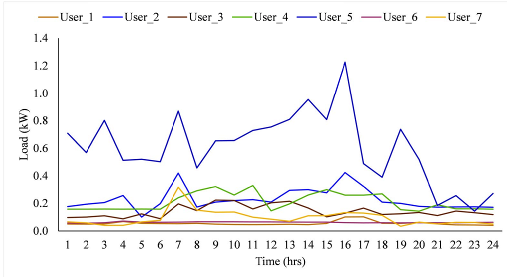
$$E^{min} = SoC^{min} E^{cap} \tag{26}$$

$$E^{max} = SoC^{max} E^{cap} \tag{27}$$

$$Et_t = Et_{(t-\Delta t)} + \Delta t \Big[\eta^C \big(P_t^C + P_t^{pv}\big)^{+} - \frac{P_t^D}{\eta^D}\Big] \tag{28}$$



(a) Demand pattern for summer season (11-05-2017)



(b) Demand pattern for winter season (15-12-2017)

FIGURE 3. Seasonal residential users demand.

D. THE SCHEDULE OF CHARGING AND DISCHARGING OF STORAGE

To assure gaining further advantage from storage, a scheduling process based on the price is involved with the process to charge and discharge the energy storage. Therefore, the operational strategy of consumer can be formulated as presented from (29) to (31).

$$X_{i,t} = \frac{E_i^{max} - Et_{i,(t-\Delta t)}}{\Delta t.\eta^C} - \sum_{t=1}^{24} P_{i,t}^{pv} \tag{29}$$

$$P_{i,t}^C = min\left(P^{cap}, X_{i,t}\right) \tag{30}$$

$$P_{i,t}^D = \begin{cases} 0, \quad \lambda_t \leq \lambda_D \\ min\left(P^{cap}, \frac{Et_{i,t-\Delta t} - E_i^{min}}{\Delta t}.\eta^C, d_{i,t}^+\right), \\ \quad \lambda_t > \lambda_D \end{cases} \tag{31}$$

V. CASE STUDY

A. SYSTEM PARAMETER

The basic overview of different battery technologies has been explained in section II with each technology having different economic cost (Rs/kWh). The investment cost of different batteries has been taken from [2] for the economical and management analysis purpose. In the analysis, summer and winter seasons' impact is embedded, and the analysis demonstrates the calculated one-day total electricity consumption cost ($Rs.$). The seasonal analysis for energy storage reflects the feasibility of the system. The simulations have been done for seven user having their own PV systems and storage installed at their premises. In this study the simulation has been considered for 24 hours with 1 hour duration because PV, price and demand data are available with 1 hour interval. In the scenario of CES, all prosumers used in cloud base storage to store excess pv generation. The user's installed PV capacity, energy, and power capacity are presented in Table 2.

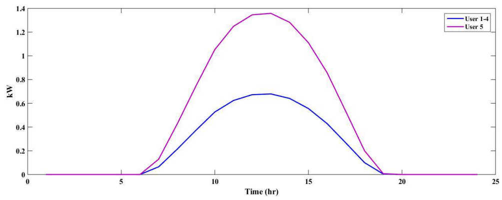
The demand pattern data of users has been taken from IIT Bombay, India [92].The hourly sample frequency of collected data for different days of the year 2017. The demand profile of users in summer shown in Fig.3a is high as compared to winter as shown in Fig.3b. The 2017-05-11 for the summer season and 2017-12-12 for winter season days have been chosen randomly for the analysis. The generalized PV generation profile are based on ''ninja renewable'' [93] accounting for the same day and location.The 72.91°longitude angle and 9.13°latitude angle for the location of solar PV. The PV system power rating and energy storage capacity have been assumed with respect to the demand profile. The seasonal PV generation peak varies according to their installed capacity as presented in Fig.4. The installed PV systems rating and their energy rating (kWh) and the inverter rating (kW) are presented in Table 3. For scenario 3, the storage capacity (9 kWh) is equal to the sum of individual user's storage capacity installed in scenario 2, and the inverter rating is taken as 2 kW. The forecasted electricity price has been taken from the IEX web portal [94] for both seasons (winter and summer) as demonstrated in Fig. 5.

TABLE 2. User PV, energy, and power capacity.

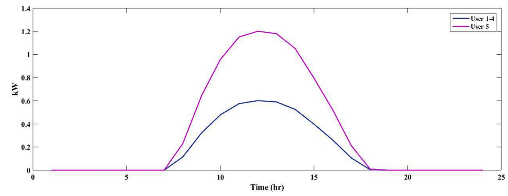
User Id	PV Capacity (kW)	Energy Capacity (kWh)	Power Capacity (kW)
User 1	1.00	1.50	0.50
User 2	1.00	1.50	0.50
User 3	1.00	1.50	0.50
User 4	1.00	1.50	0.50
User 5	2.00	3.00	1.00
User 6	1.00	1.50	0.50
User 7	1.00	1.50	0.50

B. CHARGING/DISCHARGING THRESHOLD PRICE STRATEGIES

CES users would be charging/discharging the booked storage space based on their demand and PV profile [95]. If the PV generation and store energy in their booked CES space do not meet the demand, then the user sends the information to the CES operator for the charge of the storage space from the electric grid supply and they pay the electricity cost to the operator and consequently, the operator pays the electric grid utility. In addition, if the grid price is high compared to the anticipated/planned value, then the user would take the electric supply from the storage. For this model users decide charging (λ_C) /discharging (λ_D) thresholds price. The λ_C/λ_Dthresholds values are decided based on daily electricity price. Here, authors choose the value of λ_C representing the



(a) PV profile for summer season (11-05-2017)



(b) PV profile for winter season (15-12-2017)

FIGURE 4. Seasonal PV profile.

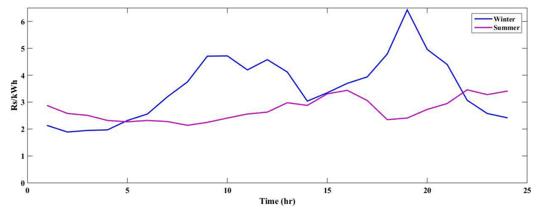


FIGURE 5. Real-time price for summer and winter.

