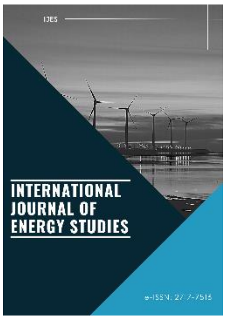
INTERNATIONAL JOURNAL OF ENERGY STUDIES

e-ISSN: 2717-7513 (ONLINE); homepage: https://dergipark.org.tr/en/pub/ijes



Research Article

Int J Energy Studies 2023; 8(3): 513-534

DOI: 10.58559/ijes.1321550

Received : 03 July 2023
Revised : 10 Aug 2023
Accepted : 11 Aug 2023

Evaluation of technical and financial benefits of battery energy storage system control strategies

Fatih Oguzalp[a], Musa Terkes[b], Alpaslan Demirci[c*]

[a]Deparment of Electrical Engineering, Yıldız Technical University, Istanbul, Türkiye, ORCID: 0009-0000-2127-0913
[b]Deparment of Electrical Engineering, Yıldız Technical University, Istanbul, Türkiye, ORCID: 0000-0002-4411-411X
[c]Deparment of Electrical Engineering, Yıldız Technical University, Istanbul, Türkiye, ORCID: 0000-0002-1038-7224
*(*Corresponding Author: ademirci@yildiz.edu.tr)*

Highlights

- The demand profile highly affects the feasibility of BESS-based energy control methods.
- Energy management control methods' performance is evaluated under different solar irradiances.
- Feed-in damping and fixed feed-in methods can reduce daily costs by up to 22.3% for prosumers.
- Feed-in damping and fixed feed-in methods perform best; schedule mode is the worst strategy.

You can cite this article as: Oguzalp F, Terkes M, Demirci A. Evaluation of technical and financial benefits of battery energy storage system control strategies. Int J Energy Studies 2023; 8(3): 513-534.

ABSTRACT

The recent increase in renewable energy generation can balance consumption and reduce carbon emissions. With battery energy storage optimizing supply and demand, it is more important than ever to manage charge control to the benefit of all stakeholders. In this paper, the developed and proposed energy management control methods based on the technical operating criteria of battery energy storage (BESS) and considering self-consumption rate (SCR), self-supply rate (SSR) and curtailment rate are compared in terms of environmental index and economics for daily and annual demand profiles for various household prosumer demand profiles in Istanbul and Antalya. Considering the supply-demand matching based on demand profile, feed-in damping, fixed feed-in, schedule mode, schedule mode with constant charging power and self-consumption control methods are proposed for optimum operation for each prosumer profile. The results show that feed-in damping and fixed feed-in methods can reduce household prosumer costs by up to 22.3% in the daily analysis. Moreover, similar control methods can increase SCR by up to 29.5% and reduce costs by up to 10.62% for higher irradiances in the annual analysis. Proper management of BESS charge control can facilitate sustainable development goals by assisting plans of many stakeholders.

Keywords: Battery energy storage system, Photovoltaic power systems, Energy efficiency, Energy-management control strategies, Self-consumption

1. INTRODUCTION

Battery energy storage systems (BESS) have become more critical daily, even with battery charge control strategies [1]. BESS being able to give flexibility to energy generation and consumption with the help of control strategies has been important for the residential sector because they can provide demand response without affecting electric consumption [2]. Also, in recent years countries have begun to reduce feed-in tariff rates in counter to the high number of photovoltaic systems [3]. This means that the self-consumption rate (SCR) needs to be increased for household demand [4]. Lastly, peak power demands can cause blackouts if grid power is not distributed between hours properly [5]. Developing effective control charging strategies for BESS can prevent energy outages, increase revenues, reduce daily or annual bills, and facilitate compliance with carbon emission targets [6,7].

It is essential to consider factors such as grid regulations, self-consumption targets, contractual obligations, operational requirements [8], and cost optimization in determining the most appropriate control strategy [9]. Adjusting battery charge and discharge cycles according to household energy demand can reduce grid energy dependency and increase renewable energy utilization [10,11]. On the other hand, if there are time-varying electricity tariffs, the total energy costs of the consumer can be reduced by optimizing the program mode or time of use [12]. The ability to adjust the power output according to real-time grid conditions and signals by assessing the desired flexibility in the operation of the energy storage system is crucial to respond to varying grid requirements [13,14]. Prosumers may have contractual obligations towards operating energy storage systems with utilities or energy providers [15,16]. Some grid regulations may affect the battery charge control strategy, limiting the energy fed back to the grid or the instantaneous power injection and instantaneous ramp rate [17,18]. The charge control strategy must be compatible with the obligations arising from this contract, such as energy exports [19], participation in grid services [20], etc., to potentially benefit from any benefits or incentives [21]. It should also consider the preferences and operational requirements of prosumers. Thus, operating costs can be reduced by controlling energy use and aligning it with internal load needs [22–24].

On the other hand, since some control strategies will require more frequent charge-discharge cycles, potentially affecting the battery's cycle life, control strategies that put less load on the battery and contribute to longer battery life should be preferred [25]. Operational requirements of prosumers, such as grid outages, the need for backup power, or load shifting optimization, can influence the charge control strategy [26]. For example, if backup power is a priority, the charge control strategy should maintain an energy reserve in the battery during outages. If load shifting is desired, the charge control strategy should allow charging during periods of low energy demand and discharging during periods of high demand. Thus, strategies considering electricity tariffs, peak shaving, or load shifting can enable consumers to reduce their energy costs by minimizing grid energy dependence, especially during peak energy demand hours [27]. In addition, prosumer benefits can be maximized through control strategies considering individual consumer priorities and constraints, such as backup power requirements, system capacity, and battery life.

Accordingly, many BESS control methods must be evaluated in their own right. Feed-in damping is not set manually but by estimation from the available radiation data. This way, photovoltaic (PV) panel power is not wasted, and the BESS can be easily charged. In addition, BESSs that are not fully charged at the required hours can be used for electricity demands at high electricity tariffs. The battery charge rate should be allocated in an estimated way according to the available data to avoid losses due to weather forecasting [28]. The main difference from fixed feed-in is that feed-in damping uses a rough irradiance estimate to define the charging time. The main disadvantage of this strategy is that the BESS may not be fully charged at the end of the day. The fixed feed-in method technically performs similarly to the feed-in damping method. However, the curtailment rate of this method is limited to 50%. This limits how much PV generation can be sold to the grid, but in historical terms can also provide better results [29]. This method avoids voltage swells by limiting the power supply and uses the residual energy for BESS charging. In this method, the reactive power is well compensated by the threshold set for voltage peaks, but weather conditions should be addressed. The self-consumption method is based on generating and consuming electricity and the fact that it is more profitable to self-consume locally generated electricity than to absorb it from alternative sources. With this logic, if the generated PV power can be stored directly in BESSs, it can reduce the electricity purchased from the grid during peak electricity tariffs. This cost-effective method stores PV power directly in BESSs from sunrise to sunset. If PV power is consumed directly in loads, it increases the purchase of electricity from the grid in the evening, reducing economic profitability. When the BESS is fully charged, excess PV power can feed loads and be sold to the grid to raise additional revenue [30]. Conversely, it can increase SCR and minimize voltage swells by limiting power factor-based supply power and reactive power compensation. Another method, called schedule mode with constant charging power, is based on charging the BESS continuously with the same power. Starting to benefit from solar radiation later and charging the BESS with constant charging power reduces the probability of BESS fullness on low radiation days [31]. The main disadvantage of this method is that the SCR may decrease slightly if there is not enough radiation during the charging period. The schedule mode method focuses on fast charging of the BESS at high irradiances by using solar radiation later than constant charging power. Considering weather conditions, energy demand, energy storage capacity, and renewable energy potential, this method can minimize BESS power losses [30–32].

