



Optimizing PV power utilization in standalone battery systems with forecast-based charging management strategy

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Abstract

Optimizing photovoltaic (PV) power utilization in battery systems is challenging due to solar intermittency, battery efficiency, and lifespan management. This paper proposes a novel forecast-based battery charging management (BCM) strategy to enhance PV power utilization. A string of Li-ion battery cells with diverse capacities and states of charge (SOC) is contemplated in this constant current/-constant voltage (CC/CV) battery-charging scheme. Significant amounts of PV power are often wasted because the CC/CV mode cannot fully exploit the available power to maintain appropriate charging rates. To address this issue, the proposed BCM algorithm selects an optimal set of battery cells for charging at any given time based on forecasted PV power generation, ensuring maximum power is obtained from the PV system. Additionally, a support vector regression (SVR)-based forecasting model is developed to predict PV power generation precisely. The results indicate that the anticipated BCM strategy achieves an overall utilization rate of 87.47% of the PV-generated power for battery charging under various weather conditions.

Keywords: Battery-charging management (BCM); Energy sustainability; Maximum utilization of PV power; Forecasting PV power; Constant current/-constant voltage (CC/CV)

0 Introduction

Owing to their promising techno-economic and environmental merits, the integration of photovoltaic (PV) systems to satisfy electricity demands and reduce the negative impacts of global warming is increasing [1,2]. In 2023, the global cumulative solar PV capacity reached 1,624 GW, with 447 GW of new installations that year alone, contributing to three-quarters of renewable capacity additions worldwide [3]. The abundant availability of solar resources and rapid technological advancements have fueled the widespread adoption and growth of PV installations [4].

Various PV configurations are utilized in modern society, including grid-connected residential and community solar systems [5]. However, standalone PV systems have gained significant recognition over the years, owing to their effectiveness in rural electrification and isolated regions [6]. In addition, as a sustainable mode of transportation, the rise of electric vehicles (EVs) has increased the demand for distribution networks [7]. PV-based charging stations help manage the EV demand by providing clean energy while reducing carbon emissions and energy costs [8]. When integrating PVs into battery-charging systems, key features such as power density, power-to-weight ratio, and life cycle make Li-ion batteries popular [9,10]. Different charging schemes are employed to recharge batteries based on battery chemistry [11]. Li-ion batteries need a constant current/constant voltage (CC/CV) charging scheme, whereas nickel batteries require only a CC. Maintaining

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Nomenclature

Abbreviations and acronyms

Symbol Meaning

x_i	Input values
y_i	Output values
L	Lagrange function
k	Kernel function
α_i and α_i^*	Lagrange multipliers
C	Penalty factor
ε	Tolerance margin
γ	Kernel co-efficient
w	Weight vector
b	Bias term
ζ and ζ^*	Slack variables
d_{norm}	Normalized data
U_R	Utilization rate

PV	Photovoltaic
SOC	State of charge
EV	Electric vehicle
PHEV	Plugin hybrid electric vehicle
BCM	Battery-charging management
SVR	Support vector regression
CC/CV	Constant current/constant voltage
HRES	Hybrid renewable energy resources
nRMSE	Normalized root means square error
MAPE	Mean absolute percentage error
CEMS	Central energy-management system
MPPT	Maximum power-point tracking
PV	Photovoltaic
V2G	Vehicle-to-grid

appropriate charging current and voltage is critical for battery performance because unmanaged charging can lead to voltage fluctuations and power losses [12–14]. Managing the charging current and voltage is more challenging in a PV battery system due to the uncertainties in solar power generation, making it challenging to keep these parameters within optimal limits [15,16].

During peak demand periods, renewable energy sources are incorporated to compensate for excess demand for battery-charging systems [17–19]. In [20], the grid-connected PV/battery system was shown as an efficient substitute for meeting energy demand. However, power generation can fluctuate owing to uncertainties in solar irradiance and PV system size, which are influenced by weather conditions and customer demand [21]. To mitigate these uncertainties, [22] designed a grid-connected PV battery system in which PV-generated energy is stored in the battery through off-peak periods and supplied to the grid during peak demand periods. Several grid-connected PV-based charging systems have been designed where the battery is primarily charged by the PV system or supplemented by the grid when the PV power is insufficient [23,24]. These battery-charging systems present technical challenges, including voltage violations, overloading, and power losses [25,26]. In addition to PV systems, vehicle-to-grid (V2G) systems are popular for reducing peak demand [27,28]. However, battery degradation remains a critical issue. These aspects make grid-independent systems the most cost-effective alternatives for battery charging, particularly in remote areas and island regions [29].

Many researchers have introduced hybrid renewable energy resources (HRES) as effective solutions for battery-charging systems [30–33]. HRES reduces dependency on single sources and enhances resource optimization [33,34]. However, implementation faces challenges such as high initial costs, complex system integration,

and the need for advanced control strategies, leading to the continuation of a standalone PV system. Owing to its intermittent properties, standalone PV-based charging faces challenges in maintaining optimal charging performance [35]. Optimizing battery charging through PV systems requires accurate solar forecasting [36]. This forecast helps manage battery charging efficiently and reduce energy wastage [37]. It also supports effective energy storage and interactive grid decision-making, minimizing reliance on grid sources. However, accurate PV forecasting requires advanced models to account for weather variability, which is a critical aspect of system optimization.

Research has been conducted to determine better charging management techniques for standalone PV battery systems. In [38], a charging system was proposed that maintains the DC voltage and state of charge (SOC) within standard limits while reducing the current stress on the battery. In [39], a control method for a DC-DC buck converter was utilized in an efficient standalone PV-based charging framework. In [40], a power management strategy for a standalone system was proposed in which the final SOC was constrained to 99.5 % to prevent overcharging and battery degradation. The literature review indicates that previous studies have extensively discussed and improved various crucial features, including maximum power tracking from PV systems, DC-DC voltage control, battery protection mechanisms to prevent damage during charging, and charging control strategies to extend the battery lifespan [41,42]. However, power flow management is indispensable in standalone PV-based charging mechanisms.

