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A review on capacity sizing and operation strategy of grid-connected photovoltaic battery systems

Yijie Zhang [a], Tao Ma [b,*], Hongxing Yang [a,*]

[a] Renewable Energy Research Group (RERG), Department of Building Environment and Energy Engineering, The Hong Kong Polytechnic University, Hong Kong, China
[b] School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, China

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ABSTRACT

Due to the fluctuation and intermittency of distributed PV generation, battery energy storage is required with higher renewable installation towards carbon neutrality. Thus, the photovoltaic battery (PVB) system receives increasing attention. This study provides a critical review on PVB system design optimization, including system component sizing and strategy improvement studies, from mathematical modeling, evaluation system establishment to feasibility and optimization studies. Several PVB simulation software packages are compared and evaluated, and acknowledged system models are presented. The evaluation indicators are summarized from various aspects with cases of various evaluation systems combining different indicators or using the Pareto front for multi-criteria system designing. The PVB system feasibility study is analyzed from system configuration variation, critical technical and economic parameter analyses, rule-based operation strategies to future expectations like large-scale energy storage profitability, grid parity, and energy community trading platform. The targets, methods, tariff and time resolution influences, and PVB system capacity optimization design recommendations are critically discussed. The research directions for system operation development and future expectations are analyzed from system feasibility, flexibility to resilience. The co-planning of PVB system capacity and operation design optimization makes the problem complicated, leading to relatively short time resolution but more flexibility to system operation strategy. This study could provide guidance and references to distributed PVB system future design and optimization studies.

1. Introduction

To deal with the energy crisis and environmental problems related to fossil fuel usage, renewable energy resources are increasingly used worldwide and set to remarkably lead the global electricity sector with the recent policy momentum [1]. Photovoltaic (PV) technology is one of the acknowledged driving renewable currently under the carbon neutrality target, especially in China which experienced a sharp increase from 3,108 MW in 2011 to 306,403 MW in 2021, as shown in Fig. 1(a) [2]. The congestion problem in grid transmission and curtailment of renewable power production are emphasized in the utility grid with high renewable penetration [3], thus the trend of transferring the centralized electricity system into decentralized ones with higher grid reliability and resilience [4,5] and larger environmental potential [6]. The study conducted by Yang et al. [7] provides a comprehensive research on household solar PV (HSPV) in China, showing that HSPV is economically feasible without subsidy for 86% of the cities and estimated to have a large increase potential from 2 to 31.8% by 2035. Also, the grid parity of distributed PV systems, which is gradually achieved in over 60% of the Chinese cities with a moderate or higher financial return, accelerates the PV deployment in China [8].

To further improve the distributed system energy flow control to cope with the intermittent and fluctuating nature of PV production and meet the grid requirement, the addition of an electricity storage system, especially battery, is a common solution [3,9,10]. Lithium-ion battery with high energy density and long cycle lifetime is the preferred choice for most flexible photovoltaic battery (PVB) systems that respond quickly to load demand and grid limits [11]. Moreover, the large-scale renewable source with electricity storage systems has considerable potential for grid load leveling, with demand side management (DSM) emphasizing energy efficiency and demand flexibility [12,13]. The PVB system has recently been a hot topic that turns electricity consumers into electricity prosumers [14]. The apparent reduction of battery cost, which decreased from 1000 $/kWh in 2010 to 132 $/kWh in 2021, as presented in Fig. 1(b) [15,16], especially the Li-ion battery with high energy density and fast energy response, accelerates the PVB system study and practical use to a large extent.

* Corresponding authors.
E-mail addresses: tao.ma@sjtu.edu.cn (T. Ma), hong-xing.yang@polyu.edu.hk (H. Yang).

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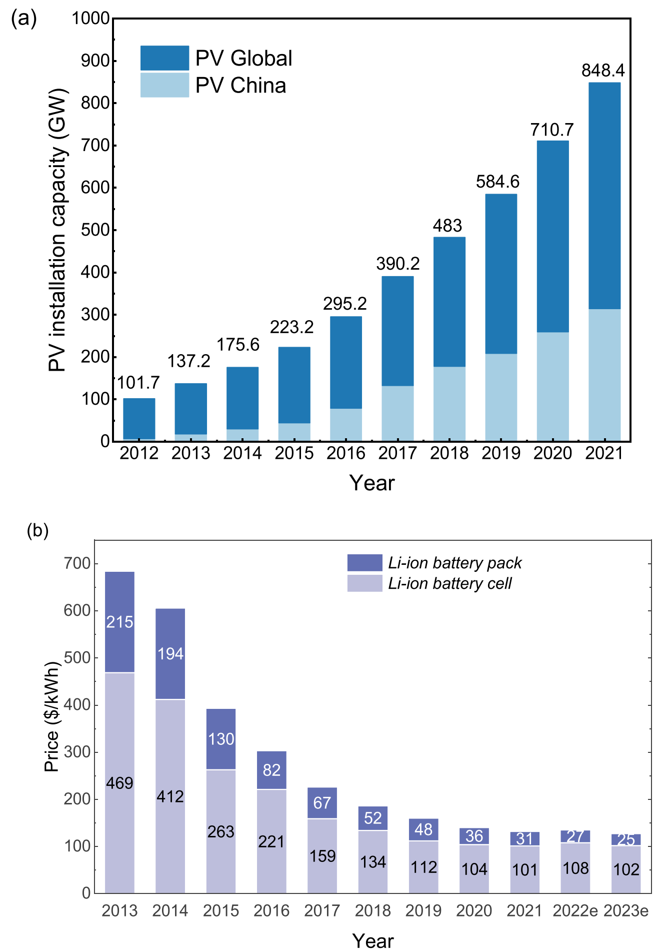

Fig. 1. Recent background: (a) PV installation increase; (b) Li-ion battery cost decrease.

To better deal with the onsite consumption of renewable resources and relieve grid burden, the design of the distributed PVB system has become a recent focus, from system configuration, component capacity to operation strategy separately or combined studies. The study conducted by Dong et al. [17] discusses the technical (consumer self-consumption/self-sufficiency rate, network operator peak demand) and economic (profitability, levelized cost of storage) feasibility for household and community energy storage systems with PV under time-of-use (TOU) tariff with DSM. Besides, the work from Koskela and his colleagues [18] optimally sizes the PV panel with a storage system to achieve the highest profitability. The joint optimization of PV and battery sizes is presented by Li et al. [19] under TOU for minimizing total annual system electricity cost. Moreover, the optimal PVB system operation is scheduled by Alramlawi et al. [20] to address the grid blackouts with longer battery lifetimes via model predictive control (MPC). Both PVB system optimal sizing and energy dispatch are scheduled together in the study completed by Talent et al. [10] for the highest system net present value (NPV). The work by Sardi et al. [21,22] conducted separate optimizations for the site, size, and battery operation in the PVB system to satisfy the requirements of the highest NPV within grid voltage and load factor limits. Under the improvement of system variation and introduction of heuristic algorithms, the optimization problem tends to have higher complexity from large system scale, multi-aspect objectives, dynamic tariff influence, and system size and operation co-planning.

The previous review studies on PVB systems or distributed renewable energy systems have not provided the researchers with a specific vision of PVB system optimal scheduling. At the very beginning, the study focuses on the system components. For example, the three-port DC-DC converter topologies are summarized to combine renewable energy and energy storage systems in the field of power electronics [23]. In the research field of system development and study, the research focus first lies on an energy storage component, such as techno-economic feasibility [11], environmental issues [24], grid favors and market-oriented preferences [25], and community energy storage (CES) challenges [26]. Then the system optimal sizing methods are concluded, including the study for an off-grid PVB system [27], PV sizing models and software [28], battery impact on PV sizing [29], and temporal resolution influence on renewable resource scheduling with energy storage system [30]. In addition, the influence of outside factors such as feed-in tariff (FIT) [31] and human health-related impacts [32] could also be found in the previous review studies. Furthermore, the PVB system operation review is also focused on conducting DSM [33] and MPC [29] for higher energy flexibility and system resilience. However, the PVB system feasibility and optimization study review are not discussed clearly. Also, there is a limited review study about system size and operation co-planning. The current status and future suggestion of PVB system study with a focus on electricity tariffs is still valuable to discuss.