This study compares all these control methods daily and annually regarding SCR, self-supply rate (SSR), and cost rather than evaluating power quality criteria at busbars. In this direction, the purpose for which BESS-based energy management control methods are used and the results obtained are shown in Table 1 for the references that form the motivation of the study. Feed-in damping [28,29], fixed feed-in [29], self-consumption [29,30,32], schedule mode with constant charging power [29,31], and schedule mode [29], the majority of studies have yet to evaluate these control methods simultaneously. The researchers in reference [29] conducted a technical examination focusing more on busbars' voltage profile and power quality. It neglected economic and environmental analysis. This study simultaneously evaluates these control methods from environmental and economic perspectives in a self-index based on household demand elasticity daily and annually. Optimal control methods are proposed for various prosumer demand profiles considering energy balance, BESS technical criteria, SCR, SSR, and curtailment ratios. The main contributions of this study are as follows:

- The solutions to be proposed for the feasibility of BESS-based energy control methods are highly affected by prosumers' demand profile.
- Feed-in damping and fixed feed-in methods can reduce daily costs by up to 22.3% for prosumers.
- Feed-in damping and fixed feed-in methods can increase SCR by up to 29.5% and reduce costs by up to 10.6% under higher irradiances.
- The fixed feed-in method can increase the SSR to 56% and 59% in Istanbul and Antalya.
- The feasible strategies are determined by considering the prosumer-based BESS control methods' performance criteria.

Table 1. Comparison of related studies regarding motivation

Ref.	FD	FF	SC	SMCP	SC	Aim
[28]	✓					Getting the best use out of PV storage systems.
[29]	✓	✓	✓	✓	✓	Finding best results for residential PV storage systems.
[30]			✓			Investigating possible outcomes in household systems.
[31]				✓		The importance of control strategies has been investigated.
[32]			✓			Investigating over-voltage problems in PV systems.
Our Study	✓	✓	✓	✓	✓	Investigating five different control strategies and finding the best result.

FD: Feed-in damping, FF: Fixed feed-in, SC: Self Consumption, SMCP: Schedule mode with constant charging power, SC: Schedule mode

This article is organized as follows. Section 1 presents the literature review and contributions. Section 2 explains the battery charge control strategies, mathematical modeling, and assumptions. The results are compared and evaluated in Section 3. Finally, the conclusions and future suggestions are given in Section 4.

2. METHODOLOGY

Integrating PV panels with batteries for energy reliability and sustainability in grid-connected houses and the energy exchange and management provided by the converter will reduce the environmental concern of conventional sources [33]. BESS performs superior to its peers and often increases self-consumption and renewable potential [34]. Converters used for DC and AC electricity conversion include inverters and rectifiers. It is estimated that replacement costs will be high over the project's lifetime [35]. If the BESS is fully charged, the excess electricity from the PV is sold to the grid or used in demand, depending on the energy management control methods. In this way, excess electricity can be minimized, and renewable waste can be avoided. Electricity is purchased from the grid if the demand cannot be met and the BESS state of charge (SOC) needs to be increased. Many energy management or BESS control methods are considered in the meters for comparison in hybrid power systems. The aim is to reduce cost and increase environmentally-indexed self-consumption and renewable potential via feasible energy management. Although the cost of each functional unit in the hybrid system is significant, component costs are not considered in this study. The general hybrid configuration is shown in Figure 1.

Modeling for PV panels is performed using output power, cell temperature, and panel efficiency. The PV panel power is calculated in Equation (1) using the output power at standard test conditions (STC: 1000 W/m^2 solar radiation, 25°C cell temperature, air mass equal to 1.5, and ASTM G173-

03 standard spectrum). In addition, the incident radiation rate ($\frac{I_{PV}}{I_{PV,STC}}$) according to the STC condition, PV derating factor (f_{DF}), temperature coefficient of power (α_{PTC}) and cell temperature at STC ($T_{PV,STC}$) and nominal operation ($T_{PV,CT}$) are considered. The temperature power coefficient (α_{PTC}) expresses the dependence of PV array power output on cell temperature and is usually available in manufacturer catalogs. Derating factor (f_{DF}) considers panel pollution, cable losses, shading, snow cover, and aging characteristics. The PV cell temperature at nominal operation ($T_{PV,CT}$) is determined in Equation (2). The constant 800 refers to the solar radiation defined considering the nominal operating cell temperature (NOCT). NOCT refers to 800 Wh/m^2 irradiance, ambient (20°C), and cell temperatures at no-load operation. Also, the T_{C-RO} expressed as NOCT is subtracted from the ambient temperature at NOCT (20°C). Equation (2) is completed by considering solar radiation (I_{PV}) and ambient temperature (T_A). The solar PV panel efficiency is calculated in Equation (3) considering module efficiency (η_{STC}), solar radiation intensity coefficient (γ), logarithmic solar radiation ($log_{10}(I_{PV})$), temperature coefficient of power (α_{PTC}) and cell temperatures at any condition ($T_{PV,CT}$, $T_{PV,STC}$). The solar radiation intensity near the surface can be 635 W/m^2 [36], where the solar radiation intensity coefficient is used to scale the panel installation for the house's roof [37].

$$P_{PV} = P_{PV,STC} . f_{DF} . \left(\frac{I_{PV}}{I_{PV,STC}}\right) . \left[1 + \alpha_{PTC} . \left(T_{PV,CT} - T_{PV,STC}\right)\right] \tag{1}$$

$$T_{PV,CT} = T_A + \left[\frac{(T_{C-RO} - 20)}{800} I_{PV}\right] \tag{2}$$

$$\eta_{PV} = \eta_{STC} . \left([\gamma . log_{10}(I_{PV})] + \left[1 - \alpha_{PTC} . \left(T_{PV,CT} - T_{PV,STC}\right)\right]\right) \tag{3}$$