Based on the literature review, the challenges and gaps in optimizing PV power utilization in battery charging through a forecast-based energy-management strategy are summarized as follows:

- 1) Traditional charging schemes, such as CC/CV, fail to fully exploit the available PV power, leading to significant energy wastage, especially under changing weather conditions. Hence, an accurate PV forecast considering weather variations is necessary for optimal battery charging.
- 2) Despite extensive research on improving PV-based battery-charging systems, gaps remain in the integration of robust power flow management techniques to optimize system efficiency and reliability. In addition, limited focus has been given to practical approaches addressing power flow, battery lifespan, and system performance under varying operating scenarios.
- 3) Although extensive research exists on grid-connected systems, standalone PV systems for battery charging, particularly in remote and isolated regions, have been less explored. These systems face unique challenges, such as the intermittency of PV power and system efficiency.

To address these issues, this paper presents a comprehensive forecast-based charging management (BCM) strategy that integrates accurate PV power forecasting and optimized battery utilization to enhance the efficiency of standalone PV systems. In this process, an SVR-based prediction model was developed using empirical data from real PV systems to accurately predict PV power generation. The system recharges a string of Li-ion battery cells using a three-stage CC/CV charging strategy, relying solely on PV-generated power. Although maximum power-point tracking (MPPT) ensures maximum power extraction from PV modules, it does not guarantee optimal utilization of the generated power. A novel energy-management algorithm was proposed for optimization. It is the PV-generated power flow in batteries. This algorithm reveals the best combination of battery cells based on the

forecasted PV power to ensure that the maximum amount of PV-generated power is utilized at any arbitrary period. The proposed strategy enables efficient battery charging with optimal use of PV power under different weather circumstances.

The rest of the paper is organized as follows: Section 2 details the methodology of the PV power forecasting model, including the mathematical analysis of SVR and performance evaluation metrics. This section also describes the proposed PV-based battery-charging system, including the three-stage CC/CV charging strategy and the algorithm for maximizing the utilization of PV-generated power. Section 3 presents the results and discusses the various contexts. Finally, Section 4 summarizes the findings and directions for future research.

1 Methodology

This section provides a detailed description of the methods employed in this study, including forecasting and charging management. Fig. 1 depicts the conceptual methodology for this study, comprising all the essential blocks for optimizing PV power using forecast-based charging management.

1.1 Forecasting of PV wutput power

The PV power depends on various meteorological factors, including solar irradiance, temperature, wind pressure, and humidity. This variability poses challenges for its efficient use, particularly in standalone PV-based battery systems. Accurate PV power forecasting reduces uncertainty, enhances reliability, maintains power quality, and promotes PV system integration [43]. An SVR model utilizing historical data from a real PV system has developed to improve the accuracy of PV power generation forecasting. This study collected historical PV output

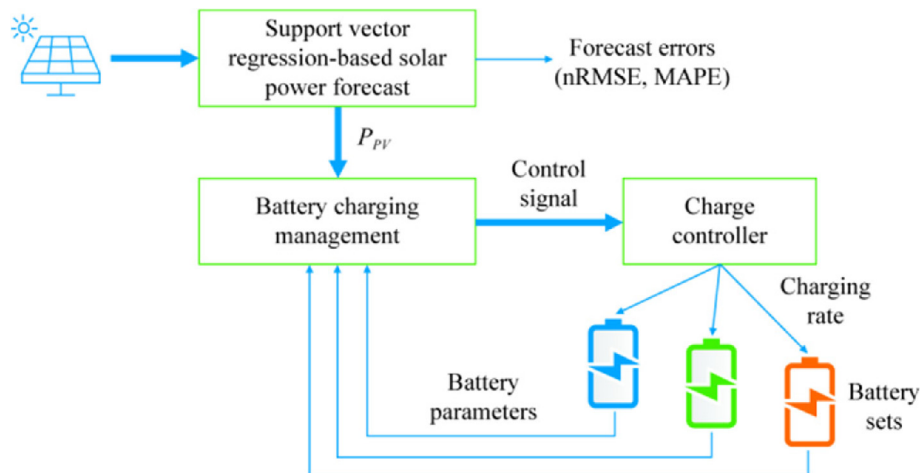


Fig. 1. Conceptual overview of forecast-based charging management strategy.

and corresponding meteorological data from a real PV system between January 1, 2017, and December 31, 2017, at five-minute intervals.

1.1.1 Support vector regression

Support Regression (SVR) is a widely used supervised machine learning approach for time series analysis and prediction. SVR excels in learning and prediction accuracy even with limited training data [44]. SVR uses nonlinear mapping to transform input data into a high-dimensional feature space where linear regression is performed. It assumes training datasets $\{(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)\}$ where $x_i \in R^n$ is the input vector, and $y_i \in R^1$ is the equivalent output value. The approximation function $f(x)$ is presented in Eq. (1):

$$y' = f(x) = w \times \psi(x) + b \quad (1)$$

where $w \in R^n$ and $b \in R$ are the weight vector and bias term, respectively. In the SVR, the regression problem is reformulated as an optimization problem, as shown in Eq. (2).

$$\begin{aligned} \min : & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m (\xi_i + \xi_i^*) \\ \text{Subject to : } & y_i - f(x) \leq \varepsilon + \xi_i^*; \\ & f(x) - y_i \leq \varepsilon + \xi_i; \quad \xi_i^*, \xi_i \geq 0 \end{aligned} \quad (2)$$

where ε is the radius of ε -insensitive tube that specifies the tolerance margin. SVR was also used to fit the training data. The penalty factor C controls the trade-off between empirical risk and model flatness. Both ε and C are user-defined parameters. The forecasting accuracy of an SVR-based model depends significantly on the proper selection of its parameters. This constrained optimization problem was solved using the Lagrange multiplier method. According to this method, the Lagrange function can be described by Eq. (3).

$$\begin{aligned} L(w, b, \xi, \xi^*, \alpha, \alpha^*, \gamma, \gamma^*) = & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m (\xi + \xi^*) - \sum_{i=1}^m \alpha_i \xi_i \\ & + \varepsilon - y_i + f(x_i) - \sum_{i=1}^m \alpha_i^* \xi_i^* + \varepsilon \\ & + y_i - f(x_i) - \sum_{i=1}^m (\xi_i \gamma_i + \xi_i^* \gamma_i^*) \end{aligned} \quad (3)$$

where ξ and ξ^* are two slack variables that represent the gap between the actual value and the corresponding boundary value of the ε -insensitive tube at the top and bottom of the tube, respectively. Hence, $\alpha, \alpha^*, \gamma, \gamma^* \geq 0$. To calculate the saddle point of L , Eq. (4) can be used.