TABLE 3. DES and CES parameter.

S.No.	Parameters	Value
1.	η^C	0.96
2.	η^D	0.96
3.	Capital cost of E_j^{cap}	18000 Rs/kWh
4.	Capital cost of P_j^{cap}	6000 Rs/kW
5.	Capital cost of E^{cap}	12000 Rs/kWh
6.	Capital cost of P^{cap}	6000 Rs/kW
7.	SOC^{min}	20%
8.	SOC^{max}	80%

mean daily average electricity price and the minimum value of electricity price in a day. Similarly, λ_D representing the mean the daily average electricity price and the maximum value of electricity price in a day. So, λ_C/λ_D represents lower/higher electricity price compared to the price of summer and winter respectively. If we consider the threshold value of λ_C/λ_D higher from the respective mean values in scenario 2 and scenario 3, the electricity cost will increase. Case 1: Storage is charged from the grid at a higher than mean price to meet user demand, hence the cost of electricity will increase. Case 2: In peak price period the user discharges the storage at a threshold price to meet his demand. If the grid price falls below the threshold price after some time, but the price varies between the threshold value and the mean value, there is some storage charge and the user takes the supply from the grid, that means the price is higher than the average price. Therefore, the user's one day electricity cost may increase.

Even when the authors consider the threshold price to be less than the average price, the electricity cost may increase as their storage charging/discharging process is frequent. Case 1: User discharge in peak price duration is less than the average price at the storage threshold value and if storage is fully discharged to meet demand but peak price duration is still in place, they need to Therefore, they will consider purchasing electricity from the power grid at a higher price in comparison to the average price, hence the cost of electricity may increase. Case 2: If the user decides to charge the storage space at the threshold price (below the mean price), in this case the users one day electricity cost may be reduced. But there is a risk, if the threshold price time interval is small and the storage capacity is not fully charged in this period and the user will discharge the storage in this period when the price is high, at that time the storage does not meet their demand because the storage is not fully charged. Therefore, the user will need to buy power from the power grid at a price that is higher so he/she can meet his/her demand. higher price to meet the demand. Therefore, the total cost of electricity for the user may increase.

In both the cases if the charging/discharging threshold price is below and above the mean price, the storage scheduling is not working properly and this may impact the CES service. Due to which, users will be less interesting to take CES service, hence the profit of CES operator may also decrease. In both cases, the user's cost may increase and the CES operator's profit may be reduced.

For this study, a threshold value of price is assumed to manage the discharging process. The threshold price is 2.5 Rs/kWh for summer season and 3.5 Rs/kWh for winter season. If the user demand is increased, then the demand will be met by either the storage or grid supply. If the grid price is less than CES operator plan then demand to would be met by the grid supply otherwise user will use storage facility.

Energy storage scheduling is directly influenced by seasonal fluctuations in demand and PV generation. The amount of space available for energy storage is obtain considering not only the amount of PV power generated but also the demand profile. In scenario 3, users give the information of required storage space day ahead to CES operator. That means daily storage space varies with respect to the prosumer's PV generation and demand profile. Based on the prosumer's information, CES operator manages the CES space capacity for reliable operation. The prior information of prosumers the support the storage scheduling to reduce the users' electricity costs. The various required simulation parameters of DES and CES are presented in Table 3. In addition, when the extra PV power generation cannot able to fully charge to storage, then

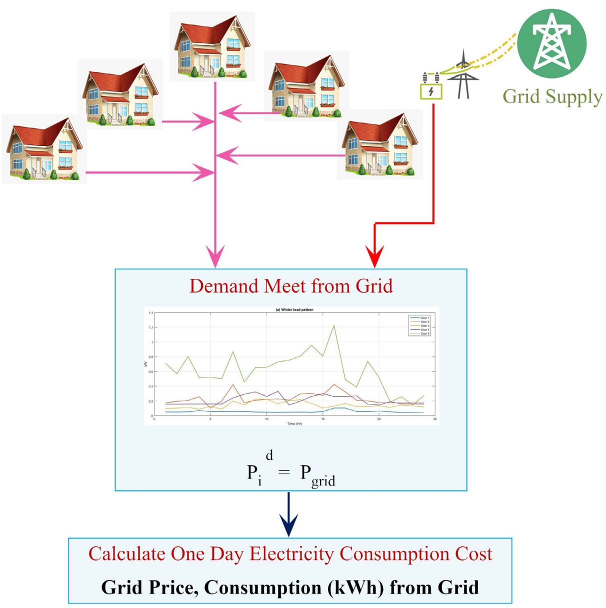


FIGURE 6. Grid connected user.

user's charges some space of the storage from the power grid given the price at that time is low. How much space charge by user's from grid is obtained based on next day excess PV generation with respect to the demand.

C. OPERATION STRATEGIES

Energy storage technologies are under development. Therefore, all technologies have different investment costs. The impact of battery technology on residential user's has to be analyzed. Battery storage allows users to store surplus generated energy by PV system and use it when they need. The storage technologies and their characteristics affect the overall performance of users and hence they have to be considered. The power generation from PV (P_i^{pv}) is calculated at each instant and compared with the user's power demand (P_i^d) and based on this decided whether users should use the PV output immediately or store it in battery storage. If the $P_i^{pv} > P_i^d$, then $P_i^{pv} - P_i^d$ is used for the battery charging. If the battery is at the state of full charge (SOC 100%) during this instant, then surplus P_i^{pv} generation is lost. If $P_i^{pv} < P_i^d$, then all PV generation is supplied to the user demand. If the P_i^{pv} does not meet the P_i^d, then the left demand is to be satisfied by the available energy in battery, but battery SOC should greater than 20%. It has also been considered that even though the users are connected to the grid and the demand has not been met by $P_i^{pv} + P_i^{bat}$ the reaming unmet demand will be met by the grid. Based on this methodology, user's one-day electricity is cost calculated. The grid supply unit (kWh) cost has been calculated according to the grid price. The cost of energy produced by PV system is calculated considering the PV infrastructure cost, including the battery storage cost.