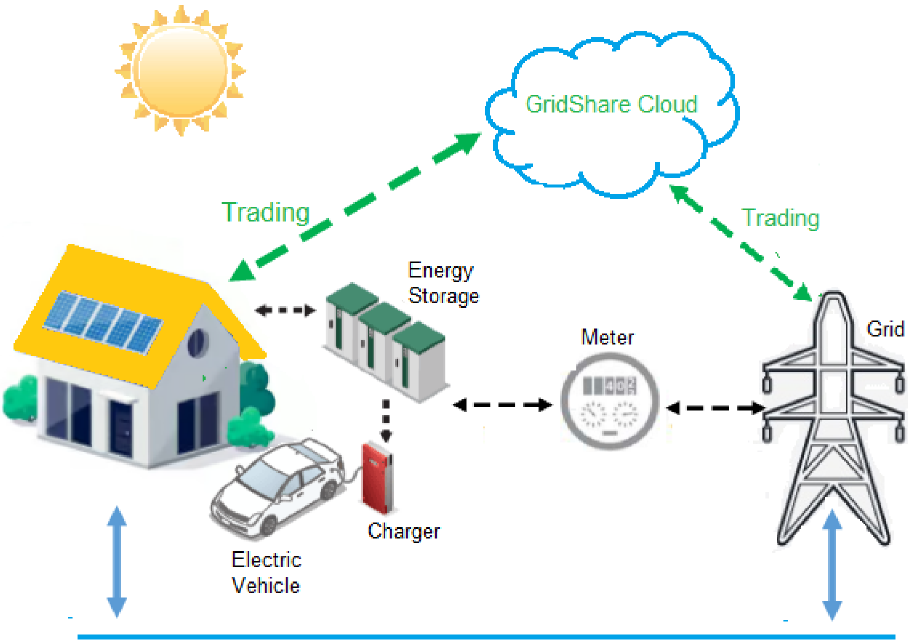


Figure 1. Grid-connected PV-powered household operation

A power conversion system (PCS) operating in inverter and rectifier mode is used for AC to DC or DC to AC energy conversion. The inverter power is calculated in Equation (4) based on the inverter operating efficiency and DC operating power. In contrast, the rectifier operating efficiency and AC operating power are used in Equation (5) to determine the rectifier output power. From the ratio of PV array output power to PCS power, the converter efficiency is calculated in Equation (6) [38].

$$P_{inv} = P_{DC} \cdot \eta_{inv} \tag{4}$$

$$P_{rec} = P_{AC} \cdot \eta_{rec} \tag{5}$$

$$\eta_{DC/AC} = \frac{P_{PV}}{P_{PCS}} \tag{6}$$

The functionality of BESS energy management control methods is directly related to renewable potential. Therefore, the PV power generation efficiency, which is the share of PV power generation directly transferred to demand in total PV power generation, is calculated by Equation (7). Similarly, the share of PV power generation that is directly transferred to demand in total demand, i.e., the beneficial utilization rate of PV in demand, is calculated by Equation (8). The

SCR and SSR in the self-indices can be the favorite of governments and prosumers for BESS control [39]. Here, the annual PV energy transferred to demand is expressed as $\sum E_{PV}^{cons}$, PV's total annual energy generation is $\sum E_{PV}^{gen}$, and the load's annual energy demanded is $\sum E_L$.

$$SCR = \frac{\sum E_{PV}^{cons}}{\sum E_{PV}^{gen}} \tag{7}$$

$$SSR = \frac{\sum E_{PV}^{cons}}{\sum E_L} \tag{8}$$

In renewable energy systems, curtailment refers to reducing or limiting renewable energy generation due to various factors, such as grid constraints or oversupply. When renewable energy sources such as wind or solar generate more electricity than the grid or system can accommodate or utilize, curtailment is applied to manage the excess generation. The curtailment rate measures the amount of renewable energy that is reduced or discarded compared to the total renewable energy generated. It is usually expressed as a percentage. A higher curtailment rate indicates that more renewable energy generation is curtailed or wasted [29].

Finally, SOC is also considered in Equation (9). SOC indicates how long the battery can be used and how long it can be charged. Therefore, a low battery charge may mean life will be reduced. It is, therefore, essential to monitor the battery charge status regularly and to charge the battery correctly [40]. Here, $SOC(t)$ and $SOC(t + \Delta t)$ are the occupancy rate of the BESS at time t and t+Δt respectively, C_n is the charge rate during BESS charge and discharge, η is coulomb efficiency and I(t) is BESS current at time t. Coulomb efficiency defines the released battery capacity. As a fraction less than 1, this parameter expresses the discharge capacity ratio after a full charge to the charge capacity of the same cycle [41].

$$SOC(t + \Delta t) = SOC(t) + \frac{1}{C_n} . \int_t^{t+\Delta t} \eta . \mathrm{I(t)dt} \tag{9}$$

Self-consumption control is represented by PV power generated from sunrise to sunset is not used to meet demand but is stored directly in BESSs and then consumed on demand at higher electricity purchase prices. In schedule mode control, BESS charging is performed in the higher radiation zone (11.00). The BESS charging is maintained for a long time until fully charged, preventing power losses when the batteries are empty. In this way, a full charge of the BESS is prevented, and the battery is not self-discharged over time, enabling its beneficial use in the evening hours. Schedule mode with constant charging power is logically similar to schedule mode. The main difference is that BESS charging starts around 09.00 and is continuously charged at the same power until 15.00. In this way, the battery is not fully charged before the programmed time, and the probability of BESS charging is increased with early charging in low-radiation areas. The fixed feed-in limit control limits the voltage sag by limiting the curtailment rate to 50%. The energy above the curtailment rate is transferred to the BESS, eliminating energy waste. In feed-in damping control, the load and energy dispatch are not customized. A forecast based on radiation data is generated, and BESS charging is managed according to the radiation. This way, PV power charges the BESS without wasting, efficiently meeting the demand in the required time intervals. The BESS charging rate is allocated predictably according to the data to eliminate losses due to weather forecasts. Finally, the BESS control strategies based on the daily energy balance are shown in Figure 2.

Daily and yearly data have been used in this study to get better results. First daily data was used to make sense of the system, and daily data was used again to include selling excess PV production to the grid, but in both of these scenarios using only daily data has not been precisely fruitful because irradiation changes through the year which causes PV production through the year [42]. In the yearly scenario, different charge control strategies and data from two cities (Istanbul and Antalya) have been used to get more realistic results since data changes throughout the year. Antalya in Türkiye is located at 36°53.8' latitude and 30°42.8' longitude. Antalya's average daily radiation, temperature, and clearness index (CI) data are 4.54 kWh/m^2/day, 18.23 °C, and 0.541%. Istanbul's latitude is 41°0', and its longitude is 28°58'. Istanbul's average daily radiation, temperature, and CI are 3.94 kWh/m^2/day, 14.46°C, and 0.481% [43].