$$\begin{aligned} \frac{\partial}{\partial w}(L) = 0 \Rightarrow w &= \sum_{i=1}^m (\alpha_i - \alpha_i^*) \Psi(x_i), \\ \frac{\partial}{\partial b}(L) = 0 \Rightarrow \sum_{i=1}^m (\alpha_i - \alpha_i^*) &= 0, \\ \frac{\partial}{\partial \xi_i}(L) \Rightarrow C - \alpha_i - \gamma_i &= 0, \\ \frac{\partial}{\partial \xi_i^*}(L) \Rightarrow C - \alpha_i^* - \gamma_i^* &= 0. \end{aligned} \quad (4)$$

Substituting Eq. (4) into the original function (3), we obtain the model in Eq. (5):

$$\begin{aligned} \max : & \bar{w}(\alpha, \alpha^*)_{w, b, \xi, \xi^*} = -\frac{1}{2} \sum_{i,j=1}^m (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) \langle \psi(x_i), \psi(x_j) \rangle \\ & - \sum_{i=1}^m (\alpha_i + \alpha_i^*) \varepsilon + \sum_{i=1}^m (\alpha_i - \alpha_i^*) y_i \\ \text{Subject to : } & \sum_{i=1}^m (\alpha_i - \alpha_i^*) = 0; \\ & 0 \leq \alpha_i, \alpha_i^* \leq C \end{aligned} \quad (5)$$

Introduce the kernel function $k(x_i, x_j)$ instead of the real function $\langle \psi(x_i), \psi(x_j) \rangle$, then the model can be obtained as Eq. (6).

$$\begin{aligned} \max : & \bar{w}(\alpha, \alpha^*)_{w, b, \xi, \xi^*} = -\frac{1}{2} \sum_{i,j=1}^m (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) k(x_i, x_j) \\ & - \sum_{i=1}^m (\alpha_i + \alpha_i^*) \varepsilon + \sum_{i=1}^m (\alpha_i - \alpha_i^*) y_i \\ \text{Subject to : } & \sum_{i=1}^m (\alpha_i - \alpha_i^*) = 0; \\ & 0 \leq \alpha_i, \alpha_i^* \leq C \end{aligned} \quad (6)$$

The appropriate selection of the kernel function and its parameters is crucial for developing an SVR model. Among the various kernel functions, the Gaussian radial basis function (Gaussian RBF) is widely used owing to its strong universal estimation capability in the feature space. Consequently, a Gaussian RBF kernel is employed in this study to develop an SVR-based forecasting model. The mathematical equation for the Gaussian RBF kernel is as follows in Eq. (7).

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) = \exp\left(-\gamma \|x_i - x_j\|^2\right), \quad \gamma > 0 \quad (7)$$

where σ^2 is the bandwidth of the RBF kernel function.

By solving the optimization problem, the optimal values for α_i and α_i^* can be obtained, leading to the best-fitting regression function, which is described in Eq. (8).

$$f(x) = \sum_{i=1}^m (\alpha_i - \alpha_i^*) \times k(x_i, x_j) + b \quad (8)$$

where α_i and α_i^* are the Lagrange multipliers. Nonlinear cases can be converted into linear cases by mapping the original variables into a higher-dimensional feature space using kernel $k(x_i, x_j)$.

1.1.2 Data processing

In SVR, the input data are mapped nonlinearly into a higher-dimensional space before linear regression is applied. However, if the data range is excessively large, it can lead to inaccurate fitting and reduced regression precision. Because the ranges of the PV output power and solar irradiance are quite high, preprocessing is necessary to scale the data to a smaller range before model input. Normalization is an effective technique for scaling

data to zero or one. The normalization process is described by the following formula in Eq. (9) [2]:

$$d_{\text{Norm}} = \frac{d_{\text{actual}} - d_{\text{min}}}{d_{\text{max}} - d_{\text{min}}} \quad (9)$$

where d_{Norm} is the normalized input data; d_{actual} is the original input data; d_{max} and d_{min} are the maximum and minimum values of the original input data, respectively. The entire data vector, such as the PV-generated power and all the meteorological vectors, must be normalized separately.

1.1.3 SVR-based model for forecasting PV power generation

Owing to its ability to efficiently handle nonlinear relationships between input and output data, SVR is commonly used to precisely forecast PV power generation. The model utilizes a kernel function, such as the radial basis function (RBF), to enhance its ability to handle complex data patterns. Its robustness against overfitting and capability to generalize well with limited training data ensure reliable predictions under varying weather conditions. While a previous study [45] recommended a day-ahead hourly PV power forecasting model, this study developed a five-minute resolution day-ahead forecasting model. Five-minute average data samples were used for training and testing for the five-minute resolution SVR approach. A flow diagram of the SVR-based forecasting model is shown in Fig. 2.

The SVR-based PV output forecasting model collected five-minute average historical data on power and relevant meteorological vectors (i.e., solar irradiance, atmospheric temperature, and wind pressure) from an experimental PV system using an automatic data acquisition system. These meteorological vectors and PV output power served as the input and output datasets, respectively, for training the model. A suitable subset of the historical data was initially selected for training and testing. The entire dataset was normalized to minimize regression error while preserving data correlation. Approximately 80 % of the data was used for training, and the remaining data was used for testing. The model was developed by setting up three key SVR parameters (C , ϵ , and γ) through the grid-search method. This is a systematic approach to tuning hyperparameters by exhaustively searching for the best combinations while minimizing prediction error and mean squared error (MSE). Although it can be computationally expensive for large datasets, it is suitable for situations in which accuracy is critical. This study minimizes the computational burden by reducing the search space based on prior knowledge from previous studies. The model was optimized based on selected parameters. To predict PV power generation, the five-minute average normalized meteorological data for a day, obtained from a nearby meteorological center, was input into the model. Because the model processes normalized data, the output must be anti-