This study critically reviews the PVB system study and summarizes a clear comprehensive clue for grid-connected PVB system methodology, evaluation system, basic feasibility study, size, operation and combined optimization studies. The following sections discuss the system variation and the PVB system study overview. Then the system numerical simulation methodology, with mostly used PV system, battery degradation model summarization, necessary constraints, software recommendation and evaluation and model-free simulation method, are displayed. Besides, the system performance evaluation indicators are categorized in different aspects and three evaluation system prototypes are summarized. Moreover, the PVB feasibility study is reviewed with three basic elements and the future directions like large-scale planning are proposed. Furthermore, the capacity and strategy optimization studies are discussed in detail, especially on tariff and time resolution influence. The basic operation strategies are displayed and the development for different sides in the PVB system with future directions for system flexibility and resilience are summarized. Also, the novel system size and operation co-planning research is discussed.

2. System description

The components of a distributed PVB system include the PV array, PV inverter, alternating current (AC) or direct current (DC) load demand, grid connection, electricity energy storage system, battery converter, system controller, and other auxiliary systems. The system configuration diagram with basic variations of the distributed grid-connected PVB system is depicted in Fig. 2, with DC load and AC-connected battery system.

The system configuration could vary according to the specific circumstances. For example, the load distribution system could be converted into a DC system for higher energy efficiency [35–37], and the part of the flexible load could be controlled based on DSM and MPC for better system performance [38]. The variation could also come to the battery system, which is connected to the DC busbar for lower energy transformation loss [39], or the addition of bi-directional charging/discharging electric vehicle (EV) [40,41] and pump hydro storage (PHS) system [42] in the near future. The PVB system is a basic distributed renewable energy system with a storage system and could be extended to larger scale, more complex ones with various novelties in system design.

3. Research on PVB system

3.1. Overview of the research and development of PVB

The distributed grid-connected PVB system research stems from the off-grid renewable energy system study. The addition of grid connection

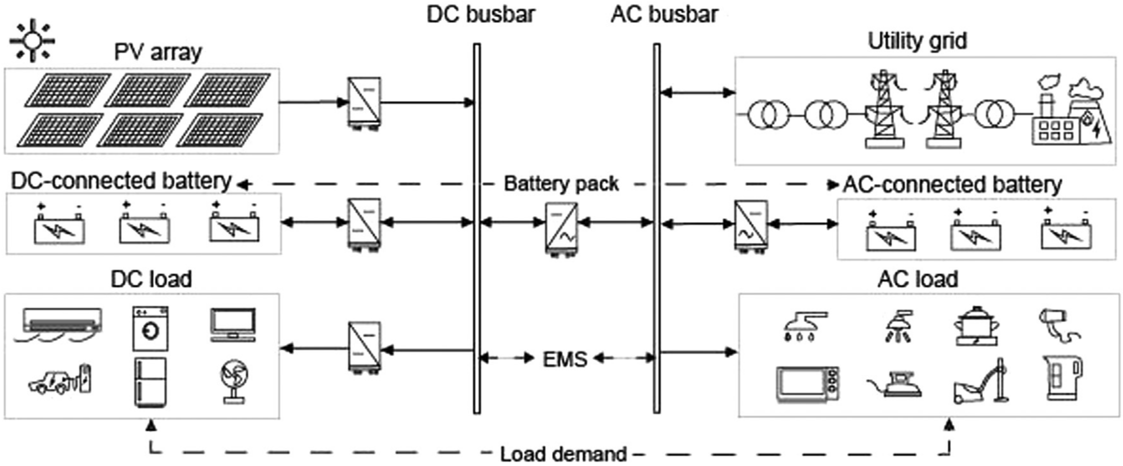

Fig. 2. System configuration of a grid-connected PVB system (adapted from [34]).

and consideration adds to the complexity and emphasis on energy flexibility from energy storage systems, DSM, and forecast-based control. This study comprehensively discusses the target, methods, current vital findings, and future expectations of PVB system feasibility study and system size and operation optimization studies. The PVB system study development in recent years is shown in Fig. 3. Among the selected studies, the feasibility study for parametric analyses and system configuration variation appears at the early stage. In contrast, the system strategy optimization study is the mainstream focus. The recent feasibility studies mainly focus on novel system configurations, large-scale system operation, and complex nano-grid design, which are the primary stages for future energy community studies. The joint optimization of system capacity and operation optimization is gradually paid more attention to for higher complexity and more comprehensive analysis. Based on the global map, the studies in China and US are two significant places in recent years. The studies in Germany, the UK, Australia, and Switzerland are novel, with focus on renewable energy development.

The system contains a PV system, battery system (mainly on the AC side), load demand, grid connection and constraints from the utility grid, and physical components like the battery. The mathematical model of the whole system is physically established in most cases without a smart algorithm to make the study model-free. The energy balance equation is the core of the system simulation model. The 5-parameter model of the PV system provides relatively high accuracy for long-term simulation, while the battery model is gradually improved to better determine the battery degradation state. Furthermore, the evaluation system could be constructed via the preferences of different participants, including end-users, the utility grid, aggregators, etc. The self-consumption rate (SCR) and self-sufficiency rate (SSR) are two wide-used indicators to assess the renewable usage technically, and NPV, as well as levelized cost of energy (LCOE) for user, generation, battery sides, are commonly used for economic evaluation. Also, indicators from other aspects, like carbon emission reduction, could be considered in the multi-criteria optimization study. However, the targets in this stage lie mainly in a single aspect due to the system complexity.

In this early stage, the simulation is the foremost tool that promotes the PVB system study from feasibility study to optimization study on system size and operation strategy design. The technical parametric analyses emphasize the renewable system usage and grid transmission performance improvements carried out by the effective system components. The economic feasibility study, especially sensitivity analyses on battery profitability, shows significant concern about Lithium-ion batteries under the basic maximum self-consumption (MSC) strategy. The system capacity optimization starts with the battery size sensitivity analysis. Then it turns to solve the optimization problem from linear to nonlinear programming, introducing intelligent algorithms, community-level simulation with group battery, multi-objective targets, and PV and battery size joint design under the time-varying tariffs. The system operation strategy stems from the rule-based strategies, MSC, and TOU strategies to algorithm-based strategies controlling battery action, flexible load use, and energy priority management considering present and future market electricity prices for various participant preferences.

3.2. Simulation and mathematical modeling

The numerical simulation of the PVB system is mainly based on specific mathematical modeling, and the energy balance is the core to the system energy flow simulation, as shown below:

$$E_{pv} + E_{bd} + E_{so} = E_{lo} + E_{bc} + E_{bo} + E_{el} \tag{1}$$

Where E_{pv} is the photovoltaic power generation (kWh), E_{bd} and E_{bc} are battery discharge and charge energy (kWh), E_{so} and E_{bo} are sold electricity to the grid of the PVB system and bought energy from the grid (kWh), E_{lo} is the load demand energy (kWh), and E_{el} is the energy loss (kWh).

3.2.1. Component modeling

(1) Solar PV

The model of a PV system includes a simple model which only considers PV electricity generation efficiency with relative temperature coefficient or a complex model based on single and double-diode modeling with five or seven parameters. The component modeling part only addresses several commonly used ones.

The simple PV model could be generated based on the STC parameters of the solar panel, and the maximum power point algorithm is often considered to reach the highest PV power output [43]. The model utilized by Alramlawi et al. [20] is based on a single diode PV-cell with a series resistance could be expressed as at time step t:

$$P_{pvcell,m}(t) = V_{occell,m}(t) I_{sccell,m}(t) FF_{cell,0}(t)\left[1 - r_{cell,s}(t)\right] \tag{2}$$

where the standard filling factor $FF_{cell,0}$(t) could be determined by the maximum power output, open-circuit voltage and short-circuit current under STC condition and the normalized series resistance $r_s(t)$ could be determined by the open-circuit voltage and short-circuit current at time step t and the series resistance of the solar cell.