The targeted problem is a linear programming optimization problem and solution to the problem can be attained as the

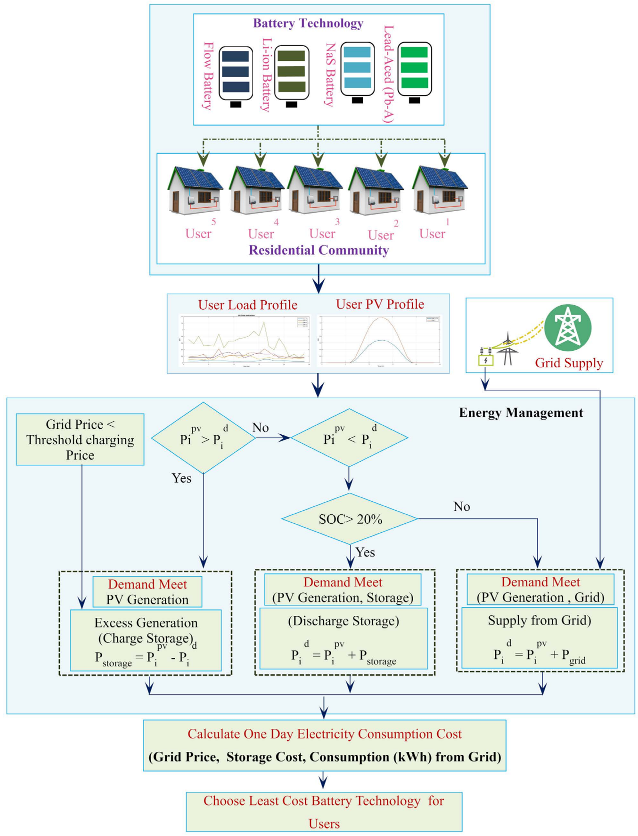


FIGURE 7. Different battery technology.

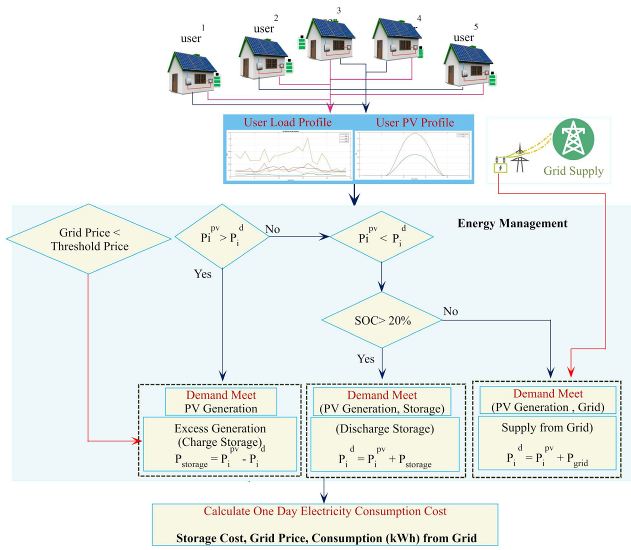


FIGURE 8. Distributed energy mode (DES).

flowchart in Fig. 6 to Fig. 9. The computer machine specifications are Intel(R) Core(TM) i7-8700 CPU @ 3.20GHz, 16.0 GB (15.8 GB usable), 64-bit operating system, and x64-based processor.

VI. RESULTS AND DISCUSSION

Storage technologies have individual merits and demerits in terms of cost, energy density, and self discharge rate.

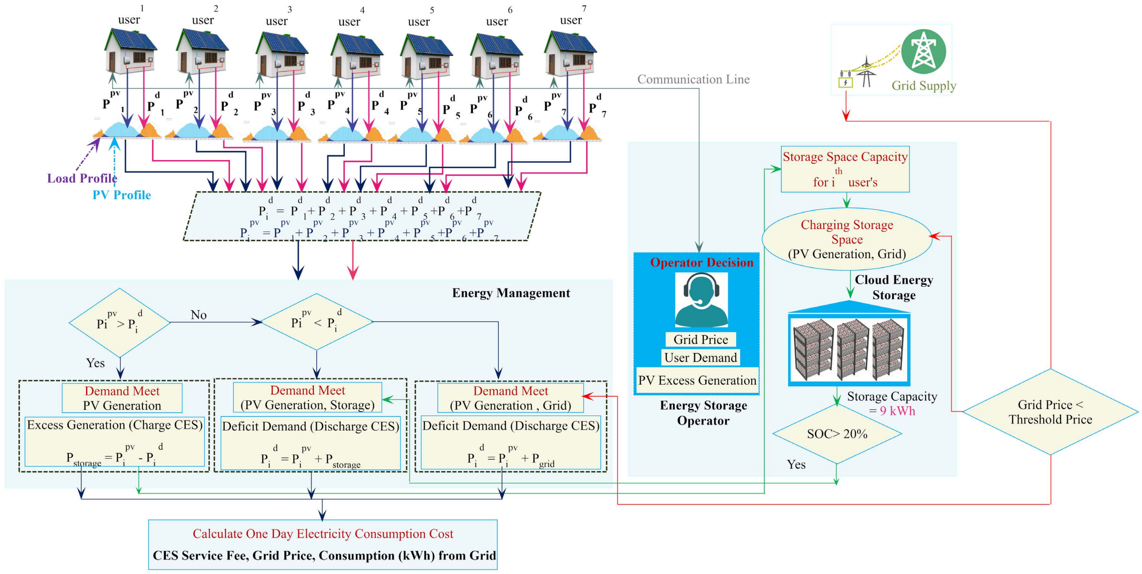


FIGURE 9. CES with increased number of users.

TABLE 4. One-day electricity cost (RS) with different technology in summer and winter seasons.