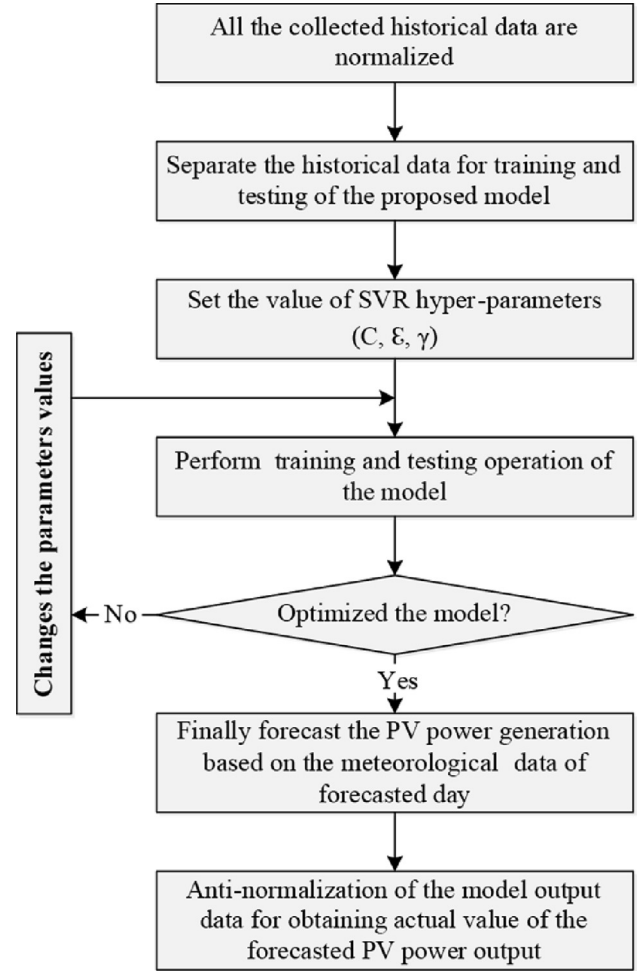


Fig. 2. Flow diagram of SVR-based PV power forecasting model.

normalized to retrieve the original PV output power values and perform a performance analysis.

1.1.4 Performance evaluation metrics of the forecasting model

Numerous performance evaluation metrics are available for forecasting models. In this study, the two standard and widely used metrics are the normalized root mean square error (nRMSE) and mean absolute percentage error (MAPE). These metrics are used to evaluate the accuracy of the forecasting model. The mathematical expressions for these metrics are given in Eqs. (10) and (11).

$$n_{\text{RMSE}} \% = \left(\sqrt{\frac{1}{N} \sum_{i=1}^N (P_{\text{forecasted}} - P_{\text{actual}})^2} \right) \times \frac{100}{P_{\text{actual(max)}}} \quad (10)$$

$$M_{\text{APE}} = \frac{1}{N} \sum_{i=1}^N \frac{|P_{\text{forecasted}} - P_{\text{actual}}|}{P_{\text{actual}}} \times 100\% \quad (11)$$

where P_{actual} and $P_{\text{forecasted}}$ are the measured and forecasted values of the PV-generated power, respectively,

for each period. $P_{\text{actual(max)}}$ is the maximum value of the assessed PV-generated power, and N is the total number of samples.

Owing to their internal chemistry, CC/CV charge controllers are highly appropriate for charging Li-ion batteries. The three-stage CC/CV controller specifies two levels of constant current, followed by a constant voltage, to the battery cell depending on the SOC. Fig. 3 shows a flowchart of the proposed three-stage CC/CV charging strategy.

In CV charging scheme, the battery is charged at a fixed voltage, and the current gradually decreases as the battery reaches its maximum charge. In CC mode, the battery is charged with a constant current until it reaches a certain voltage threshold. The CC technique ensures that the battery is charged at a controlled rate to prevent overheating and damage. The CC/CV charge controller monitored the SOC of the battery cell and adjusted the charging to a constant current or voltage based on the observed SOC level. However, if the battery is severely discharged or damaged, Li-ion cells may not be able to accept the standard CC/CV charging process. In such cases, the battery is pre-charged with a moderate current until it is ready for regular CC/CV charging. Typically, this tiny CC is about 30 % of the normal CC and is called a “trickle charge,” usually applied to maintain the charge level without overcharging. If the battery cells fail to reach the specified minimum voltage level after the trickle charge within the allotted time, the cell is considered damaged, and charging is halted until

the damaged cell is replaced. Fig. 4 illustrates a typical three-stage CC/CV charging profile for a Li-ion battery cell, demonstrating CC, CV, and trickle charging.

A trickle current, I_{trickle} , is applied until the battery voltage reaches the stated threshold voltage, indicating the desired SOC. Once this threshold is achieved, a regular constant current, I_{cc} , charges the battery until the SOC reaches the desired level. Subsequently, constant voltage charging is used until the SOC reaches its maximum level, at which point the charging process is completed, and the

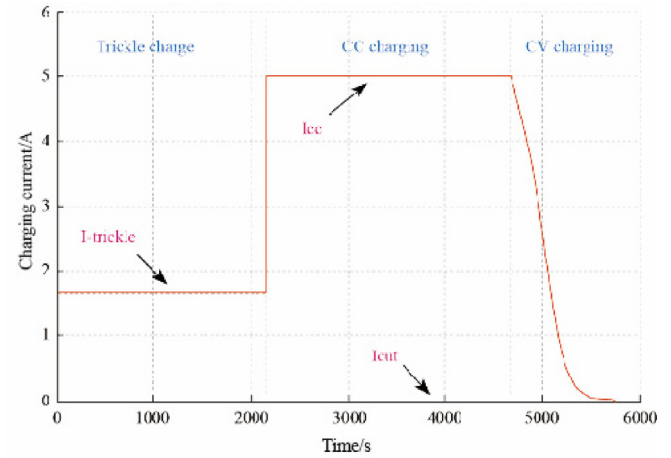


Fig. 4. Typical charging current profile of three-stage CC/CV charge controller.