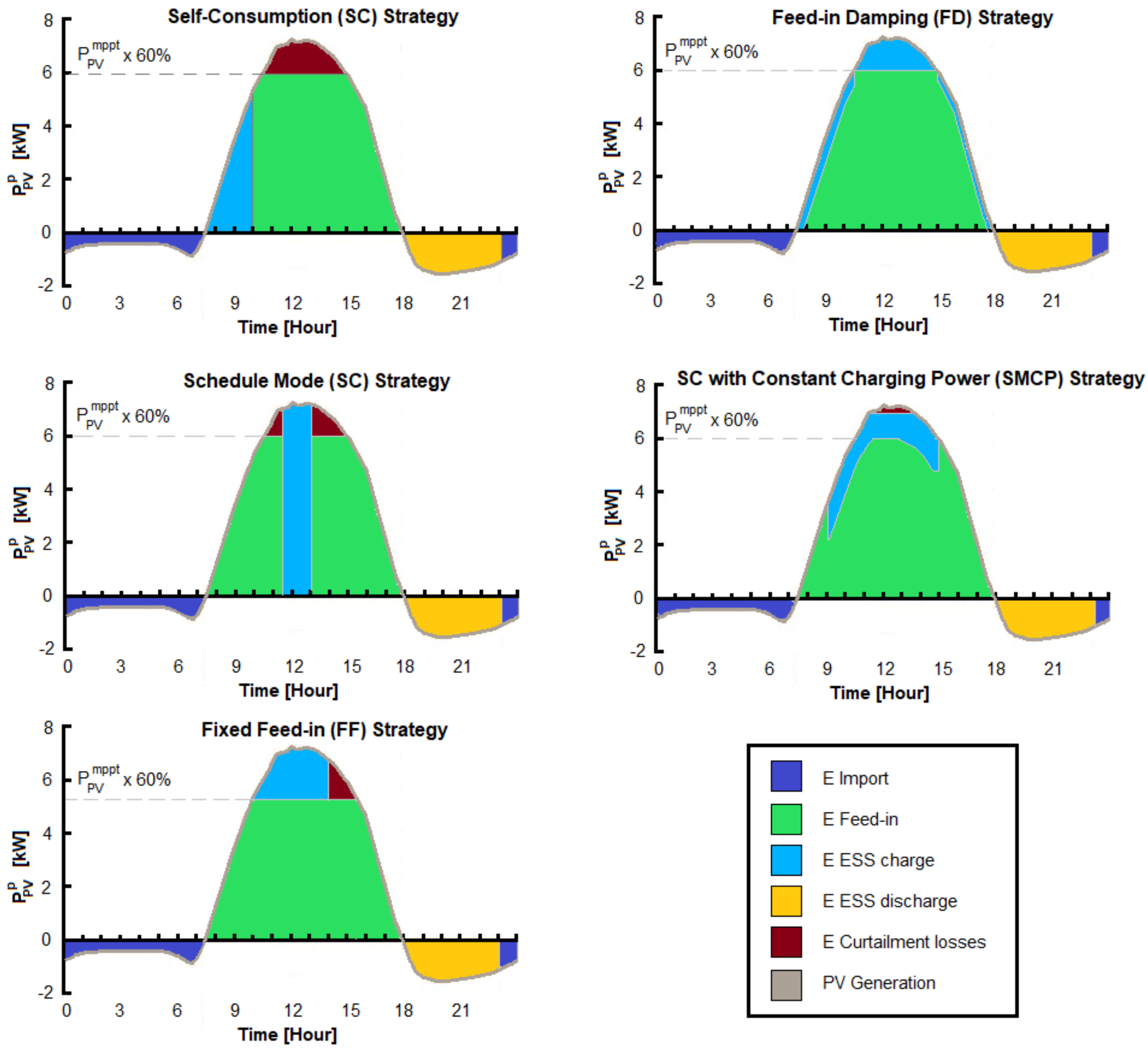


Figure 2. Daily energy balance based on BESS control strategies

The charge control strategies mentioned above were also tested, as was the daily method. In the study, various control methods are evaluated in terms of economic and self-index on a daily or annual basis for household prosumers with and without electricity sales to the grid in Istanbul and Antalya. The scenarios are shown in Table 2. All these energy management control methods are evaluated for five different prosumer demand profiles in Figure 3. The installed PV capacity for prosumers 1 and 2 are 3 kW and 2 kW, respectively, while the rest of the prosumers' installed PV capacities are 1 kW each. According to [44], optimal battery capacities are defined as 1 kWh per 1 kWp PV system. The operating range is limited to between 20% and 90% of the state of charge (SOC) to increase the battery's life. In this context, depending on the demand flexibility, the effectiveness of energy management control strategies is evaluated based on the supply-demand balance in the BESS-focused framework. The performance of the control strategies is realized in this study by using the MILP solver via Gurobi Python. Gurobi provides solutions for various problems such as linear programming, mixed-integer linear programming, quadratic programming, mixed-integer quadratic programming, quadratic constrained programming, and mixed-integer quadratic constrained programming.

Table 2. Scenarios of the study

Scenarios	Region	Control Method					Time Horizon		Grid Sale
		FD	FF	SC	SMCP	SM	Daily	Yearly	
A	Istanbul	✓	✓	✓	✓	✓	✓		
B	Istanbul	✓	✓	✓	✓	✓	✓		✓
C	Istanbul	✓	✓	✓	✓	✓		✓	✓
D	Antalya	✓	✓	✓	✓	✓		✓	✓

FD: Feed-in damping, FF: Fixed feed-in, SC: Self Consumption, SMCP: Schedule mode with constant charging power, SC: Schedule mode

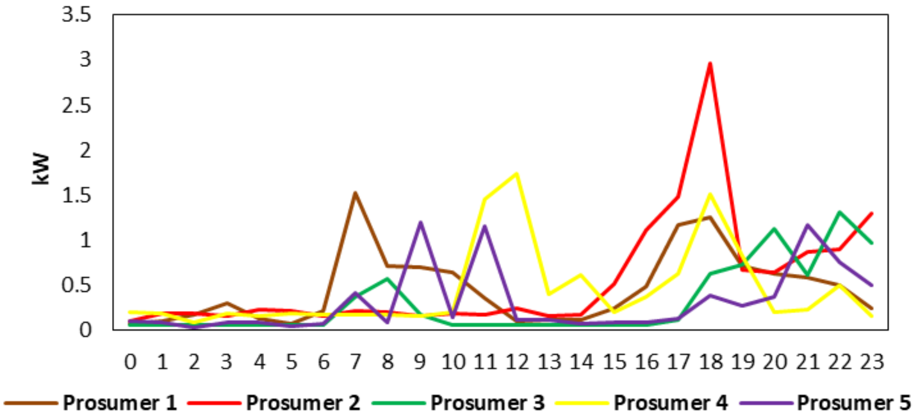


Figure 3. Prosumer demand profiles

3. RESULTS

The main difference between scenarios A and B is the consideration of electricity sales to the grid. Selling excess power to the grid can be beneficial for prosumers. In the figure below, we can see the difference between the two days. Also, the hourly energy selling price is accepted as 0.06 $ in this study. In the presence of electricity sales, daily energy prices fall to a negative base, increasing economic profitability. Ignoring the sale of electricity to the grid will cause costs in daily energy prices rather than revenues. If excess electricity is not sold, even with no costs during those hours, costs cannot be minimized, and PV power is wasted. Unselling excess PV power generation increases the average daily energy price to 0.06 $. However, selling excess energy to the grid can reduce the average daily energy price to -0.16 $, further shortening payback periods. Day-to-day operations may not be correct for many control methods due to the lack of a long time horizon in scenario B, especially in cases where electricity is sold to the grid. However, it can be a viable first step in performance assessment for energy management.