Seasons	User ID	Scenario 2				Scenario 3			
		Lead-aced	Li-ion	NaS	Redox flow	Lead-aced	Li-ion	NaS	Redox flow
Summer	User 1	10.59	**9.45**	19.90	13.83	8.34	**7.93**	11.64	10.54
	User 2	29.64	**27.50**	37.96	31.88	28.72	**27.46**	39.04	35.60
	User 3	12.88	**11.74**	22.19	16.12	11.69	**11.12**	16.32	14.77
	User 4	19.55	**18.41**	28.86	22.79	18.88	**17.96**	26.35	23.86
	User 5	86.71	**84.44**	105.96	99.15	76.13	**74.44**	106.28	96.93
Winter	User 1	8.88	**7.74**	18.19	12.12	3.13	**2.83**	5.62	4.79
	User 2	16.10	**14.96**	25.41	19.34	15.67	**14.42**	25.96	22.53
	User 3	11.85	**10.71**	21.16	15.09	8.10	**7.32**	14.52	12.38
	User 4	14.50	**13.36**	23.81	17.74	11.94	**10.78**	21.40	18.24
	User 5	31.35	**40.01**	60.92	54.72	34.40	**31.09**	61.64	52.57

In scenario 1, the electricity usage is costly rather than PV with storage scenario 2 and 3, while using storage with grid and PV is more economical solution to reduce electricity bills. In terms of the economic investment, CES is feasible than DES. The price base scheduling phenomena is used for this analysis. Price based scheduling means prosumer charging the storage from grid if grid price below the threshold price.

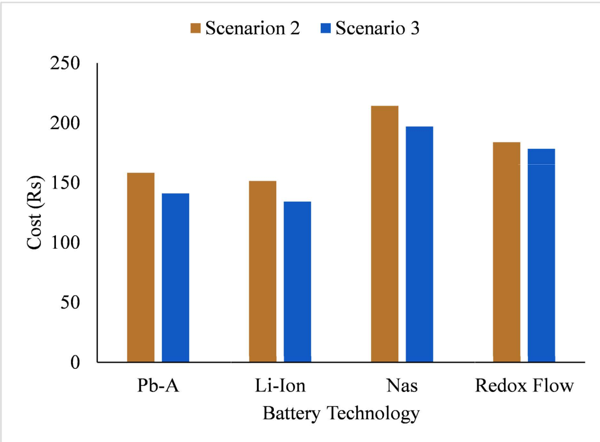
A. ECONOMIC ANALYSIS OF STORAGE TECHNOLOGIES

The effect of battery technology on the residential user energy management is analyzed as shown in Fig.7, and results are presented in Table 4. The numerical value of results are obtained based on daily demand. The total cost of energy consumption in a day with battery technologies is shown in Fig.10a and Fig. 10b. Table 4 presents the seasonal one-day electricity cost of users for scenario 2 and scenario 3. From Table 4, it is observed that Li-ion battery is an economical well performing option for both seasons as compared to other battery technologies.

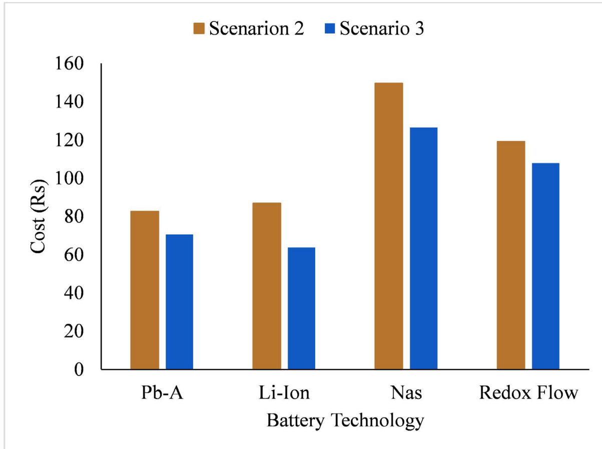
B. ECONOMIC ANALYSIS OF STORAGE ARCHITECTURE

The energy storage system with grid tied PV have real time scheduling given energy pricing system that is also on real time. During the extra power phases of PV generation, the batteries are charged up to its capacity and the remaining energy is sent to the power grid. When a deficit energy generation is experienced, such energy will be drawn from the battery or grid depending on real-time pricing of electricity. CES needs to respond to different users' demand, and the operator has to maintain SoC of storage with the scheduling control that provides the service benefits to both operator and users. Storage capacity allotted to between users must be such that each user has required capacity and SoC of CES does not exceed the limit. This management control provides benefits to all the subscribers.

All the methodologies for economic analysis and reliability depend on scheduling and real-time pricing level. Moreover, a threshold has been set up for better management of storage. The threshold of price decides on the charging/discharging pattern of storage. The economic analysis has been performed with Li-ion battery. The performance analysis depends on



(a) Summer season



(b) Winter Seasons

FIGURE 10. One-day total energy cost of five user with different battery technology.

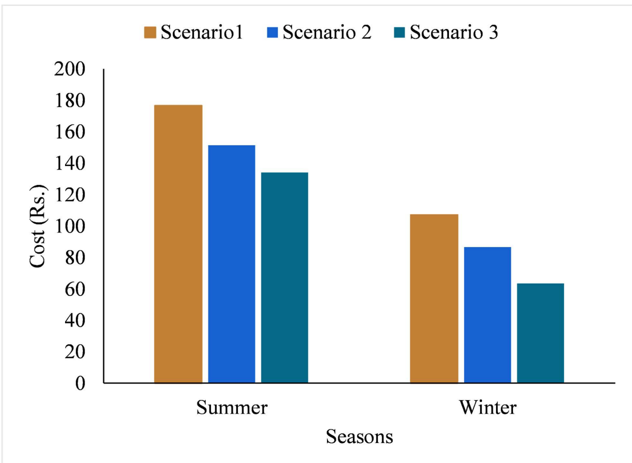


FIGURE 11. Economic comparison of three scenarios.

the storage charging/discharging profiles of each prosumer. The charging/discharging scheduling has been done based on electricity price and demand. The economic comparison analysis of storage architecture for both seasons are shown in Fig.11. In this analysis, storage architecture is compared based on one-day electricity cost of five users.The observation from analysis shows that CES is economically more beneficial as compared to others.

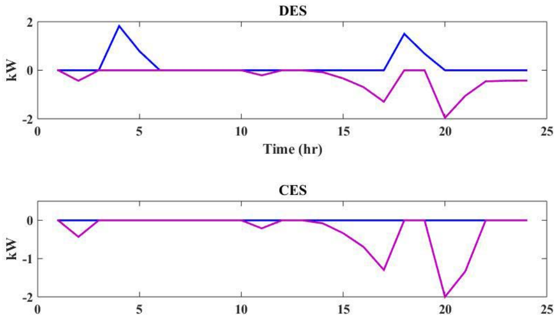
1) WITH FIXED NUMBERS OF USERS IN SCENARIO 3

The obtained scheduling profile of storage with five users are displayed in Fig. 12.The energy profile describing the charge/discharge of aggregated DES and CES utilizers for a day in each seasons (summer and winter) are shown Fig.12a and Fig.12b, respectively. The storage capacity at prosumers, homes is obtained through demand in scenario 2. In scenario 3, the capacity of storage is obtained through summing of individual prosumers' storage capacity.