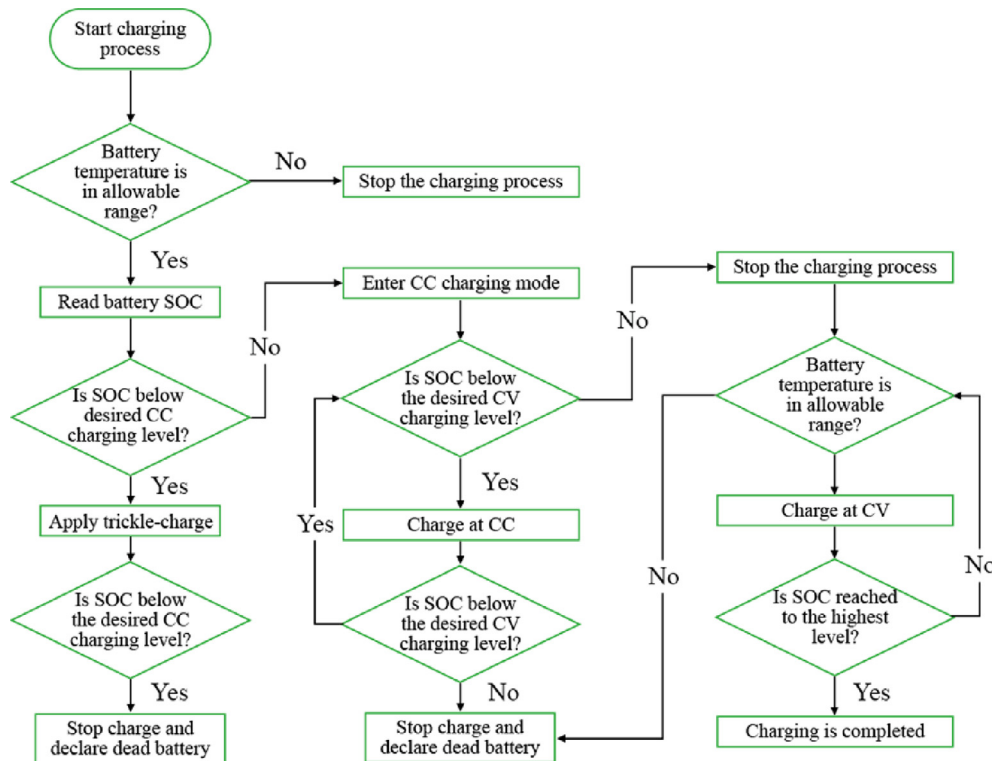


Fig. 3. Flow diagram of three stages of CC/CV charging strategy.

current becomes very low (near zero). The battery is disconnected to prevent overcharging. The proposed charging technique also monitors the battery temperature at different points throughout the charging process. Charging is terminated when the temperature exceeds the permissible limit.

1.2 Proposed battery-charging management system

A central charging control strategy exploits a single-charge controller to manage the battery or battery-string charging. If the required charging power exceeds the PV-generated power, maintaining the CC/CV charging rates becomes challenging, reducing battery performance and lifespan. Conversely, if the necessary charging power is lower than the PV-produced power, the excess power is wasted, which can be significant in large systems.

The PV power and charging rate vary continuously, owing to the changing weather conditions and the battery's SOC, respectively. Although MPPT optimizes power extraction from PVs, it does not ensure optimal utilization and requires additional strategies for storage and management. To address these issues, a novel BCM strategy for standalone PV-based systems is recommended to minimize PV power loss, maintain appropriate charging rates, and enhance battery performance and lifespan. The block diagram of the anticipated BCM system is displayed in Fig. 5, featuring a 20 W PV module. If the load is accurately matched, the DC-DC converter with MPPT provides maximum power with a nearly constant voltage. Because measuring and matching the load to achieve maximum PV-generated power is challenging, the forecasted PV power is used as an estimate.

A decentralized charging strategy is implemented in which each Li-ion battery is managed by its own CC/CV charge controller to ensure appropriate charging. The required charging power of all the batteries at any given time must be equal to or greater than the forecasted maximum PV power. Instead of continuously charging all the

batteries, a suitable combination of batteries was selected for charging. This combination ensured that the sum of the necessary charging power was approximately equal to or slightly less than the forecast PV-produced power.

The proposed strategy utilizes the five-minute resolution day-ahead forecasted PV output power for a working day. The charging power required for the Li-ion battery throughout the charging process was estimated by multiplying the applied charging current by the voltage profile of the battery. Fig. 6 illustrates the estimated charging power profile for 3.7 V, 0.5C Li-ion battery cells of various capacities concerning the SOC, and the detailed specifications are listed in Table 1.

A central energy-management system (CEMS) is integrated into the recommended charging strategy to oversee the overall charging system and ensure efficient energy management. The CEMS first receives the five-minute resolution forecasted PV-generated power. The CEMS is provided with the capacity and initial SOC of each battery at the start of the charging process. The system then determines the power requirements for each battery for the upcoming five-minute intervals based on its capacity and initial SOC. Finally, the CEMS controls the batteries in the charging process every five minutes according to the forecasted PV power and proposed algorithm.

In this study, a novel algorithm is proposed for the CEMS to execute the desired operations effectively. A conceptual diagram of the designed algorithm for the CEMS is shown in Fig. 7. After determining the necessary charging power for each cell for the upcoming five-minute intervals, the system maintains a table of all possible battery combinations. The mathematical formula for calculating the number of possible battery combinations is given in Eq. (12).

$$\text{Number of possible combinations} = \sum_{r=1}^m n_{C_r} \quad (12)$$

where n is the number of batteries considered in the charging system and $m = 1, 2, 3, \dots, n$; the CEMS calculates the

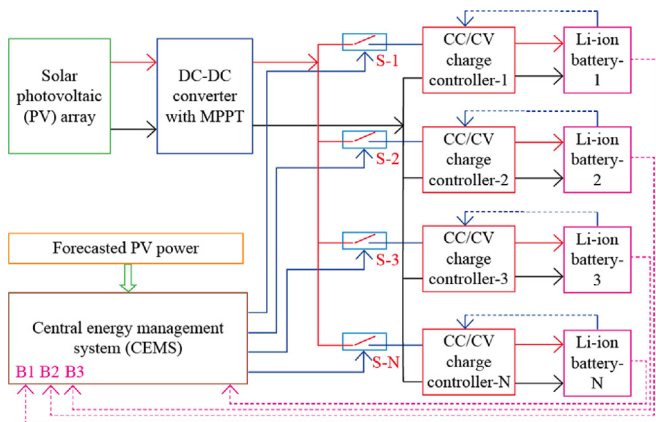


Fig. 5. Block diagram of BCM system.