The maximum open-circuit voltage $V_{occell,m}(t)$ and short-circuit current $I_{sccell,m}(t)$ could be calculated based on the NOCT model are shown below:

$$V_{occell,m}(t) = V_{occell,stc} + K_v\left[T_{cell}(t) - 25\right] \tag{3}$$

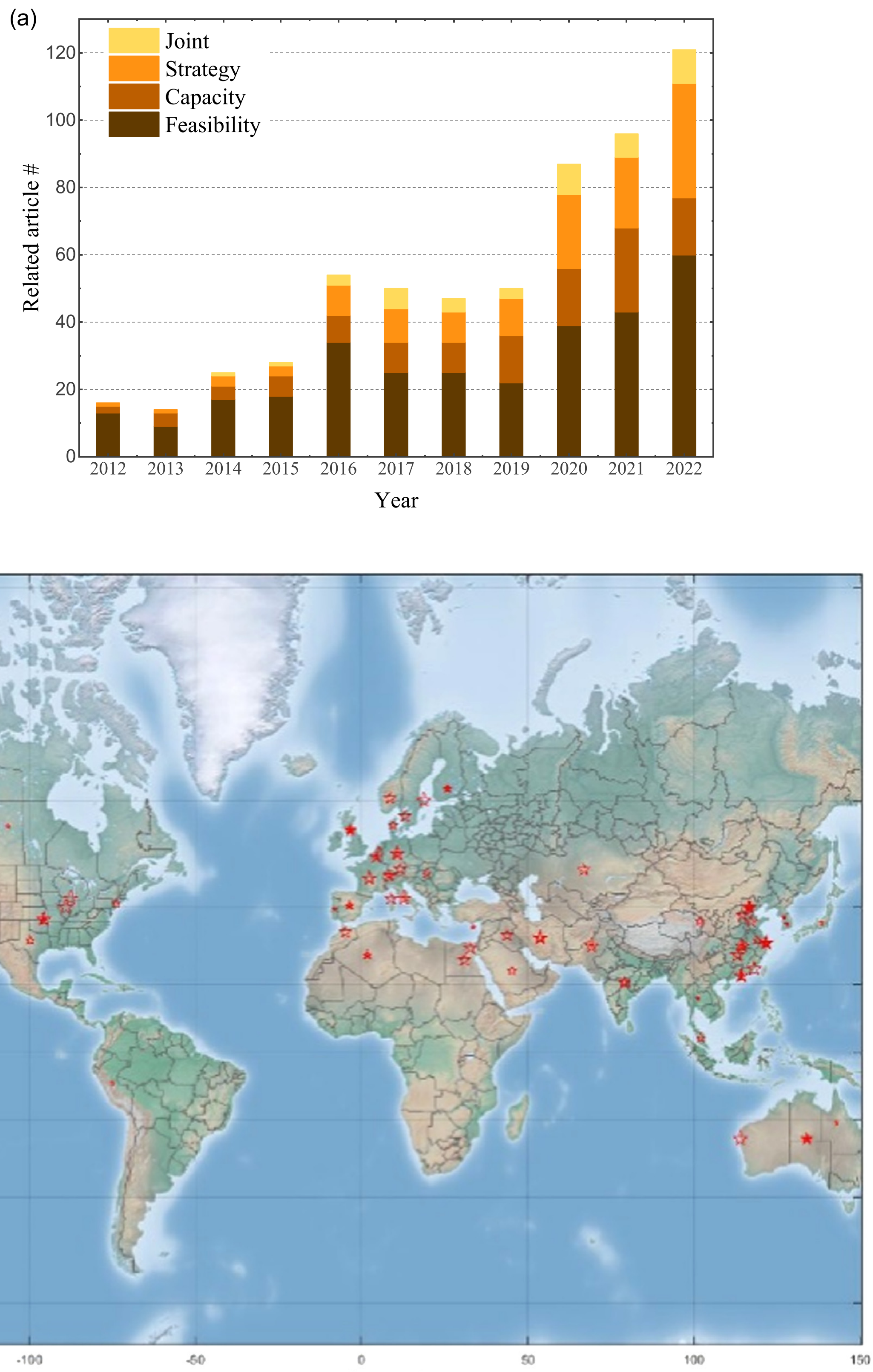

Fig. 3. PVB research development in recent years: (a) Related article number (till 2022 Nov.); (b) Global map of several selected studies (size of hollow stars increases for different studies: feasibility, capacity optimization, strategy optimization and co-planning of size and strategy).

$$I_{sccell,m}(t) = \frac{G_{glo}(t)}{1000}\left\{I_{sccell,stc}(t) + K_i\left[T_{cell}(t) - 25\right]\right\} \tag{4}$$

where $V_{occell,stc}(t)$ and $I_{sccell,stc}(t)$ are the open-circuit voltage (V) and short-circuit current (A) at STC condition, K_v and K_i are the temperature coefficient of voltage (V/°C) and current (A/°C) of the PV cell, T_{cell} is the cell temperature (°C) and G_{glo} is the global solar radiation on the PV panel (W/m^2).

Also, the five-parameter photovoltaic model could be utilized for higher accuracy. The model of the PV panel calculated by Ma et al. [44] could be expressed as follows:

$$I_{panel} = I_{ph} - I_0\left(e^{V_{panel} + I \cdot R_{sc} \cdot N_s / N_s \cdot V_t} - 1\right) - \frac{V_{panel} + R_{sc} \cdot N_s \cdot I_{panel}}{R_{pc} \cdot N_s} \tag{5}$$

where I_{panel} and V_{panel} are the output PV panel current (A) and voltage (V), I_{ph} is the light-generated current (A), I_0 is the diode reserve saturation current (A), V_t is the diode thermal voltage (V), N_s is the cell number in the PV panel, and R_{sc} and R_{pc} are the PV cell series and parallel resistances (Ω).

To estimate the PV output, several weather parameters, including global horizontal irradiance, diffuse horizontal irradiance, air temperature, wind velocity, rainfall, and soiling losses, are considered by Pillot et al. [45]. The uncertainty of PV generation could also be estimated based on the Beta probabilistic density function of historical solar radiation data [22].

The PV panel efficiency and inverter efficiency could be assumed fixed for simplicity [10]. The PV module degradation could be calculated by the derating factors considering soiling, aging, and other influences for simplicity [46].

(2) Battery

In some early studies considering both home and community energy storage systems, the battery for the community could be divided virtually into different shares for various households [38]. However, the results showing in the share factors are not clear.

The simple battery energy storage variation is featured by the SOC change, as shown below:

$$SOC(i+1) = SOC(i) + \frac{\eta_{bat,ch} P_{bat,ch}(i) - P_{bat,dis}(i) / \eta_{bat,dis}}{C_{bat,usa} \cdot SOH(i)}, \forall i \tag{6}$$

where SOC is the state of charge of the battery bank, i is the time step of the simulation iteration (h), $\eta_{bat,ch}$ and $\eta_{bat,dis}$ are the battery charging/discharging efficiency, $P_{bat,ch}$ and $P_{bat,dis}$ are the battery charging/discharging power (W), SOH is the battery state of health and $C_{bat,usa}$ is the usable capacity of the battery bank (Wh).

The SOC upper and lower limitations and battery charging/discharging power limitations should also be set to prevent overcharging, deep discharging, and overheating [20,38]. Moreover, the performance and benefits of lead-acid (PbA) and lithium-ion (Li-ion) batteries are compared, showing that Li-ion batteries are more cost-efficient and require less energy capacity [47].

The improved Shepherd battery model could describe the relationship of battery voltage and current considering SOC, with a controlled voltage source, an internal resistance, an integrator, and a current filter [9]. Also, the rain-flow counting method is a common method to calculate the battery equivalent cycle number from different practical depths of charge (DODs), which origins from the fatigue data analysis.