Depending on the flexibility in demand profiles, each prosumer profile's energy management control methods may vary. SCR and SSR criteria and environmental impacts are assessed based on the self-index, while financial performance is analyzed simultaneously. Since the SCR metric shows the utilization of PV power on its own without being sold to the grid, it aims to reduce the reactive power on sale to the grid. Accordingly, the metric can help to achieve clean energy. The SSR metric indicates how many loads can be met by PV panel power. Therefore, the higher SSR, the less power is purchased from the grid, which is beneficial for clean energy as it reduces energy use. Figure 4 compares the control methods' daily SCR and SSR values for each prosumer demand profile.

The flexibility in demand causes a significant variation in SCR and SSR. Since feed-in damping and fixed feed-in have a similar performance (±0.01%), fixed feed-in is not shown in the comparison. Due to the high SCR and low SSR, consumers in the prosumer 5 demand profile can more effectively reduce environmental concerns with the proposed control methods.

The schedule mode with constant charging power and feed-in damping suggests similar SCRs for prosumer 5, but the feed-in damping performance is higher for many demand flexibilities. The similar performance of the criteria emphasizes the annual analysis since the time horizon of the criteria is daily. Self-consumption control offers the worst SCR and SSR performance, even during day-to-day operations. Therefore, even in daily analysis, PV power charging the BESS immediately is not a recommended method. However, the self-consumption method suggests the highest SSR based on the prosumer 1 demand profile. The high SSR of prosumer 1 is evidence that the dispatch ratio of residential loads is also effective. In contrast, schedule mode promises the best SCR except for prosumer profiles 3 and 5. Feed-in damping is suggested for prosumer profiles 3 and 5. Feed-in damping and schedule mode can easily meet the demand flexibility for SSR and show the best performance.

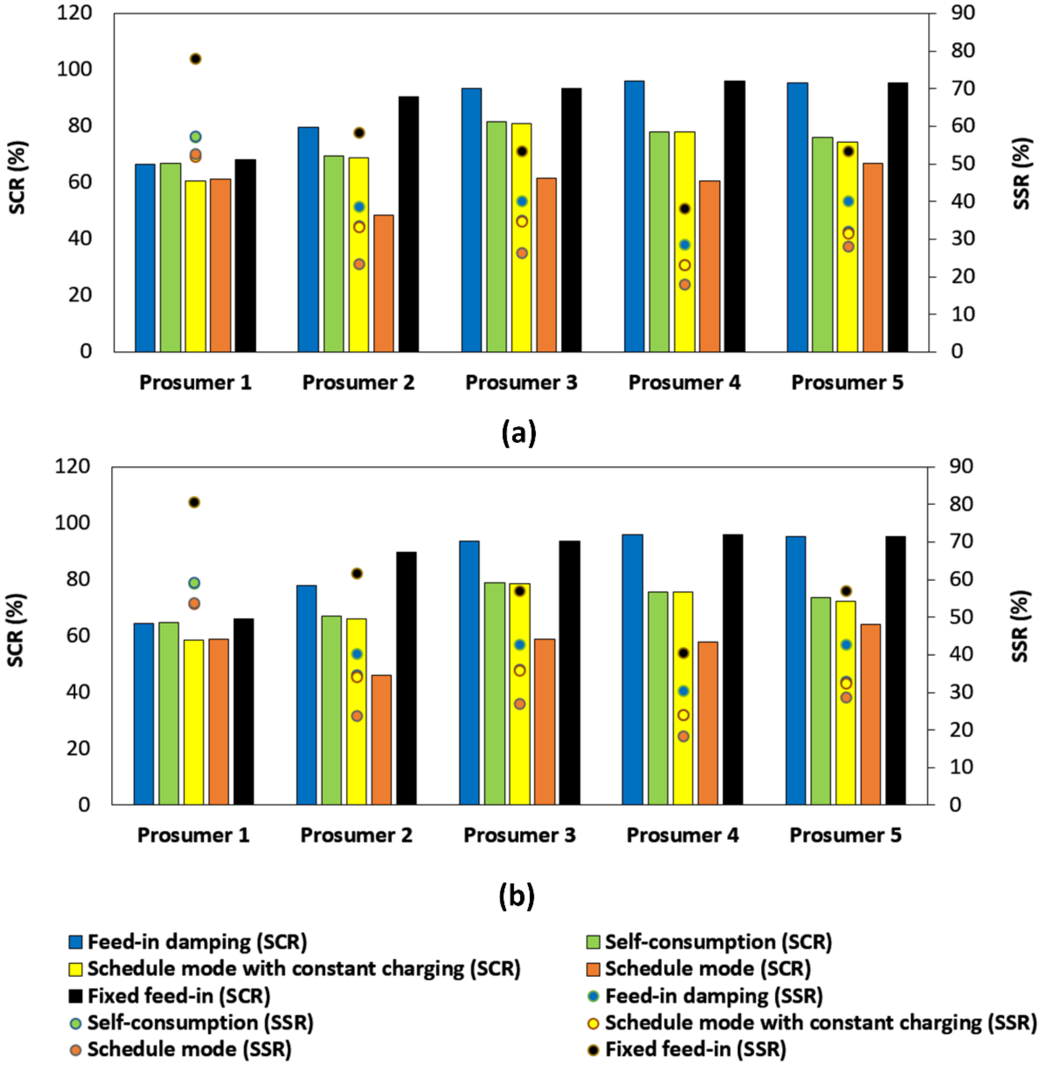


Figure 4. Daily comparison of prosumer-based control methods with SCR and SSR: (a) Istanbul and (b) Antalya

In contrast to SCR and SSR, daily costs are evaluated in Table 3. Although the lowest cost is obtained with the self-consumption method, feed-in damping (fixed feed-in with similar performance) has on average the best economic performance considering SCR and SSR. However, the self-consumption method is an attractive alternative with the lowest cost for the prosumer 1 demand profile. Feed-in damping and schedule mode can provide more economical results by 11.2%, 18.3%, and 22.3% for prosumer 2, 3, and 5 profiles. Feed-in damping can reduce the cost by up to 32.6% in the prosumer 4 profile. Excluding the prosumer 1 profile, the feed-in damping method provides the best economic performance with a cost reduction of 63.9% in the prosumer 5 profile. Similarly, the schedule mode can reduce the cost by 75.7% compared to other demands for the same demand profile. However, the prosumer 3 profile can offer the best economic performance with self-consumption and schedule mode with constant charging power reducing costs by 55.5% and 71.8%. Extending the analysis to an annual analysis would provide more detailed and more precise performance results compared to the daily.