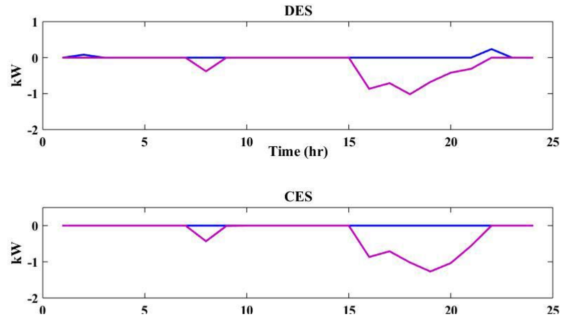
In scenario 1, the total cost of users is determined using real-time grid price and their total consumed energy. Table 5 presents the one-day total electricity cost of users, including operational as well as investment cost for different scenarios. The user-5 daily demand is high as compared to others as shown in Fig.13a and Fig.13b and thus their one-day electricity cost is high. In scenario 2, storage user electricity cost decreases as compared to scenario 1. In the daytime, users use PV generated power to meet their demand. Whenever the demand is not meet by PV supply, the remaining demand is supplied from the grid. If the PV generation is on excess, then it will get wasted because DES facility is a fixed capacity storage. In this scenario, storage cost includes in total investment cost. It is assumed that energy storage investment cost has been scaled in 10 years and similar PV infrastructure cost has been scaled in 25 year. In scenario 3, one-day electricity cost value is more economically attractive. The overall cost is also less than that of other scenarios. The PV infrastructure cost has been handled by the user, and the storage installation cost has been handled by the storage operator. All users have to pay the operator of the storage a service cost to use the energy storage facility. All type of charges from the user side are included in services fee.

2) WITH INCREASED NUMBER OF USERS IN SCENARIO 3

In this case, the number of users is increased by seven from five in scenario 3. The energy storage capacity did not changes from the case of five users. The one-day electricity cost of 7 users is presented in Table 6. The observation from this table is that in scenario 3, the one-day electricity cost of each user is less than the case of scenario 2. Table 7 and Table 8 presents the demand met by grid, PV, and storage in both summer and winter seasons for scenario 2 and scenario 3, respectively of individual users. Table 9 and Table 10 presents the in both summer and winter seasons for scenario 2 and scenario 3, respectively. In scenario 2, user 2, user 4,

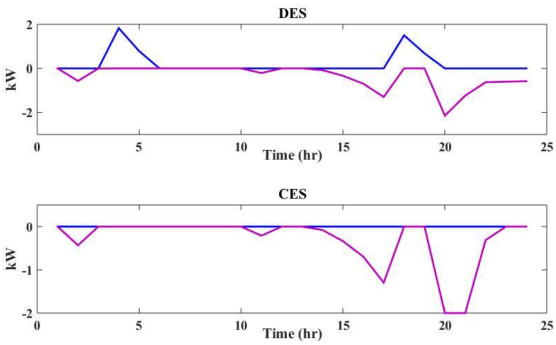


(a) Storage profile for summer season

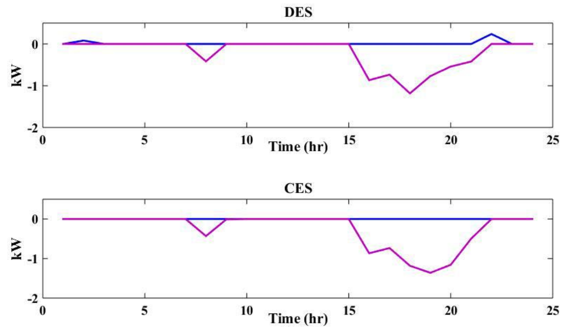


(b) Storage profile for winter season

FIGURE 12. Seasonal Storage charging/discharging profile.



(a) Storage profile for summer season



(b) Storage profile for winter season

FIGURE 13. Seasonal storage profile for seven users.

TABLE 5. One day energy cost (Rs.) in different scenario with five users.

User IDs	Summer Season (11-05-2017)			Winter Season (15-12-2017)		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
1	10.54	9.45	7.93	1 4.72	7.74	2.83
2	32.88	27.50	27.46	19.51	14.96	14.42
3	14.87	11.74	11.12	10.71	11.74	7.32
4	23.28	18.41	17.96	18.35	13.36	10.78
5	95.11	84.44	74.44	52.03	40.01	31.09

TABLE 6. One day energy cost (Rs.) in different scenario with increased number of users (seven).

User IDs	Summer Season (11-05-2017)			Winter Season (15-12-2017)		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
1	4.72	9.45	7.84	10.53	7.38	2.82
2	19.51	27.51	24.49	32.87	14.96	11.68
3	12.63	11.74	10.99	14.87	10.71	7.29
4	18.35	18.41	17.76	23.28	13.36	10.74
5	52.03	84.44	71.63	95.11	40.01	30.95
6	5.27	5.74	3.11	4.20	7.71	3.18
7	8.19	9.35	7.39	9.74	9.18	4.81

and user 5 need to purchase power from grid to charge their storage. But in scenario 3, any user does not required to purchase energy from grid. The results from Table 7 and Table 10 are obtained based daily PV generation and demand profile for scenario 2 and scenario3.

3) COST OF CES USERS AND OPERATOR PROFIT

The mean value of one day energy cost of seven users is less than that of five users in both seasons as shown in Fig. 14. The total revenue of CES operator is presented in Table 11. With the increased number of users case study, the operator's

TABLE 7. Demand (kW) met by the grid, PV, and storage for scenario 2.