Furthermore, the degradation of the battery capacity, which is the combination of battery cycle and calendar life aging mechanisms, is also emphasized in the battery modeling. The major factors include the battery cycle number, operation temperature, and DOD. Several studies on Li-ion battery degradation, which is more commonly used and complicated than that of PbA battery, are presented in Table 1. In the studies conducted in the early stage, the calendar life is the only aging factor for the battery model, however, it is of low accuracy and not useful in the studies considering more system flexibility. The equivalent battery lifetime based on the rain-flow counting method is the basic method, with considerations on both calendar life loss and cycle loss. The DOD and charge/discharge period are mainly concerned. The more complicated and accurate battery aging model could be determined by the experiment data or specific from the manufacturer, with temperature influence analysis and SOC sub-models, while it is time-consuming and needs experiments. According to the previous studies [48,49], it could be seen that the dominant factor for calendar life loss is battery temperature history, and the following ones are discharge/charge rate, SOC variation and swing, and cell temperature, with low SOC and small SOC swinging cycle both disadvantageous.

The calendar aging is calculated by Zou et al. [54] according to the empirical equation. However, the study determined battery aging by adding the battery calendar aging and cycle aging together. Also, the factor, state of health, is considered to present the battery's total aging as shown below:

$$SOH(i) = 1 - 0.2 \times \beta_{total}(i) \tag{7}$$

A study indicates that cycle life is no longer a major factor for Li-ion battery revenue as PbA, concerning the tradeoff relationship between battery cycle and calendar lives in practical usage [63].

(3) Common simulation software

In the cases of commercial use or system design without or with simple optimization requirements, the simulation software or open-source models are suitable. The basic introduction of the PV system simulation software could be found in the previous study [64]. However, some widely-used software with mature basic system numerical modeling, especially PVsyst [44], SAM, PVsol, Transient Energy System Simulation Program (TRNSYS), and PVLIB software/ programs, are still up-to-date useful PV(B) system simulation tools during recent decades, as presented in Table 2. In practical PV system cases, the PVsyst software is the most acknowledged for off-grid and grid-connected PVB systems, with updating functions like shading analysis and integration of global maps. With the financial consideration and HVAC load estimation as the useful auxiliary functions, TRNSYS [65] is also frequently found in the current studies. Other building load simulation software are also recommended to synthesize the load demand curve as the data input for the PVB system study, including Energy Plus [66] and Modelica [37]. Although several other software are also utilized in the existing studies, such as integration of BEopt (building simulation) and REopt (optimization) [67], GridLAB-D simulation tool [52] and PVLIB model [68,69] for PV generation, APROS [70], Grasshopper [71], ReEDS capacity expansion model [72] and RODeO price-taker model [73], the study via simulation-based mature software is limited. The limitations include the conventional optimization method, rule-based strategies, and simple evaluation system with only fundamental economic and technical indicators. The mainstream novelties in the PVB system study are mostly conducted by the coding software like Matlab (Simulink [74–78]), and pay more attention to the novel topics, i.e., battery aging model, smart algorithm for multi-objective optimization, and environmental considerations.

(4) Model-free simulation

With the introduction of smart algorithms, especially data-driven reinforcement learning methods, the specific mathematical model may be neglected in some novel studies with complex configurations or various participants on a large scale. The probability distribution function with Weibull/Gaussian, Beta, and normal density functions for PV, wind, and load generation forecast are utilized with the help of Monte-Carlo simulation and Latin hyperbolic sampling generating scenarios based on uncertainties in the recent study [95]. The agent-based modeling (ABM) is also a novel method to deal with the demand side uncertainties for

Table 1
Battery model comparison in the studies on PVB system.

Degradation model	Consideration factors	Calendar loss	Cycle loss	Specific description	Ref.
SOC model with aging sub-model(s)	Cell temperature, load, discharge period (DOD)	Arrhenius formula for battery temperature	Linear round-trip capacity loss by DOD	Separate the degradation SOC into different sub-models (mostly linear) but requires battery capacity loss experiment	[47,48,50-52]
Equivalent circuit model	Charge/discharge power	Calendar lifetime	Linear decrease by DOD	Use Rain-flow counting method for equivalent model and linear decrease of cycle loss with SOH	[53–57]
SOC with battery lifetime loss model	DOD, discharge amp-hour (Ah) capacity, discharge Ah	Calendar lifetime	Effective discharge Ah based on DOD and actual discharge Ah capacity	Use Rain-flow counting method and (improved) Ah throughput model based on the given discharge curves.	[9,20,58-60]
SOC model only consider calendar life	Calendar lifetime	Calendar lifetime		Replacement only when the calendar lifetime ends	[61,62]

load forecast [96]. Due to the complexity of the energy internet with various components, the asynchronous advantage actor-critic reinforcement learning (RL) algorithm helps optimally schedule the energy dispatch to minimize system cost without specific mathematical models. In an intra-day market of a hybrid microgrid, a reinforcement learning method is utilized for the multi-objective optimization, which outperforms the linear MPC method [97].

The model-free feature appears to be a novelty in a complex system. However, the training cost is consuming with the pre-study offline information crucial to RL training, and the stability, feasibility, and robustness of RL remain challenges. Thus, the specific mathematical model is still recommended for PVB system studies with simple configurations.

3.2.2. Constraints and outside factors

(1) Utility grid

The grid electricity tariff is a basic but crucial outside condition to the PVB system study, especially for peak shaving and energy arbitrage profitability. The various usage electricity tariff may include the flat electricity tariff [50,98,99] with fixed electricity price, TOU tariff [10,50,56,98,100] with several fixed electricity prices for different predefined periods, step tariff [56] with different electricity prices for different ranges of cumulative load demand and RTP tariff [10,50,98,100] with fluctuating electricity prices depending on specific conditions like system demand, system peak demand, grid network service, community service, tax, and incentives. Other common electricity tariffs also include FIT [56,101] for the surplus renewable generation sold to the grid and subsidies [56] for total renewable generation. The different tariff conditions are compared in the PVB system in countries with relatively high renewable proportions like the UK [98,100], Belgian [99], China [56], Switzerland, Germany [50], and Italy [101].

Thus, the peak load demand and grid importation in different time periods are the focus of the electricity transaction between the utility grid with high penetration of renewable energy and the PVB system [10,54,65,102]. Other key points in the PVB system study may also include ramp rate limitation [102], grid voltage security [103], and economic earnings under different tariffs considering relatively high battery prices [10,101].

Besides the impact of the grid on the PVB system, the even larger and prevail distributed renewable energy system also influences the utility grid [99]. The feed-in-limit (FIL) on the grid is a common method for dealing the excessive PV generation with less burden on the utility grid, namely flattened peak grid transmission via feed-in power to relieve stress from the PVB system to the grid [99,104]. The PV curtailment is then caused and regarded as a crucial parameter for system control [104].

Also, the other limitations of the utility grid contain the grid maximum absorption and injection [38], scheduled grid blackout, which is the designed electricity power cut down [20], and the emergent operation under extreme weather events [105].

(2) Auxiliary factors

The other limitations of the system device, socioeconomic conditions, and climate influence should also be concerned. The commonly used system limitation lies in the system power balance, battery charging/discharging rate limits, battery SOC upper and lower limits, and equipment lifetime especially considering the battery aging in Section 3.2.1. The social and economic situation usually includes the equipment device cost, operation and maintenance cost, replacement cost, labor cost, discount rate, electricity tariffs, and government subsidies as mentioned in the first part, utility gird, in this Section. Also, social concerns focus on the government regulations like electricity selling licenses, electrical measurement systems, and consumer lifestyle. The climate condition should be paid attention to if the energy system plan is for practical use [106].

(3) Load demand

Although the load profile may include curves from the residential, commercial, and public buildings, the residential load with household device management is the most focused in the distributed rooftop photovoltaic system with battery storage. Among the optimization studies considered in Fig. 3(b), the residential load from houses or communities takes up more than 70%, and the rest is suitable for the application on residential, commercial (mainly lie in the office building), and industrial loads.

The duck curve proposed by the California Independent System Operator [107] is a typical example for residential load with PV generation. The load curve remains low during the night without the user's action; however, the daytime curve is lowered obviously by the self-consumption of onsite PV, and the difference between the peak and valley of the load curve is enlarged due to the disappearance of PV generation at night. Several solutions to the grid transmission fluctuation, such as using flexible loads, reducing load peak at night, and adding a battery system, are proposed [108]. The match of the load curve with time-varying tariff with the duck curve brings more economic potential for the addition of battery and DSM method, as depicted in Fig. 4.