Table 3. Comparison of prosumer-based control methods with daily cost

Method	FD	SC	SMCP	SM
Prosumer 1	**-0.163**	**-0.166**	**-0.155**	**-0.163**
Prosumer 2	0.323	0.355	0.364	0.323
Prosumer 3	0.134	0.158	0.164	0.134
Prosumer 4	0.482	0.559	0.581	0.715
Prosumer 5	0.174	0.227	0.174	0.174

FD: Feed-in damping, FF: Fixed feed-in, SC: Self Consumption, SMCP: Schedule mode with constant charging power, SM: Schedule mode

In Scenarios C and D, a reliable comparison environment is created by focusing on annual examinations and evaluating the yearly equivalents of generally accepted tables. Table 4 compares various control methods within the self-index scope based on the prosumer demand profile for Istanbul and Antalya. Depending on the ratio of PV panel power to load, the SCR would be expected to be much different in two cities where the PV power generated is so different. However, less PV generation contributes slightly to the SCR. In terms of methodology, the fixed feed-in method performs the best, with an average of 88% for both cities. This shows the importance of varying the curtailment rate. In the prosumer 4 profile, feed-in damping and fixed feed-in methods can increase SCR by up to 29.5% and reduce SSR by up to 40%. The prosumer 1 profile can offer the best performance for SSR with the fixed feed-in method. On the other hand, there is a similar trend in Antalya. Prosumer 1 profile can increase SSR to 47.3%, while the prosumer 4 profile can increase SCR to 31.4%. In contrast, it is worth stating that the prosumer 3 profile offers the best SCR in self-consumption and schedule mode with constant charging power.

Table 4. Comparison of prosumer-based control methods for annual SCR and SSR

Region	Method	FD		SC		SMCP		SM		FF	
	Self-index (%)	SCR	SSR	SCR	SSR	SCR	SSR	SCR	SSR	SCR	SSR
Istanbul	Prosumer 1	66.6	76.23	66.79	76.45	60.6	69.36	61.18	70.32	68.3	78.18
	Prosumer 2	79.73	51.48	69.49	44.87	68.68	44.34	48.49	31.31	90.58	58.48
	Prosumer 3	93.53	53.56	81.51	46.67	80.88	46.31	61.66	35.31	93.58	53.59
	Prosumer 4	96.08	38.18	77.95	30.98	77.93	30.97	60.53	24.2	96.13	38.2
	Prosumer 5	95.29	53.53	76.05	42.72	74.52	42	66.81	37.53	95.34	53.56
Antalya	Prosumer 1	64.48	78.76	64.68	79	58.45	71.4	58.8	71.81	65.98	80.6
	Prosumer 2	78	53.73	67.04	46.19	66.14	45.57	45.97	31.67	89.71	61.8
	Prosumer 3	93.48	57.09	78.87	48.19	78.56	48	58.95	36.02	93.48	57.12
	Prosumer 4	95.9	40.65	75.48	32	75.45	32	57.88	24.55	95.89	40.67
	Prosumer 5	95.21	57.05	73.47	44.05	72.42	43.41	64.23	38.5	95.21	57.08

FD: Feed-in damping, FF: Fixed feed-in, SC: Self Consumption, SMCP: Schedule mode with constant charging power, SM: Schedule mode

In contrast to SCR, there is no significant difference (3%) in SSR. PV generation makes less difference in the SSR metrics than in the SCR metrics. However, the main difference from the SCR metrics is that the SSR for Antalya is higher. The SSR may perform better if PV generation is high. Like SCR, the fixed feed-in method has the best average performance of 56% in Istanbul and 59% in Antalya. High SCR indicates that low PV generation will be more beneficial, and high SSR indicates that high PV generation will be more beneficial. Also, considering that prosumer 1 provides high values in both conditions, the amount of load is the most critical factor for SCR/SSR. Table 5 shows the annual cost comparison of the control methods for both cities. The higher SCR and SSR and lower annual cost puts Antalya at the top of the BESS-based energy control methods. Although there are minimal financial differences between fixed feed-in and feed-in damping, the curtailment rate is the most important difference in both methods, depending on the limit of the curtailment rate. Antalya can reduce costs by 10.43% for feed-in damping, 9.63% for self-consumption, 9.52% for schedule mode with constant charging power, 8.7% for schedule mode, and 10.62% for fixed feed-in. Better irradiation, feed-in damping, and fixed feed-in methods can reduce annual costs by up to 10.62%.

Table 5. Comparison of the average annual cost of prosumer-based control methods

Region	FD	SC	SMCP	SM	FF
Istanbul	55.79	57.32	57.78	59.98	55.16
Antalya	49.97	51.8	52.28	54.76	49.3

FD: Feed-in damping, FF: Fixed feed-in, SC: Self Consumption, SMCP: Schedule mode with constant charging power, SC: Schedule mode

Table 6 shows the performance evaluation of the control methods regarding SCR, SSR, and cost. The feed-in damping and fixed feed-in methods offer the best performance. At the same time, self-consumption shows well performance, schedule mode with constant charging power shows moderate performance and schedule mode shows the worst performance. The government and stakeholders' steps towards feed-in damping and fixed feed-in methods will increase the potential for self-sufficiency and promise minimum-cost hybrid configurations for sustainable development goals.