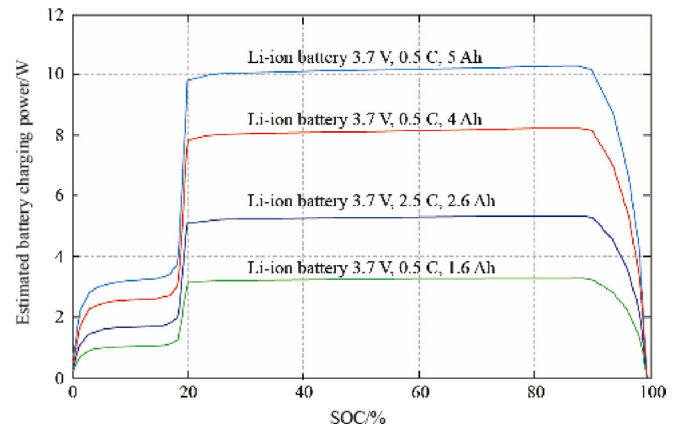


Fig. 6. Estimated power needed for Li-ion battery cells.

Table 1
Energy storage parameters.

Parameter	Specification
Type	Li-ion
Nominal voltage	3.7 V
Fully charged voltage	4.2 V
Cutoff voltage	2.5 V–3.0 V
Capacity	500 mAh to 5000 mAh
Charge current	Standard: 0.5C; Fast: Up to 1C
Max discharge current	Continuous: 1C–3C; Peak: Up to 10C
Energy density	200–265 Wh/kg; 500–700 Wh/L
Cycle life	~300–1000 cycles
Operating temperature	Charge: 0 °C to 45 °C; Discharge: –20 °C to 60 °C

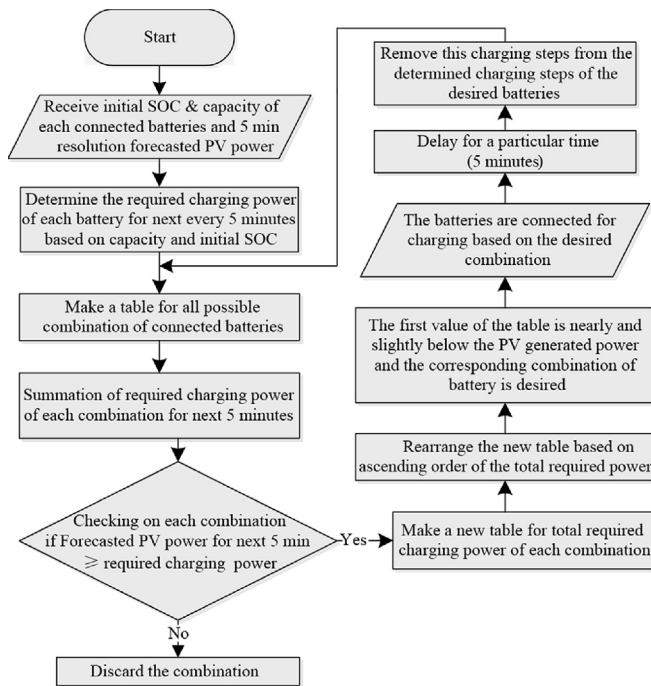


Fig. 7. Proposed flowchart for central energy-management system.

total required charging power for each combination of batteries during a five-minute interval. This total was then compared with the predicted PV-produced power for the same duration. The system identifies the optimal battery combination, where the sum of the essential charging powers is approximately but marginally below the forecasted PV power. The chosen batteries with the best combination were then connected to the power source (DC-DC converter) for that five-minute interval. This process was repeated at intervals throughout the daylight period.

2 Results and discussion

2.1 Forecasting of PV output power

This forecasting model uses a 20-W polycrystalline PV system. Because the sunrise and sunset times in the region

are approximately 7:00 and 19:00, respectively, the PV output power is only expected during these hours. Therefore, only daytime experimental historical data were utilized to reduce computational costs and enhance model training precision. To forecast the PV power generation, September 24 (a clear-sky day) and September 29 (a cloudy/rainy day) of 2017 were selected for this study.

Fig. 8 shows the determined and anticipated PV output power from the developed model on a clear-sky (sunny) day. This shows that the forecasted values closely match the actual measured output. Fig. 9 presents the same comparison for a rainy or cloudy day, where the forecasted PV-generated power aligns well with the actual measurements, except for a few early-day points. However, because the PV output power at these points is very low, the impact on the overall performance of the forecasting model is minimal.

Fig. 10 illustrates the point-wise deviation between the measured and forecasted PV output powers. The deviations were within an acceptable range, except at the start and end of the day, when the PV output was very low. The forecasting error of the developed model was evaluated using different metrics, and the results for clear skies and cloudy/rainy days are summarized in Table 2.

In Table 2, the model demonstrates a clear distinction in performance across different day types. On clear-sky days, MAPE was relatively low (12.48 %), indicating that the model performed well when the conditions were stable and predictable. The MAPE increased to 16.05 % on cloudy or rainy days, which was expected because of the rapid changes in solar power generation under such conditions. It is also evident that the model maintains nearly the same level of accuracy under different weather conditions. These forecast errors can disrupt battery-charging schedules and maximum power utilization, leading to potential battery degradation. Although an average MAPE of 14.265 % is generally considered acceptable in renewable energy systems, higher errors under cloudy conditions necessitate real-time monitoring, adaptive-charging algorithms, and safety margins in the charging strategy. A charging strategy is presented in the next section to adopt BCM to utilize maximum PV-generated power.

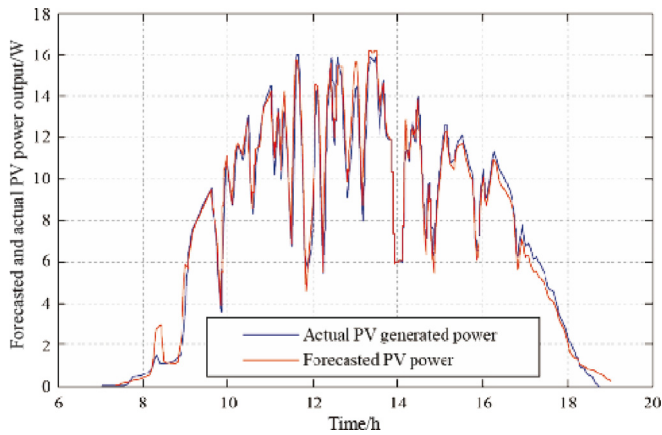


Fig. 8. Actual and forecasted PV output power on clear-sky day.