The forecast of the load focusing on the equipment use time and rate variation could also be emphasized as the basis of the DSM part, and the user action influence in the ABM model could also be considered [96] for better MPC control results.

3.3. System performance evaluation

To assess the system performance, the evaluation system with indicators from various aspects is necessary. The traditional evaluation system concerns fundamental technical and economic indicators, and the recent improvements add other concerns like environmental and social

Table 2
Numerical simulation for PVB system based on software or model.

Software/Model	Developer	Technical	Financial	Environmental	Advantages	Disadvantages	PVB system case study
HOMER software	National Renewable Energy laboratory (NREL)	Electrical and thermal energy flows	Net present cost (NPC), cost of energy (COE)	None	Size optimization; consider thermal energy flow; dispatch strategy variation; with sensitivity analysis	Only cost optimization (min NPC); Low accuracy component models; without user-defined functions	Residential system with agricultural and deferrable loads [79]
RETscreen software [80]	United Nations Environment Program and the National Aeronautics & Space Administration	Electrical and thermal energy flows	Financial cost, benefits	Greenhouse gas emission	Feasibility study with user defined coding; consider thermal energy flow.	Without optimization	Preliminary optimal size determination [81]
Solar advisor model (SAM) [82,83]	NREL	Electrical energy flow	Cash flows and financial metrics	None	With size optimization and sensitivity analysis	Without thermal energy flow consideration	Battery size and policy change for residential system [84]; Evaluation model [84,85]
TRNSYS software [86]	Solar Energy Laboratory, University of Wisconsin-Madison	Electrical and thermal energy flow	Could add user-defined functions	Could add user-defined functions	Building load estimation; linked to other coding software; modular approach; with thermal energy systems.	Need extra software for optimization study, like jEPlus+EA	Residential [87,88] and office [89] building capacity optimization; Techno-economic sizing [90]
PVsol software [91]	Valentin software	Electrical energy flow	Financial tariffs, cashflow	CO2 emission saving	Different tracking systems and location climate data	Without thermal energy flow consideration	Feasibility study on system with EV [92]
PVsyst software [83,93]	University of Geneva to a standalone company, André Mermoud and Bruno Wittmer	Electrical energy flow and power loss	Feed-in tariff, installation, operating, (customized) costs	None	3D near shading construction and climate data management; Bifacial calculation included.	Without thermal energy flow consideration	Feasibility study on battery addition [94]

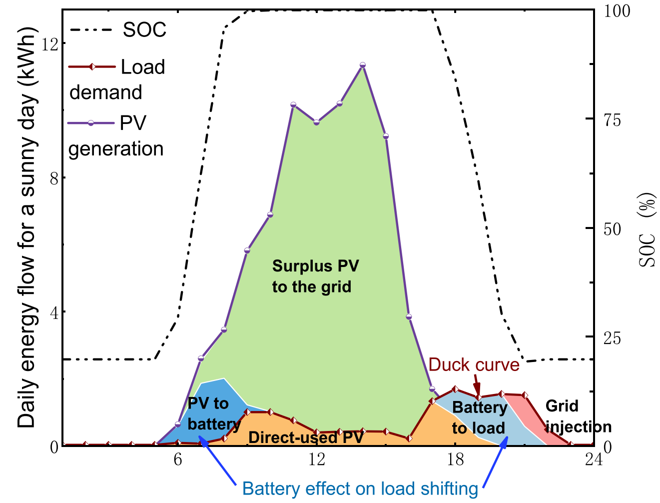

Fig. 4. Peak shifting effect of battery storage under TOU tariff.

factors. The commonly used evaluation system in technical, economic, and environmental aspects are presented in Fig. 5.

The technical ones are the basic and most direct indicators for distributed PVB systems. The SCR and SSR are two most used ones for the renewable part performance. The energy flow, especially the grid transmission and battery power, is also crucial [54]. Besides the common technical ones, the technical index could be defined according to the need of authors, such as the cumulative energy demand from the battery system [7], system average interruption frequency index, system average interruption duration index, customer average interruption duration index and loss of load probability[30].

As for the basic economic index, the LCOE is used for grid parity analysis, with NPV for discounted cash flow analysis and payback period for visualized years to break even the cost. Other economic indicators include levelized cost of storage, the value of load [30], operation and maintenance cost, investment cost, primary energy saving [109], grid parity index, and levelized profit of electricity [110].

The indicators from other aspects are gradually added to the multi-aspect evaluation system, especially the environmental ones. Other indexes may include air pollutant emission and health benefit parameters [7], and carbon emission [88].

Several evaluation systems with single or indicator combinations in recent studies are summarized in Table 3. The cost optimization based on the minimum system electricity cost, NPC, or LCOE is the early prototype in the single-objective optimization. The techno-economic evaluation system is a more mature prototype with highlights from different sides, i.e., user load shifting, grid frequency support, grid transmission, PV prediction and error penalty, PV usage ratio, battery ramp rate control and aging. The economic indicator is basically the annual electricity cost, NPC or LCOE for overall evaluation of the system economic performance. The addition of environmental indicators, CO_2 emission reduction, improves the prototype to the techno-economic-environmental one to provide a more comprehensive optimization study. Besides the carbon emission, the carbon trading in the emerging carbon market is a new highlight, while the evaluation system is still based on the multi-objective economic optimization in the multi-trading market. To deal with the complex nonlinear optimization problem in very recent studies, most of the optimization method are the smart algorithms and their variations. Although the analytic hierarchy process (AHP) method [111] provides the basic indicator combination method for multi-criteria decision-making (MCDM) techniques, the Pareto optima are recommended for the tradeoff relationship and is more commonly used, especially the non-dominated genetic algorithm (NSGA-II). More approaches to the MCDM could also be found in the grid-connected PVB

Table 3
Various system performance evaluation systems.

Technical/ Economic indicators	Other indicators	Highlight	PV side	Battery side	Grid side	User side	Objective type	Optimization method	Combination method	Ref.
Electricity cost		Cost optimization			Electricity bill		Single	(AA)PSO		2017 [95]
LCOE, IRR		Cost optimization				LCOE	Single	ANN		2017 [113]
Energy cost		Cost optimization	Investment, O&M, capital replacement cost	Investment, O&M, capital replacement cost	Grid exchange cost and revenue	LCOE	Single	GA		2019 [114]
Electricity cost		Cost optimization			Electricity purchase cost		Single	Enumeration		2019 [18]
Peak shaving load & power loss, replacement cost		Load shifting	Capacity limit			Bus voltage magnitude, line current	Multiple	PSO	Pareto-optima	2019 [115]
NPC, COE		Cost optimization	Overall cost	Overall cost	Grid exchange cost and revenue		Single	TLBO (GA, PSO)		2020 [116]
Investment cost	Carbon emission	Carbon emission	Capital, O&M, replacement cost	Capital, O&M, replacement cost	Grid exchange cost and revenue, carbon emission		Multiple	NSGA-II	Pareto-optima	2020 [117]
Battery capacity, frequency support		Grid influence	Ramp rate	Ramp rate, size	Frequency support		Simple	Enumeration		2020 [78]
Equivalent cost		Battery aging and grid influence	Ramp rate	Ramp rate, operation cost	AGC payment		Multiple	Rolling optimization	AHP	2020 [118]
Net income, battery balance, prediction error cost		PV estimation	Prediction error penalty cost	Battery charge/discharge balance			Multiple	HS-MOPSO	AHP	2020 [119]
LCOE	CO_2 emission reduction	Carbon emission			CO_2 emission	LCOE	Multiple	NSGA-II	AHP/ Pareto-optima	2021 [88]
Electricity cost, peak load shifting	Carbon emission, user comfort	Grid influence, carbon emission			Carbon emission, electricity cost	Peak power consumption ratio, delay time rate	Multiple	Hybrid GA and ACO (ACO, PSO, GA, HGPO)	Multiple Knapsack Problem	2021 [120]
Battery SOC, Electricity cost	Carbon emission	Techno-economic-environmental		Battery SOC	Electricity purchase cost, CO_2 emission		Multiple	MOEA/D-DE (ANN, SVM)	Pareto-optima	2021 [121]
Electricity cost		Size-operation joint optimization	Investment, O&M cost	Investment, O&M cost			Multiple	MINLP	AHP	2022 [122]