User ID	Summer (11-05-2017)					Winter (15-12-2017)				
	Total Demand (kW)	Total PV Generation (kW)	Demand Met from PV Generation (kW)	Demand Met from Storage (kW)	Demand Met from Grid (kW)	Total Demand (kW)	Total PV Generation (kW)	Demand Met from PV Generation (kW)	Demand Met from Storage (kW)	Demand Met from Grid (kW)
User 1	3.89	5.153	2.067	0.39	1.435	1.326	3.974	0.599	0.054	0.672
User 2	12.149	5.153	4.958	1.003	6.187	5.479	3.974	2.938	0.199	3.063
User 3	5.456	5.153	2.923	0.464	2.069	3.416	3.974	1.643	0.124	1.652
User 4	8.809	5.153	4.539	0.474	3.796	5.04	3.974	2.512	0.154	2.591
User 5	35.525	10.302	9.968	2.132	23.426	14.517	7.951	7.132	0.737	7.468
User 6	1.543	5.153	0.773	0.184	0.587	1.495	3.974	0.764	0.059	0.791
User 7	3.665	5.153	1.851	0.314	1.608	2.258	3.974	1.14	0.034	1.12

TABLE 8. Demand (kW) met by the grid, PV, and storage for scenario 3.

Users	Summer Season (11-05-2017)				Winter Season (15-12-2017)			
	Total Demand (kW)	Demand Met from PV Generation (kW)	Demand Met from Storage (kW)	Demand Met from Grid (kW)	Total Demand (kW)	Demand Met from PV Generation (kW)	Demand Met from Storage (kW)	Demand Met from Grid (kW)
For 7 Users	71.042	27.081	6.215	37.856	33.531	7.414	6.215	19.901
For 5 Users	65.832	24.456	6.383	34.994	29.778	7.669	6.663	15.446

TABLE 9. Storage charge from PV and grid for scenario 2.

User ID	Summer Season (11-05-2017)		Winter Season (15-12-2017)	
	Grid (kW)	PV (kW)	Grid (kW)	PV (kW)
User 1	0	0.948	0	0.96
User 2	0.815	0.194	0.023	0.176
User 3	0	0.913	0	0.919
User 4	0.246	0.613	0	0.674
User 5	1.823	0.333	0	0.818
User 6	0	0.999	0	0.837
User 7	0	0.855	0	0.904

TABLE 10. Storage charge from PV and grid for scenario 3.

No. of User	Summer Season (11-05-2017)		Winter Season (15-12-2017)	
	Grid (kW)	PV (kW)	Grid (kW)	PV (kW)
7 Users	0	6.383	0	6.663
5 Users	0	6.215	0	6.215

TABLE 11. Seasonal CES operator revenue.

Seasons	Revenue (Rs.)	
	Five users	Seven Users
Summer	134.24	143.24
Winter	63.75	74.57

profit increases by 6.70% in summer and 16.97% in winter as compared to the cases of fixed number of users. If the more number of users are participating in scenario 3, then the required storage size is to be increased. The storage capacity will have to be decided according to the average demand of the number users.

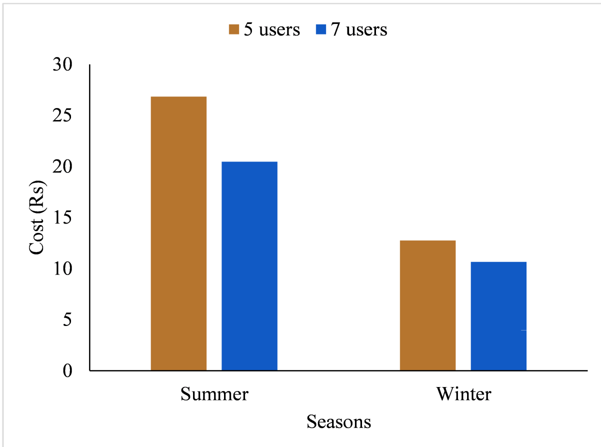


FIGURE 14. Mean value of one-day energy cost of five and seven users with CES.

C. UNCERTAINTY ANALYSIS WITH SEVEN USERS

In the section VI-B of this article, only demonstrated the deterministic forecasting (point forecasting) and not consider meteorological and load uncertainties. Generally, in deterministic forecasting assumed prediction errors are unrelated. The results based on point forecasting are shown from Table 6 to Table 10. If we consider uncertainty, then uncertainties would impact the results. As per the reviewer's suggestion, authors have included meteorological and load data uncertainty analysis using interval forecasting as shown Fig. 15. First, the load and PV day ahead forecasting are run separately based on historical data set. Then after, the observed last 24 hours forecasting error $(\varepsilon_1 \ldots\ldots \varepsilon_{24})$ as per the obtained data considering the variation between the actual

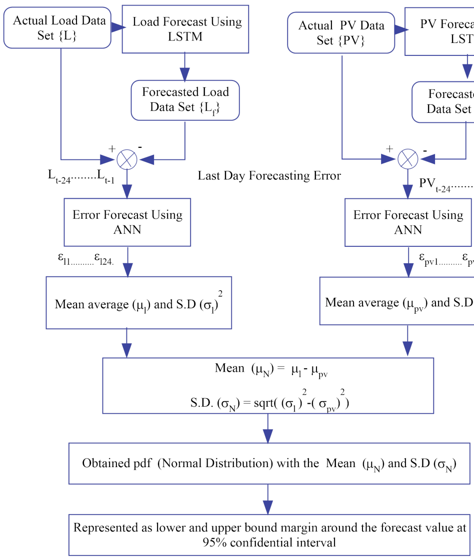


FIGURE 15. **Mean value of one-day energy cost of five and seven users with CES.**

data and forecasted data of load and power. The mean (μ_l, μ_{pv}) and standard deviation (σ_l, σ_{pv}) are obtained respectively. The μ_l and μ_{pv} are the mean value of actual data set and forecasted values for last 24 hours respectively. Similarly, the σ_l and σ_{pv} are the S.D. value of actual data set and forecasted values for last 24 hours respectively. As shown in Fig. 15, the new values of μ_N and σ_N are obtained from two independent variables (the mean and S.D of the load and PV error predictions, respectively). A normal probability distribution function (pdf) is obtained using new μ_N and σ_N.Forecast errors (ε) are a random variable due to uncertainty, the range of errors (ε) is $[-\infty, \infty]$. The range of the normal distribution also varies between $[-\infty, \infty]$. The probability density function (PDF) of a random variable accurately describes a standard distribution.The error (ε) is a random variable distributed according to the PDF. There usually a normal distribution is used. The error histogram bar plots with normal distributions for the summer and winter seasons are shown in Fig. 16. This figure represents only one user's PV and load prediction error histograms with normal distributions, for the remaining other users can be obtained in a similar way. In this study forecasting uncertainties of PV as well as load data as lower and upper bound margin around the predicted value at 95% confidential interval.