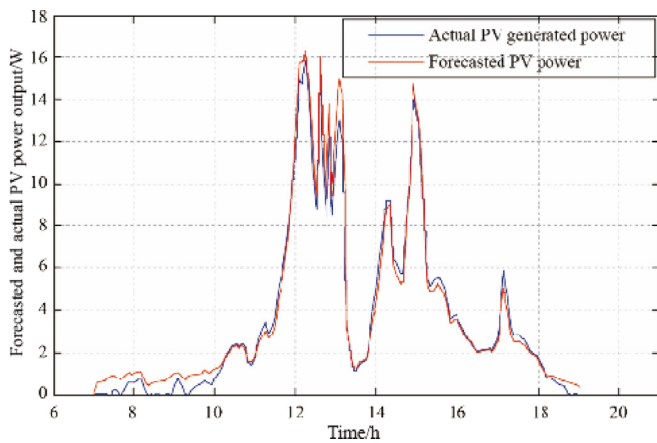


Fig. 9. Actual and forecasted PV power on rainy or cloudy day.

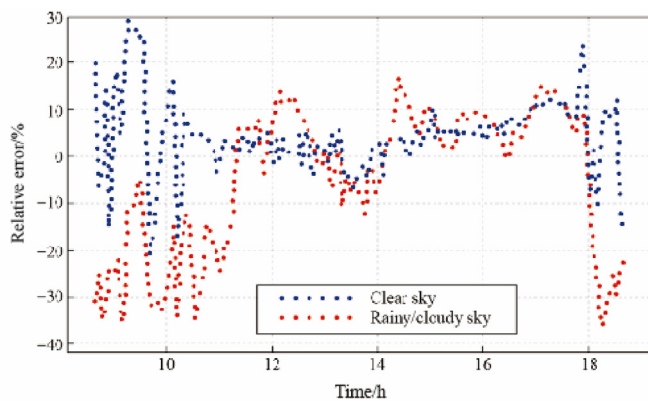


Fig. 10. Relative errors of actual and forecasted PV power on different days.

2.2 Three-stage CC/CV charge controller

Maintaining an appropriate charging rate for standalone PV-based battery charging is difficult because of

Table 2

Error in different metrics of developed PV power forecasting model.

Metric	Day type	Error	Average
nRMSE (%)	Clear sky	3.22	3.385
	Cloudy/rainy	3.55	
MAPE (%)	Clear sky	12.48	14.265
	Cloudy/rainy	16.05	

the intermittency of PV power generation. This paper presents a three-stage CC/CV charge controller for charging Li-ion battery cells. The specifications of the Li-ion battery are listed in Table 1. The design concept of this charge controller has been described previously. The proposed controller, which supplies a constant current or voltage to the battery cells as required, was implemented in MATLAB/Simulink. A control signal was generated based on the battery SOC, ensuring that CC/CV charging was appropriately applied. The charging profiles of the battery set with different SOC levels obtained using this controller are shown in Fig. 11. The simulation results indicate that the three-stage CC/CV charge controller effectively charges Li-ion battery cells. The voltage levels of the Li-ion battery cells at different SOC levels during the charging period are shown in Fig. 12. The initial SOC values range from 5 % to 60 % and are not intended to represent typical operating conditions but rather provide a broader impact on the performance of the model. By including extremely low values of 5 %, this study ensured that the model was thoroughly evaluated across a wide range of SOC levels.

2.3 Utilization of PV-generated power in battery charging

Ensuring the maximum utilization of PV-generated power is crucial in a standalone PV-based battery-charging system. Although the voltage supplied to the PV system remained nearly constant, the current varied with time and weather conditions. An unstructured PV system may impede the charging process because of insufficient power, or excess PV-generated power being wasted when it exceeds the battery-charging requirements. To address this issue, the battery-charging power must be balanced with the PV-produced power. This study proposes a novel BCM strategy to optimize PV-generated power while maintaining an appropriate charging rate.

The previous sections detailed the proposed CEMS algorithm and the system design. The developed charging strategy, including the CEMS, was implemented using MATLAB/Simulink. In this setup, eight Li-ion cells with varying capacities and SOC were connected to a charging system. These cells were selected based on the total required charging power of the eight cells and the forecasted PV-generated power for the day. For optimal performance, the required charging power should be slightly higher than the projected PV-generated power. Because

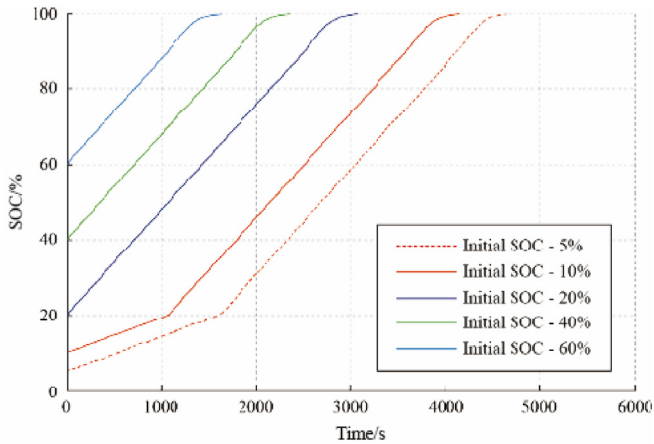


Fig. 11. Charging profiles of Li-ion set with different SOC.

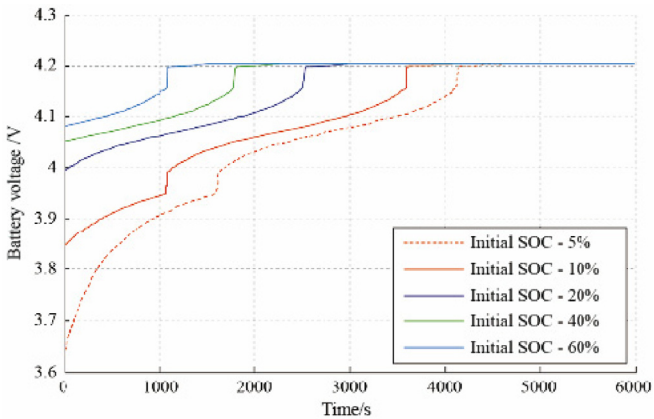


Fig. 12. Voltage profile of Li-ion battery set for various SOC.