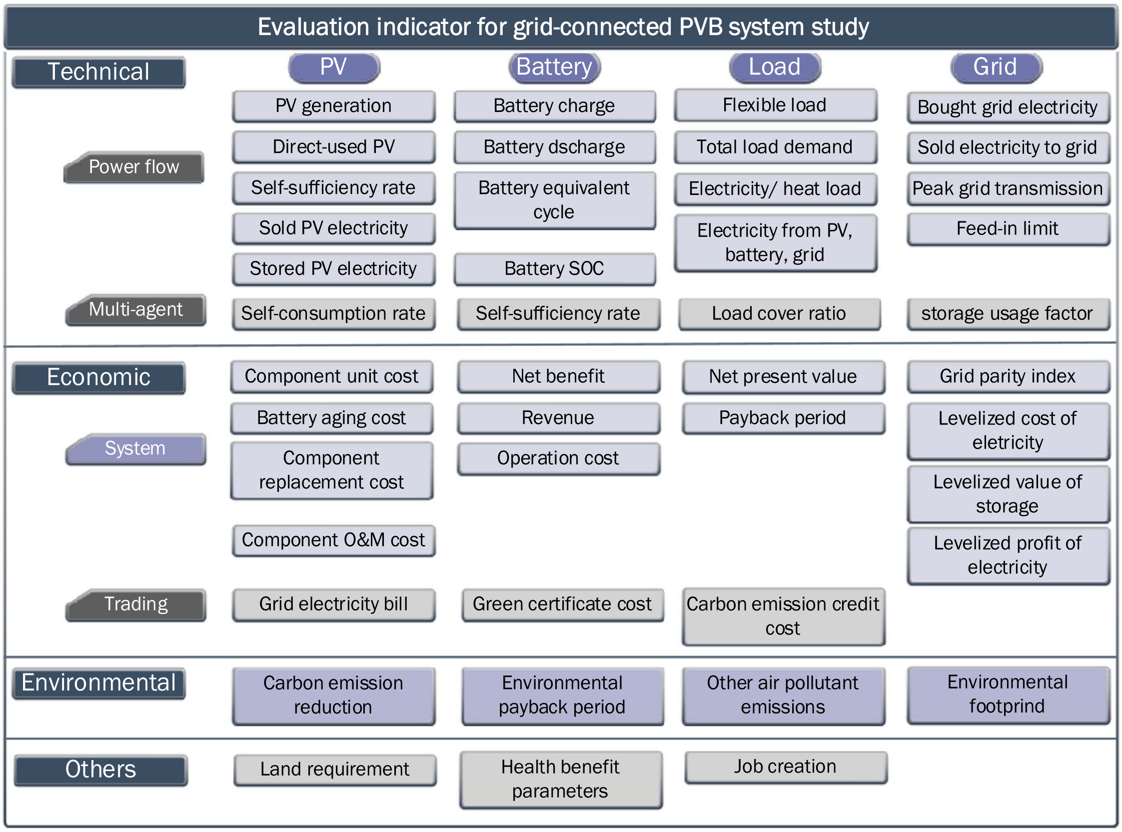

Fig. 5. Performance indicators from different aspects.

system study or learned from the off-grid microgrids, including the fuzzy set theory [112], the technique for order preference by similarity to ideal solution [109], and improved algorithms, such as MOEA/D, MOPSO and SPEA-II for the multi-objective evolutionary algorithms. More novelties on the evaluation system are expected to lie in the improvement on the multi-objective algorithms and combination method for indicators of different priorities.

3.4. PVB system feasibility study

The system study with PV and battery started with the hybrid system in remote islands without grid connection, focusing on LPSP and COE, and was extended to the distributed PVB system with declining PV cost, attractive subsidies, and increasing load demand. The feasibility study first considers adding novel components such as solar PV [123], battery [124], and the home energy management system [95] to the existing energy systems. The energy losses during power conversion, transfer, and storage are also considered in developing specific PV and battery models [125]. The addition of a battery is required to decrease the mismatch between PV and load curves, and obvious improvements could be achieved, including 76%, 78.3% sold and bought electricity transmission reduction with the grid, and 87% electricity bill cut down [75].

The MSC strategy is taken as the basic strategy, compared to the early strategies of selling all PV generation and maximizing self-consumption without battery [126], to use the most onsite generated PV electricity with the help of a battery system. The electricity tariffs, including electricity price and government subsidy, are gradually considered when it comes to the economic feasibility study of the PVB system [50,99,101]. The battery profitability is also a concern in this stage, with the PbA battery shown to be profitable [18]. However, the high-density, flexible Li-ion battery has grabbed more attention than the PbA battery and is more promising in a large-scale study. Even the economic revenue is sharply reduced due to the battery cost in a single system by most of the early studies [38,100]. The DSM, to arrange the controllable load usage time and power according to the PV generation, grid burden, future load demand, and battery status, is also mentioned in the feasibility study [47,127]. The DSM methods, including load control group division, load limiter, smart metering, and smart appliances, were highlighted in 2014, increasing 2–15% SCR and the combination of DSM and battery could further reduce peak load consumption and electricity generation [123]. The MSC strategy is the mostly used strategy for strategy comparison, while the grid burden and the neglect of the dynamic tariffs are its disadvantages compared to other strategies like TOU. The DSM is the crucial scheme to do the PVB system operation optimization, especially with the help of other schemes like MPC. However, it adds a higher requirement to the system, e.g., turning some fixed load into controllable or deferrable load and dealing with the uncertainties from renewable production and load demand like HVAC load.

The overview of the distributed PVB system feasibility study is displayed in Fig. 6. In the preliminary stage of the distributed PVB system study, the feasibility study lies in the system configuration variation, parameter analyses, and simple improvements in operation strategy. Some studies still partly focus on the feasibility system study, with research directions, large-scale energy storage system, grid parity of PVB system, and energy trading community considered.

3.5. System capacity design

The system size optimization design is a common concern after the feasibility study. The major system types include PVB houses/buildings and communities with PV and battery systems, while PVB commercial buildings [10,37] and hybrid microgrid studies [128] are not so commonly found. The system capacity design starts with battery size optimization to obtain the highest profit. Other improvements may include