In ths study machine learning models are used, LSTM for the load and PV forecasting from actual data. The forecasted error data sample is only 24 so that, for the error forecasting, Artificial Neural Network (ANN) model is used for error forecasting. The performance measures, Mean absolute error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) have been used for analysis of the forecasting results as demonstrated in Table 12 to Table 15. By using uncertainty assessment process, the uncertainties of load forecasting and PV forecasting with 95% confidence interval. The uncertain-

TABLE 12. **Prediction performance measures on actual individual users load data.**

User ID	Summer Season			Winter Season		
	MAE	MSE	RMSE	MAE	MSE	RMSE
User 1	0.0487	0.0032	0.0573	0.0334	0.0016	0.0406
User 2	0.2560	0.0974	0.3121	0.1143	0.0203	0.1427
User 3	0.0530	0.0068	0.0830	0.0738	0.01329	0.1152
User 4	0.0397	0.0028	0.0532	0.1794	0.0618	0.2486
User 5	0.5012	0.0451	0.6722	0.3660	0.2173	0.4661
User 6	0.0216	0.0005	0.0232	0.2139	0.1619	0.4024
User 7	0.0385	0.0040	0.0634	0.0371	0.0031	0.0566

TABLE 13. **Prediction performance measures on actual PV data.**

User ID	Summer Season			Winter Season		
	MAE	MSE	RMSE	MAE	MSE	RMSE
1kW Users	0.0175	0.00047	0.0217	0.0663	0.00641	0.0801
2 kW User	0.09819	0.01666	0.1291	0.1245	0.0284	0.1576

TABLE 14. **Prediction performance measures on individual users load forecast error data.**

User ID	Summer Season			Winter Season		
	MAE	MSE	RMSE	MAE	MSE	RMSE
User 1	0.00075	0.000018	0.00134	0.0017	0.000039	0.00198
User 2	0.0137	0.00029	0.0172	0.0043	0.000037	0.0061
User 3	0.0031	0.000017	0.0040	0.0023	0.000012	0.00340
User 4	0.00075	0.000092	0.0009	0.0047	0.000055	0.00741
User 5	0.02068	0.000047	0.0218	0.0158	0.00033	0.01815
User 6	0.00044	0.000040	0.00063	0.0136	0.00031	0.0177
User 7	0.0012	0.000027	0.0016	0.00072	0.0000683	0.00083

TABLE 15. **Prediction performance measures on PV forecast error data.**

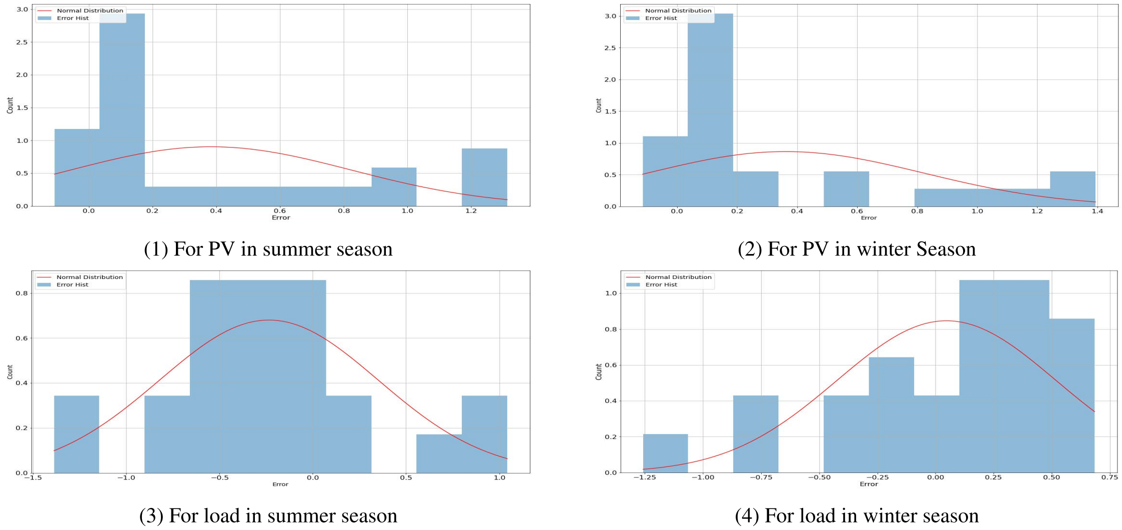
User ID	Summer Season			Winter Season		
	MAE	MSE	RMSE	MAE	MSE	RMSE
1kW Users	0.00215	0.000015	0.0038	0.0371	0.00016	0.0126
2 kW User	0.009587	0.000265	0.0161	0.0546	0.00026	0.0161

TABLE 16. **Demand (kW) margin to be met by the grid, PV, and storage in in 24 Hrs for scenario 2.**

User ID	Summer Season (11-05-2017)				
	Total Demand Margin (kW)	Total PV Generation Margin (kW)	Demand Met from PV Generation Margin (kW)	Demand Met from Storage Margin (kW)	Demand Met from Grid Margin (kW)
User 1	3.13-5.01	3.91-5.28	1.53-2.21	0.28-0.49	1.32-2.31
User 2	6.81-18.19	3.91-5.28	3.19-4.11	0.78-1.52	2.84-12.56
User 3	2.13–8.55	3.91-5.25	1.54-4.26	0.28-0.79	0.30-3.49
User 4	4.40-11.15	3.91-5.25	1.43-4.70	0.32-0.96	2.64-4.48
User 5	28.68-43.39	7.23–14.25	6.73-12.26	1.73-4.73	20.22-26.40
User 6	1.40-3.57	3.91-5.25	0.55-2.31	0.17-0.30	0.68-0.95
User 7	1.52-5.64	3.91-5.25	0.76-3.01	0.11-0.54	0.69-2.08

ties in morning and evening time is less as compared to daytime duration. The increment and decrement uncertainties in PV power forecasting depends on increment and decrement in PV power respectively. The load uncertainty trends is varying in relevance to the power consumption of the user.