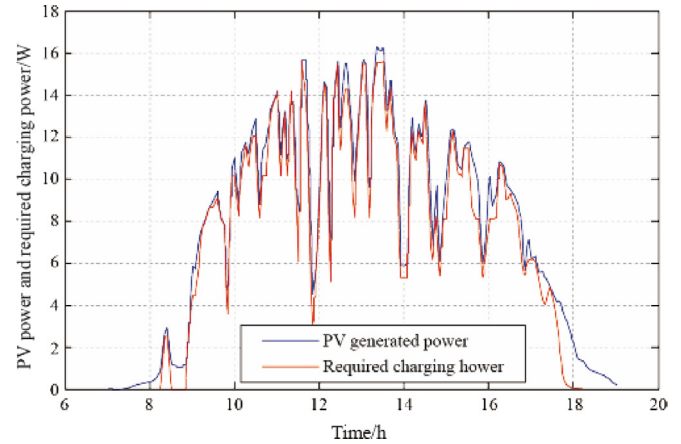


Fig. 13. PV power and battery power needed on clear-sky day.

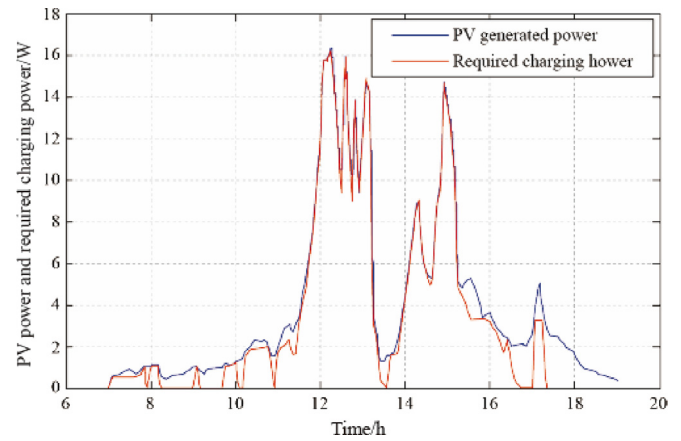


Fig. 14. PV power and battery power on cloudy/rainy days.

the PV-generated power is significantly lower on cloudy or rainy days than on clear-sky days, different cells may be connected to ensure that they are fully charged. The capacities and initial SOC of the connected cells on both clear-sky and cloudy/rainy days used to test the proposed system are listed in Table 3.

Table 3
Battery cells considered for charging on different weather days.

Day type Cell. no.	Clear-sky day		Cloudy or rainy day	
	Cell capacity (Ah)	Initial SOC	Cell capacity (Ah)	Initial SOC
1.	5	40 %	3	25 %
2.	4	60 %	3	5 %
3.	4	20 %	2	40 %
4.	4	5 %	2	20 %
5.	3	25 %	1.6	20 %
6.	3	20 %	1.6	5 %
7.	3	5 %	0.8	20 %
8.	2.6	5 %	0.8	5 %

Fig. 13 illustrates the PV-generated power and battery-charging power required on a clear-sky day. This shows that the expected battery-charging power closely matches the PV-produced power, with only a few discrepancies at the end of a typical day. Fig. 14 shows the PV and battery charging powers required on a cloudy or rainy day. The necessary charging power profile aligned well with the

Table 4
Percentage of utilized PV power in battery charging.

Parameter	Sunny day	Cloudy/rainy day	Average	Previous work
Percentage of utilization	91.39 %	83.55 %	87.47 %	82.41 % [46], 84.1 % [47]

PV-generated power, except for a few points at the beginning and end of the day. During these periods, the PV-generated power was very low, making it insufficient to charge the batteries while maintaining a suitable charging rate. The percentages of PV power utilized for battery charging under different weather conditions are summarized in Table 4.

In this study, PV utilization is calculated as the proportion of solar energy generated by the PV system used to charge the battery compared to the total available PV energy during a given period using Eq. (13).

$$U_R = \frac{\text{Energy used} * 100}{\text{Total PV energy available}} \quad (13)$$

The study showed an average forecasting error of 3.385 % for nRMSE and 14.265 % for MAPE, implying a high level of forecasting accuracy. However, the impact of forecast error on the proposed BCM system and its overall performance can be considered in a few key areas, such as battery-charging rates, lifespan, and utilization rates. An adaptive-charging strategy is proposed in this study to address these forecasting errors. The proposed charging management strategy is sufficiently robust to handle forecast errors and still achieve high utilization. The system achieved an average utilization rate of 87.47 %, with 91.39 % utilization on sunny days and 83.55 % on cloudy and rainy days, denoting its flexibility to fluctuating solar irradiance. Also, the BCM scheme shows an improved utilization rate for standalone PV-based battery systems [46,47].

3 Conclusion

This study proposes a novel battery-charging strategy to maximize PV-generated power usage while delivering optimal charging rates. The developed standalone PV-based battery-charging system incorporates a three-stage CC/CV controller for Li-ion batteries and a CEMS. The results indicated that the charge controller effectively managed the Li-ion battery cells, maintaining a proper charging rate. The algorithm designed for the CEMS, based on the predicted PV output, ensures the maximum utilization of PV power in battery charging. The SVR-based day-ahead forecasting model accurately predicted the PV power generation under various weather conditions, with an average forecast error of 3.385 % in the nRMSE and 14.265 % in the MAPE.

The proposed battery-charging system achieved an overall utilization of 87.47 % of the PV-generated power, significantly reducing the power loss and charging costs

in standalone PV systems. This system is expected to promote the use of standalone PV-based charging systems and support the increased deployment of PV power.

Future research directions include integrating the proposed BCM system with smart grid technologies to enhance real-time adaptability and efficiency. The development of advanced PV power forecasting algorithms, such as hybrid machine learning approaches, can improve the accuracy of PV power generation predictions across diverse weather conditions. Additional energy storage solutions, such as supercapacitors or alternative battery chemistries, may optimize energy utilization and system performance. Finally, a comprehensive analysis of the economic and environmental benefits of the BCM system can support policymaking and foster PV adoption.

CRedit authorship contribution statement

Utpal Kumar Das: Writing – original draft, Validation, Software, Methodology, Conceptualization. **Ashish Kumar Karmaker:** Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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