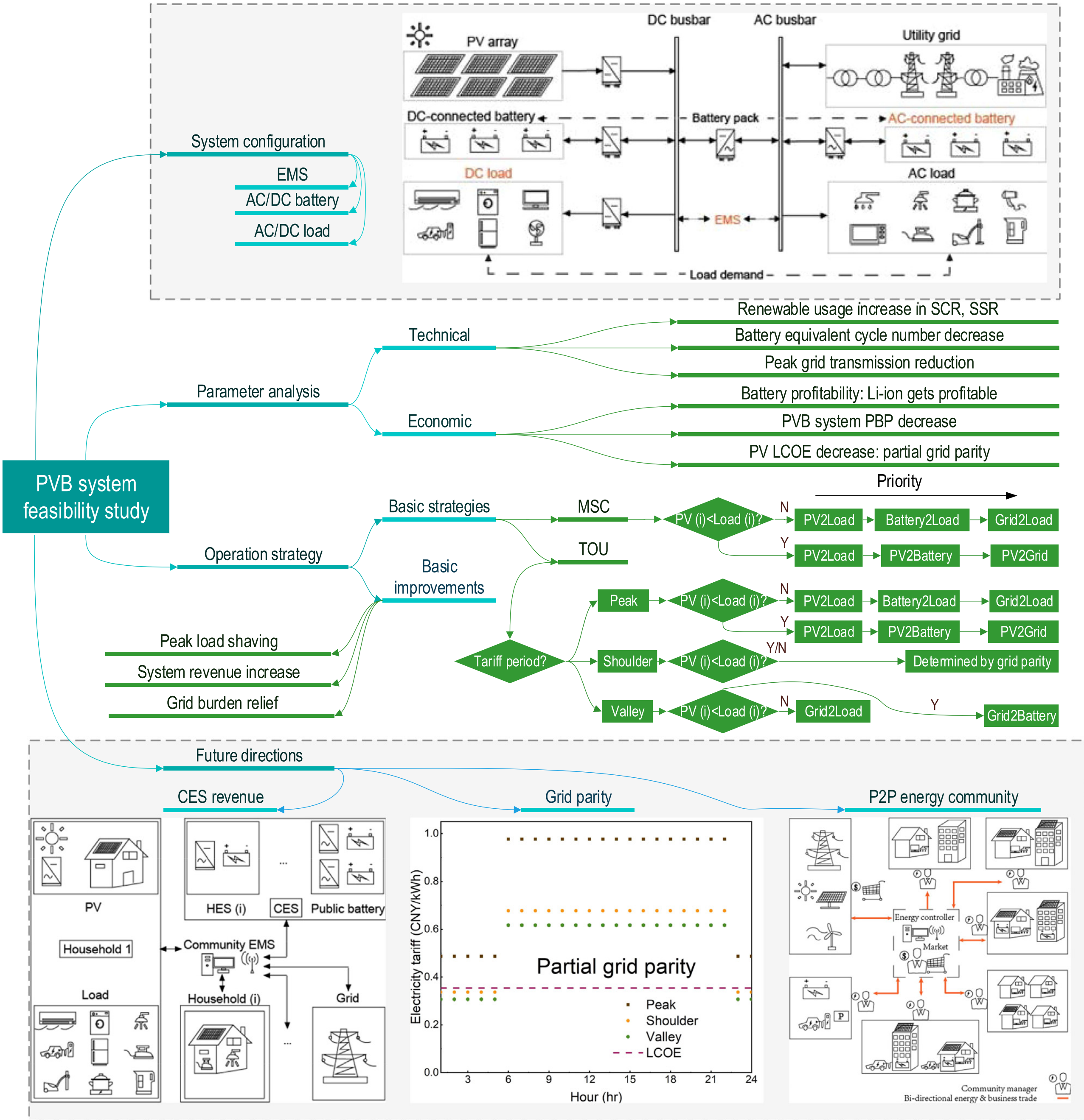

Fig. 6. PVB system feasibility study overview.

the joint optimization of PV and battery sizes [19], the multi-aspect targets and multi-objective optimizations like grid transmission, battery aging, renewable energy self-consumption, system cost, and carbon emission [88], and additional consideration of grid importation and tariff [98], self-consumption [18], and environmental impact [37].

The method of the study is correspondingly improved to solve the more complex targets with various considerations. The initial method is battery size enumeration [47,100] with parametric and sensitivity analyses [37,38], where the load shifting with battery storage and flexible load is found crucial to cut down battery size and electricity bills under time-varying tariffs [125]. Then the linear optimization of system energy flow with the lowest electricity bill as the target is commonly used. The discrete-time Mixed Integer Linear Programming (MILP) method via CPLEX solver in GAMS software is the acknowledged tool to size the system optimally [10,14,98,129], considering the time-varying tariffs, including FIT, flat, TOU, and RTP tariffs. The grid tariffs in the study tend to be applicable and practical.

With the complexity of the system configuration and operation and computational time growth, smart algorithms are introduced to solve the nonlinear optimization problems. The advanced-adaptive particle swarm optimization (PSO) is utilized to deal with Mixed Integer Nonlinear Programming (MINLP) in an Iran residential house [95]. What's more, the genetic algorithm (GA) is used for PV and battery size jointly design in an Australian residential PVB house [19]. The ant lion optimizer (ALO) optimization, gray wolf optimization (GWO), kill hear algorithm (KH), and JAYA algorithm are compared in the hybrid renewable energy system with battery system in Algeria [128]. Moreover, teaching-learning-based optimization (TBLO) is applied to a residential building

Table 4
Cases on system capacity design.

Time period (resolution)	Optimal size	Method	Tariff	Strategy	Target	Optimization type	Ref.
1 year (at least 2 s for load and 15 min for PV)	PV, battery, battery inverter	MILP (GAMS in CPLEX)	Flat, FIT	MSC	Min total discounted investment and operating cost	Deterministic	2016 [129]
1 year (1hr)	PbA/Li-ion community battery	Enumeration	TOU (7-period), RTP (4-period), FIT	Peak PV and load shifting	Min total cost with future zero emission scenario	Deterministic	2017 [100]
1 day (1hr) repeated for 1 year	Retail tariff, battery	GA	Flat, TOU, dynamic	Battery scheduling	Min daily electricity bill	Deterministic	2017 [139]
1 year (1hr)	CES	GA and MILP	TOU	MSC	Max NPV	Deterministic	2017 [22]
1 year (15 min load, 10 min PV for 30 min forecast)	Battery, PV	Enumeration	Flat	Min curtailment loss (FIL), Max SCR	Min system cost with the grid	Deterministic	2017 [134]
24 hour (0.5hr) and repeater for 1 year	PV, Battery	MILP	Flat, TOU (7-period), RTP, FIT	Optimized	Max FIT revenue, Min grid electricity import	Deterministic	2017 [98]
1 year (1hr)	Battery	AAPSO	Flat	Peak shifting	Min electricity cost	Probabilistic	2017 [95]
1 year (0.5hr)	PV, Battery	MILP	TOU, demand tariff (total and peak consumptions)	Peak grid load shaving (optimized)	Max NPV	Deterministic	2018 [10]
1 year (1hr)	PV, Battery, converter	CMA-ES	FIT, Flat	MSC, MPC for min battery aging	Min energy cost	Deterministic	2019 [114]
1 year (1hr)	PV-inverter/ battery-inverter ratios	Enumeration	Not mentioned	Price-taker dispatch	Max revenue	Deterministic	2020 [73]
1 year (1hr)	Battery, Grid limit	NSGA-II	FIT, TOU	TOU	Min LCOE, Min net grid transmission	Deterministic	2020 [88]
1 year (1hr)	PV, Battery, Grid limit	Improved ABC	TOU	Follow load	Min annual total cost and CO_2 emission, max energy conservation	Deterministic	2020 [140]

in Iran with the comparison to GA and PSO [116]. When it comes to the multi-objective optimization, NSGA-II with Pareto-optimal solution is a common resolution to performance improvements in different aspects and sides [88]. It could be expected that more multi-objective optimization study with more complex system configurations will be conducted with the help of novel smart algorithms under various time-varying tariffs. However, the choice of different algorithms may vary in specific circumstances. The multi-objective optimization method is basically limited to Pareto fronts, NSGA-II, and AHP with the existing algorithms, which needs further development.

Several system size optimization studies are shown in Table 4. The battery sizing is the major target in the PVB system design with peak shifting or TOU operation strategy for higher revenues under time-based tariffs. The deterministic optimization based on multi-objective smart algorithms tend to be the mainstream of the optimization study, though the scenario-based probabilistic optimization provides higher system flexibility [95,130], especially for the model predictive control [131].

Although most of the capacity optimization studies select the time period and resolution at one year and one hour, respectively, significant error could be caused with intermittent spikes or teeth in demand PV curves under scattered cloud conditions [132]. There are rare PVB system study based on the high temporal resolution, though relative studies [97,129] suggest 15 min load profile is sufficient for small-scale system within 2 kW and the temporal resolution influence time period is less distinct for PVB system than PV system. The 60 min temporal resolution is suitable for PVB system rough sizing, while 5 min is still recommended for specific system design [133]. Also, the high resolution data are good basis for load and PV generation forecast-based studies [134].

Another focus in the table is the electricity tariff, including the subsidies, grid electricity purchase price and FIT [101]. The subsidy may be provided based on the renewable generation or act as the additional FIT, while it will ebb if the grid parity of the PVB system is gradually achieved. The grid electricity purchase tariff is separated basically into the time-fixed and time-varying types, namely flat tariff (fixed electricity price), TOU, and real-time pricing (RTP) [100]. The additional pricing schemes may be adopted according to the requirements from countries or DSOs, such as step tariff [135] and demand tariff [10]. The feed-in limit is used at the early stage of the PVB system study to simply add the grid restriction to the PVB system simulation. The FIT and the time-based tariffs bring about the opportunity of energy arbitrage on economic benefit, with the peak shifting or TOU-matched operation strategy [31,136]. The Net-metering is a practical scheme to calculate both prosumer's total energy supply and consumption with the grid and the hourly net metering tends to be a conventional practice [18]. Although in some cases, the difference from the TOU and demand tariff structures may not be obvious enough to affect the optimal PVB system size [10], the electricity tariff with time-varying nature tend to increase the economic efficiency and fairness (less cross-subsidization signs) in the large-scale long-term P2P energy trading market with more prosumers and higher system flexibility [137,138].