The upper bound and lower bound margin on the total demand, PV generation, how much demand is met from PV power generation, how much demand is met from the storage and grid, how much PV excess is fed to the grid are listed in Table 16 and Table 17 for summer and winter seasons respectively for scenario 2. The amount of energy purchases from grid or from the PV system to charge the storage are presented in Table 18 for both seasons. Similarly, Table 19 and Table 20 are presented for scenario 3. From these tables, it is observable that the results can be vary between upper



(1) For PV in summer season

(2) For PV in winter Season

(3) For load in summer season

(4) For load in winter season

FIGURE 16. Histogram with pdf for user 5.

TABLE 17. Demand (kW) margin to be met by the grid, PV, and storage in in 24 Hrs for scenario 2.

User ID	Winter (15-12-2017)				
	Total Demand Margin (kW)	Total PV Generation Margin (kW)	Demand Met from PV Generation Margin (kW)	Demand Met from Storage Margin (kW)	Demand Met from Grid Margin (kW)
User 1	1.74-3.48	3.22-5.06	1.47-1.59	0.041-0.103	0.25-1.78
User 2	3.99-09.81	3.22-5.06	2.65-4.01	0.003-0.230	1.31-5.57
User 3	2.47-6.90	3.22-5.06	2.06-3.59	0.009-0.173	0.38-3.14
User 4	4.97-8.96	3.22-5.06	2.52-3.93	0.530-0.425	1.92-4.60
User 5	7.46-20.14	4.27- 14.09	3.67-13.11	0.320-0.901	3.47-5.74
User 6	1.62-2.13	3.22-5.06	0.71-1.06	0.043-0.0677	0.86-1.003
User 7	1.4-4.92	3.22-5.06	1.02-2.68	0.009-0.041	0.41-2.20

TABLE 18. Storage charge margin from PV and grid in in 24 Hrs for scenario 2.

User ID	Summer Season		Winter Season	
	Grid (kW)	PV (kW)	Grid (kW)	PV (kW)
User 1	0-0	0.28–1.62	0-0	0.61-1.10
User 2	0-1.025	0.77–1.17	0-0.059	0.19-0.26
User 3	0-0	0.38–1.79	0-0	0.30-1.17
User 4	0.094–0.78	0.47–0.96	0-0	0.63-0.956
User 5	1.99–3.54	0.089–0.62	0-0	0.51-0.91
User 6	0-0	0.17–1.30	0-0	0.53-0.98
User 7	0-0	0.11–0.94	0-0	0.86–1.09

TABLE 19. Demand (kW) margin to be met by the grid, PV, and storage in 24 Hrs for scenario 3.

Seasons	Total Demand Margin (kW)	Demand met by Grid Margin (kW)	Demand met by PV Margin (kW)	Demand met by Storage Margin (kW)
Summer	65.03–79.38	31.68–43.14	21.39–34.09	5.19–8.02
Winter	27.46-39.59	14.68–26.13	5.11–10.99	4.27-7.92

TABLE 20. Storage charging margin from grid and PV generation in 24 Hrs in 24 Hrs for scenario 3.

No of Users	Margin in Summer Season (11-05-2017)		Margin in Winter Season (15-12-2017)	
	Grid (kW)	PV (kW)	Grid (kW)	PV (kW
7 Users	0	5.1933-8.0152	0	4.2772–8.265

and lower bound margin values. The obtained results may support the decision-making for smooth battery management operation.

TABLE 21. One day electricity cost margin (Rs.) for scenario 2 and scenario 3.

User ID	Cost Margin in Summer season (Rs)		Cost Margin in Winter season (Rs)	
	Scenario 2	Scenario 3	Scenario 2	Scenario 3
User 1	5.26–12.81	2.03 - 6.77	4.59 - 9.99	1.05-5.34
User 2	24.36–30.13	18.34-29.14	11.66–16.52	6.35–17.15
User 3	8.77–15.80	7.85–13.49	7.98–12. 25	4.72–10.83
User 4	16.57–21.72	14.51–19.03	15.13–17.67	7.01–14.37
User 5	76.55–87.44	67.56–75.84	35.85–43.94	25.54–36.69
User 6	3.72–7.44	1.97–6.23	5.24–9.72	1.18–6.03
User 7	6.68–10.19	3.84–10.12	6.19–11.28	1.79–9.12

The uncertainties also impact on one day electricity cost of individual users. The one-day electricity cost varies between upper and lower bound margin as presented in Table 21 for both scenarios. The numerical results show the impact of PV and load data uncertainties.

VII. CONCLUSION

This study proposed an CES architecture for the reduction in electricity consumption cost as compared to DES architecture for residential users. The first part of the article identified a battery technology suitable for residential application with help of simulation. According to the analysis, it is suggested that Li-ion battery is more economical compared to other options for a residential application. Furthermore, the energy storage operation has been performed under three scenarios, and one-day electricity cost of the users have been calculated. It has been found that the one-day total electricity cost of five users reduced by 11.37% with CES as compared to DES. Thus, CES is more economical as compared to other types of energy storage for residential microgrid application. Additionally, this study, incorporated an analysis to identify the impact of the increased number of users with CES without altering the battery capacity. Results show that the mean value of one-day electricity cost with the increased number of users is reduced by 23.77% in summer and 16.47% in winter in comparison to the case of fixed number of users. With this, CES operator revenue is analysed and it is found that it increased by 6.70% in summer and 16.97% in winter in comparison to the case of fixed number of users. In scenario 2 some users may be required power purchases from grid to charge their storage but we obtained from results in scenario 3 any user does not need to purchases power from grid. Furthermore, the uncertainty analysis of PV power and load data are analysed with lower and upper bound margin value of taken around their forecasted value. This study also tried to fill the gaps in the existing literature to explore research possibilities in the energy storage area. In addition, this study can be extended in the future by considering battery degradation cost and power loss in network.

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