Table 6. Comparison of prosumer-based control methods considering performance criteria

Control Method	SCR	SSR	Cost
Feed-in damping (FD)	Best	Best	Best
Self Consumption (SC)	Well	Well	Well
Schedule mode constant power (SMCP)	Moderate	Moderate	Moderate
Schedule mode (SM)	Worst	Worst	Worst
Fixed feed-in (FF)	Best	Best	Best

4. CONCLUSIONS

In this paper, BESS-based energy control methods are compared. Their performance is evaluated regarding SCR, SSR, and cost for demand flexible household loads in Istanbul and Antalya, considering daily and annual curtailment constraints. The importance of BESS charge control strategies is proven, and feed-in methods are the most successful. It is also emphasized that control strategies are essential in responding to demand. Environmental concerns are evaluated through SCR and SSR performance indices, and the importance of control methods for carbon neutrality targets is explained. Although daily comparisons are a good first step for the performance of control methods, extending the time horizon to annual for more realistic assessments is essential. In addition, feed-in damping shows the highest daily performance, and self-consumption the lowest. For prosumer 2, 3, and 5 profiles, feed-in damping and schedule mode can provide up to 22.3% more economical results. For a comprehensive evaluation, PV generation variation and demand flexibility should be considered. In this direction, Istanbul and Antalya are evaluated in the annual analysis. The feed-in damping and fixed feed-in control methods have the most efficient performance for the prosumer 4 profile and can increase the SCR by up to 29.5% and reduce the SSR by up to 40% for Istanbul. On the contrary, similar control methods can increase the SSR by up to 47.3% for the prosumer 1 profile and increase the SCR by up to 31.4% for the prosumer 4 profile in Antalya. Antalya guarantees up to 10.62% lower costs for control methods due to its higher solar potential. Istanbul, which has a lower solar potential, promises a 2% improvement in

SCR and SSR, though the SSR performance is superior. Although effective control methods have been proposed for the relevant local load profiles, future studies must consider the costs of PV, BESS, and converter capacities. Moreover, hybrid configurations with other renewable or clean energy alternatives can be analyzed at the national or microgrid level. Finally, further data on various demand and hybrid configurations are available. In that case, radiation forecasting and control methods proposed with the help of machine learning can serve many stakeholders in the overall context and help planned development.

NOMENCLATURE

P_{PV}	The PV power output (kW)
$P_{PV,STC}$	The rated PV capacity under standard test conditions (kW)
f_{DF}	The PV derating factor (%)
I_{PV}	The solar radiation in time t (kW/m^2)
$I_{PV,STC}$	The incident radiation at standard test conditions (kW/m^2)
α_{PTC}	The temperature coefficient of power (%/°C)
$T_{PV,CT}$	The PV cell temperature in the current time step (°C)
$T_{PV,STC}$	The PV cell temperature under standard test conditions (25°C)
T_A	Ambient temperature (°C)
T_{C-RO}	The cell temperature at nominal operating conditions (°C)
η_{PV}	Solar panel efficiency (%)
η_{STC}	PV module efficiency measured under standard test conditions (%)
γ	Coefficient of solar radiation intensity
P_{inv}	Inverter power output (kW)
P_{DC}	DC operating power of the converter (kW)
η_{inv}	Inverter efficiency of the converter (%)
P_{rec}	Rectifier power output (kW)
P_{AC}	AC operating power of the converter (kW)
η_{rec}	Rectifier efficiency of the converter (%)
$\eta_{DC/AC}$	DC/AC conversion efficiency of the converter (%)
P_{PCS}	Converter power output (kW)
SCR	Self-consumption ratio (%)
$\sum E_{PV}^{cons}$	Annual PV energy transferred to demand (kWh/year)
$\sum E_{PV}^{gen}$	Total annual energy generation of PV (kWh/year)
SSR	Self-supply ratio (%)
$\sum E_L$	Annual energy demanded by the load (kWh/year)
$SOC(t+\Delta t)$	The occupancy rate of the battery at time t+Δt
Δt	Time interval (hour)
t	Time
$SOC(t)$	The occupancy rate of the battery at time t
C_n	The charge rate (A/Ah)
η	The coulomb efficiency
I(t)	The BESS current (A)

BESS	Battery energy storage systems
PV	Photovoltaic
PCS	Power conversion systems or converter
C.C.P.	Constant charging power
SOC	State of charge (%)
STC	Standard test conditions
NOCT	The nominal operating cell temperature (°C)

ACKNOWLEDGMENT

Analyzes and comments made in this document belong to the authors. Any institution, company, etc., does not support the article.

DECLARATION OF ETHICAL STANDARDS

The authors of the submitted paper declare that nothing necessary for achieving the paper requires ethical committee and/or legal-special permissions.

CONTRIBUTION OF THE AUTHORS

Fatih Oguzalp: Software, Writing –original draft.

Musa Terkes: Visualization, Supervision, Writing - review & editing.

Alpaslan Demirci: Conceptualization, Validation, Writing - review & editing, Supervision.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

REFERENCES

[1] Pippi KD, Papadopoulos TA, Kryonidis GC. Impact assessment framework of PV-BES systems to active distribution networks. IET Renewable Power Generation 2022; 16: 33–47.

[2] Lin J, Sun J, Feng Y, Zheng M, Yu Z. Aggregate demand response strategies for smart communities with battery-charging/switching electric vehicles. Journal of Energy Storage 2023; 58: 106413-106424.

[3] Dong S, Kremers E, Brucoli M, Rothman R, Brown S. Establishing the value of community energy storage: A comparative analysis of the UK and Germany. Journal of Energy Storage 2021; 40: 102709-102723.

[4] Duman AC, Erden HS, Gönül Ö, Güler Ö. Optimal sizing of PV-BESS units for home energy management system-equipped households considering day-ahead load scheduling for demand response and self-consumption. Energy and Buildings 2022; 267: 112164-112182.
[5] Elio J, Milcarek RJ. A comparison of optimal peak clipping and load shifting energy storage dispatch control strategies for event-based demand response. Energy Conversion and Management 2023; 19: 100392-100402.
[6] Chen Y, Zhao C, Wei W, Wu Q, Hou Y, Pandžić H. Guest editorial: Low-carbon operation and marketing of distribution systems. IET Renewable Power Generation 2022; 16: 2463–2467.
[7] Liu J, Hu C, Kimber A, Wang Z. Uses, cost-benefit analysis, and markets of energy storage systems for electric grid applications. Journal of Energy Storage 2020; 32: 101731-101746.
[8] Faraji J, Ketabi A, Hashemi-Dezaki H. Optimization of the scheduling and operation of prosumers considering the loss of life costs of battery storage systems. Journal of Energy Storage 2020; 31: 101655-101672.
[9] Mustika AD, Rigo-Mariani R, Debusschere V, Pachurka A. A two-stage management strategy for the optimal operation and billing in an energy community with collective self-consumption. Applied Energy 2022; 310: 118484-118495.
[10] Hossain MA, Pota HR, Squartini S, Abdou AF. Modified PSO algorithm for real-time energy management in grid-connected microgrids. Renewable Energy 2019; 136: 746–757.
[11] Hu Y, Schofield N, Shobayo LO, Zhao N. Investigation of transient energy storage sources for support of future electrical power systems. IET Renewable Power Generation 2020; 14: 1296–1303.
[12] Muratori M, Rizzoni G. Residential demand response: Dynamic energy management and time-varying electricity pricing. IEEE Transactions on Power Systems 2016; 31: 1108–1117.
[13] Tang H, Wang S. Energy flexibility quantification of grid-responsive buildings: Energy flexibility index and assessment of their effectiveness for applications. Energy 2021; 221: 119756-119772.
[14] Li X, Wang S. A review on energy management, operation control and application methods for grid battery energy storage systems. CSEE Journal of Power and Energy Systems 2021; 7: 1026-1040.
[15] Bluhm H, Gährs S. Environmental assessment of prosumer digitalization: The case of virtual pooling of PV battery storage systems. Journal of Energy Storage 2023; 59: 106487-106500.
[16] Lee ZE, Zhang KM. Regulated peer-to-peer energy markets for harnessing decentralized demand flexibility. Applied Energy 2023; 336: 120672-120684.

[17] Morey M, Gupta N, Garg MM, Kumar A. A comprehensive review of grid-connected solar photovoltaic system: Architecture, control, and ancillary services. Renewable Energy Focus 2023; 45: 307–330.

[18] Xu Y, Parisio A, Li Z, Dong Z, Ding Z. Optimization-based ramping reserve allocation of BESS for AGC enhancement. IEEE Transactions on Power Systems 2023; Early Access: 1–15.

[19] Sarfarazi S, Mohammadi S, Khastieva D, Hesamzadeh MR, Bertsch V, Bunn D. An optimal real-time pricing strategy for aggregating distributed generation and battery storage systems in energy communities: A stochastic bilevel optimization approach. International Journal of Electrical Power and Energy Systems 2023; 147: 108770-108788.

[20] Aranzabal I, Gomez-Cornejo J, López I, Zubiria A, Mazón J, Feijoo-Arostegui A, Gaztañaga H. Optimal management of an energy community with PV and battery-energy-storage systems. Energies 2023; 16: 789-812.

[21] Nousdilis AI, Kryonidis GC, Kontis EO, Barzegkar-Ntovom GA, Panapakidis IP, Christoforidis GC, Papagiannis GK. Impact of policy incentives on the promotion of integrated PV and battery storage systems: a techno-economic assessment. IET Renewable Power Generation 2020; 14: 1174–1183.

[22] Zhang Q, Yan J, Gao HO, You F. A systematic review on power systems planning and operations management with grid integration of transportation electrification at scale. Advances in Applied Energy 2023; 11: 100147-100170.

[23] Maturo A, Vallianos C, Buonomano A, Athienitis A. A novel multi-level predictive management strategy to optimize phase-change energy storage and building-integrated renewable technologies operation under dynamic tariffs. Energy Conversion and Management 2023; 291: 117220-117235.

[24] Asri R, Aki H, Kodaira D. Optimal operation of shared energy storage on islanded microgrid for remote communities. Sustainable Energy, Grids and Networks 2023; Early Access: 101104-101145.

[25] Shabani M, Wallin F, Dahlquist E, Yan J. The impact of battery operating management strategies on life cycle cost assessment in real power market for a grid-connected residential battery application. Energy 2023; 270: 126829-126843.

[26] Liu Y, Zhang Y, Cheng G, Lv K, Zhu J, Che Y. Grid-friendly energy prosumers based on the energy router with load switching functionality. International Journal of Electrical Power and Energy Systems 2023; 144: 108496-108510.

[27] Li J, Danzer MA. Optimal charge control strategies for stationary photovoltaic battery systems. Journal of Power Sources 2014; 258: 365–373.

[28] Zeh A, Witzmann R. Operational strategies for battery storage systems in low-voltage distribution grids to limit the feed-in power of roof-mounted solar power systems. Energy Procedia 2014; 46: 114–123.

[29] Resch M, Ramadhani B, Bühler J, Sumper A. Comparison of control strategies of residential PV storage systems. 9th International Renewable Energy Storage Conference (IRES), Messe, Düsseldorf, Germany, 2015.

[30] Struth J, Leuthold M, Aretz A, Bost M. PV-Benefit: A critical review of the effect of grid integrated PV-storage-systems. 8th International Renewable Energy Storage Conference and Exhibition (IRES), Berlin, Germany, 2013.

[31] Schneider M, Boras P, Schaede H, Quurck L, Rinderknecht S. Effects of operational strategies on performance and costs of electric energy storage systems. Energy Procedia 2014; 46: 271–280.

[32] Ueda Y, Kurokawa K. Study on the over voltage problem and battery operation for grid connected residential PV systems. 22nd European Photovoltaic Solar Energy Conference (EU PVSEC), Milan, Italy, 2007.

[33] Artaş SB, Kocaman E, Bilgiç HH, Tutumlu H, Yağlı H, Yumrutaş R. Why PV panels must be recycled at the end of their economic life span? A case study on recycling together with the global situation. Process Safety and Environmental Protection 2023; 174: 63–78.

[34] Zhao C, Andersen PB, Træholt C, Hashemi S. Grid-connected battery energy storage system : A review on application and integration. Renewable and Sustainable Energy Reviews 2023; 182: 113400-113418.

[35] Libra M, Mrázek D, Tyukhov I, Severová L, Poulek V, Mach J, Šubrt T, Beránek V, Svoboda R, Sedláček J. Reduced real lifetime of PV panels – Economic consequences. Solar Energy 2023; 259: 229–234.

[36] Alijanov DD, Topvoldiyev NA. Physical and technical fundamentals of photoelectric solar panels energy. Theoretical & Applied Science 2022; 108 (4): 501-505.

[37] Terkes M, Demirci A, Gokalp E. An evaluation of optimal sized second-life electric vehicle batteries improving technical, economic, and environmental effects of hybrid power systems. Energy Conversion and Management 2023; 291: 117272-117286.

[38] Terkes M, Tercan SM, Demirci A, Gokalp E. An evaluation of renewable fraction using energy storage for electric vehicle charging station. 4th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), Ankara, Türkiye, 2022.

[39] Tercan SM, Demirci A, Gokalp E, Cali U. Maximizing self-consumption rates and power quality towards two-stage evaluation for solar energy and shared energy storage empowered microgrids. Journal of Energy Storage 2022; 51: 104561-104573.

[40] Keskin B, Şora Günal E, Urazel B, Keskin K. Elektrikli araç bataryalarının şarj durum tahmini için bir model. Nicel Bilimler Dergisi 2022; 4: 161–175.

[41] Wang S, Fan Y, Stroe D, Fernandez C, Yu C, Cao W, Chen Z. Lithium-ion battery characteristics and applications. Battery System Modeling 2021; 1: 1-46.

[42] Mazzeo D, Leva S, Matera N, Kontoleon KJ, Saboor S, Pirouz B, Elkadeem MR. A user-friendly and accurate machine learning tool for the evaluation of the worldwide yearly photovoltaic electricity production. Energy Reports 2023; 9: 6267–6294.

[43] NASA. Prediction of worldwide energy resource (POWER) database. Access: June 2023. https://power.larc.nasa.gov.

[44] Weniger J, Tijaden T, Quaschning V. Sizing and grid integration of residential PV battery systems. 8th International Renewable Energy Storage Conference (IRES), Berlin, Germany, 2013.