Several system capacity design recommendations could also be concluded based on the previous studies: (1) battery addition is shown to effectively increase more than 70% SSR for PV alone houses [14], home EMS could reduce the electricity bill by 27.8% with battery earning money from TOU tariff [95] and the combination of battery and flexible loads could cut down up to 30% battery size via DSM and peak load shifting [67,125]; (2) the DC topology considering over-sizing and PV curtailment loss could help 19% SSR increase and 2% carbon emission reduction with large battery capacity via energy loss saving [37]; (3) PV system is economic with large load demand which could be directly consumed [116], and large PV capacity with small battery addition is recommended [10]; (4) the Li-ion battery is shown to be more suitable for PVB system compared to PbA, LA, Ni-Cd batteries with about 1/3–3/5 LCOEs reduction based on PbA battery, in community with large PV capacity and will be more competitive with Li-ion battery cost reduction [47,100,128]; (5) joint optimization of PV and battery system could obviously reduce the electricity bill by 2457.8$ under TOU tariff for PVB house in Australia [19]; (6) PV alone system is profitable for most consumers and PVB system profitability could be achieved with higher electricity price, FIT rate, lower battery cost and more economic incentives

[14,18,98] or scheduled in group battery instead of individual batteries [19]; (7) battery action could improve the optimal system size, indicating the necessity of the operation strategy improvement which will be discussed in the next Section. At this stage, the parametric and separate size design on basic PVB system is gradually mature, and the system capacity optimization needs more novelties on system configuration and system scale variation, or deeper model development like battery degradation model and load estimation.

3.6. Operation strategy improvement

As mentioned in Section 3.5, the operation strategy improvement, especially the battery action schedule, could further improve the system performance [19]. The rule-based control strategy is the basis of the PVB operation strategy and is used mostly in recent studies when strategy optimization is not the major focus.

The MSC strategy consuming the most renewable energy production, and the TOU strategy, utilizing the most valley grid electricity to charge the battery bank, are the two most used basic rule-based controls in PVB system operation [54]. However, battery degradation is not considered in the basic strategies. MSC could also be applied to other hybrid renewable energy systems like a PV self-consumed residential building with a ground-source heat pump, electric heater, water tank heat storage, battery electricity storage, and shiftable load for maximum PV SCR [141]. Several rule-based improvements could be added to the two basic strategies, including grid FIL control with forecast-based battery action [142], preserved battery discharge capacity at night with load prediction and energy market electricity price consideration [113], the combination of MSC and TOU strategies for high battery SOC maintenance and grid transmission power limits [9] and different priorities of various storage systems like battery and PHS [117]. The three practical tools, including forecast-based study (MPC), load shifting method (DSM), and time-varying electricity tariffs with battery action schedule (grid impact and constraints), are emphasized in this optimization study.

Besides the rule-based strategies, strategy operation optimization is also the major PVB system study. The optimization targets could be summarized as the electricity cost minimization with PV self-consumption maximization [141], PV and load limiting smoothing and shaving [78,143], peak grid transmission reduction [17,144], network problem prevention and infrastructure update deferral [145–147], battery lifetime loss reduction [20,52,148], imbalance cost reduction for community study [149], carbon emission reduction [149], and policy influence [97,135]. The dynamic electricity tariffs, including FIT, flat/TOU/RTP/CPP, and step tariffs, are utilized and sometimes compared under different conditions of the studied cases, with the TOU tariff, as the most common one to providing obvious energy arbitrage via operation strategy improvements. Also, the simulation horizon has been extended from 24 h [78,141,144,145] in the early stage to one year [141] or the system lifetime for most of the present study, considering seasonal differences and component degradations. The battery lifetime degradation consideration [20,52,54,143] and forecast-based operation [17,52,97,143,146,150] are emphasized in operation optimization. In contrast, the battery aging model and predictive model construction with forecast error reduction mechanism are required technically.

With the requirements and considerations of the operation strategy growing, more effective methods are used in the optimization study for system operation. They include MILP or MIQP solved by CPLEX as a system capacity optimization study [38,143-146], dynamic programming (DP) [54,141,148], GA [20,135], convex programming [52] and novel machine learning algorithms [65,97,150,151]. MATLAB and Python are usually utilized in the complex optimization-solving process. Based on the current operation strategy improvements, which mostly focus on single targets for the system users, the multi-objective and multi-agent optimization could be a future direction for operation optimization study. The multi-objective optimization could be conducted based on Pareto frontiers with single-optimization results [149] or via other methods like the utopia point and commonly-used AHP, a namely weighted sum of different criteria [119]. The multi-agent study takes more participants with their various preferences in the smart grid into consideration, including system users with technical requirements, the utility grid with grid transmission and safety limits, community aggregators with economic and transmission concerns, an investor with economic expectations, etc.

The main current and future research directions of distributed PVB systems are summarized in Fig. 7, focusing on three major parts, system feasibility, flexibility, and resilience: (1) Operation schemes in system feasibility - The system feasibility extends from the system configuration of grid connection and battery addition to the distributed PV system, renewable production usage and system economic benefits as two major concerns, as mentioned in Section 3.4. Based on the energy management system (EMS) [152] scheduling, the PV SCR and user SSR are generally increased in most of the studies. With the help of the rule-based battery basic model predictive control, the peak load are shifted or shaved, thus the energy arbitrage is achieved from the time-varying tariff and subsidies at this stage. (2) System flexibility schemes – The distributed PVB system is converted from the conventional prosumer to the flexible agent [141] in the distributed grid with basic energy management schemes, DSM for load adjustment and comprehensive MPC from uncertain components. Both the deterministic and probabilistic (with scenario analysis) optimization studies on system operation are emphasized. The DSM is improved from load shifting to flexible load adjustment, according to the grid requirement, i.e., the PSDF is a typical prototype [35]. The forecast-based scheme [142] adds to the system flexibility, with higher energy arbitrage, better grid transmission preference, and possibility for energy community trading. (3) Future system resilience perspectives – Based on the optimization study for the single distributed system, higher targets are raised for the distributed energy system, such as the resilience to extreme climatic catastrophes [105], thus leading to lower dependence on the grid and higher reliability on long-term energy storage. To increase the reliability and resilience of the distributed system, large scale planning with P2P energy trading and different energy vector combinations for the integrated energy system (IES) with electricity, heat, gas, and hydrogen are gradually emphasized in the academic circle. The multi-energy system with a reliable long-term hybrid energy storage system, fair energy community trading market, and mature IES structure, is expected in near future.

3.7. Co-planning of system size and operation strategy

To simultaneously design the PVB system size and operation strategy, as an emerging novelty in recent five years, is undoubtedly a highlight of complexity in the present and future system study. The relative studies are listed in Table 5 and could be categorized into single PVB system and community energy storage system, based on system complexity and scale. Studies in the small-scale system set targets from multi-aspects and focus on long-term simulation, while the large-scale system prefers a single target with shorter simulation period due to the complexity and computational time. Considering the feasibility and computation time, most of the studies in this stage size the system under different pre-defined strategies, mainly rule-based ones in single PVB systems [9,113], or separate the size, site, and operation optimizations into different stages to obtain separate objectives [21,22]. Thus, the further co-planning of optimizing system size and operation simultaneously will still be regarded as a complex and time-consuming problem, requiring more smart algorithms or reinforcement learning methods to reduce computational time. A resolution is to optimize the system size and operation simultaneously with decreased simulation time period instead of the life cycle, i.e., 24 hr control horizon and 72 hr prediction horizon with 15 min resolution [97], one other with second-level filter constant [133], and even shorter period [153]. Another resolution is to set different optimization period for size optimization and operation optimization, namely shorter optimization period for higher problem complexity

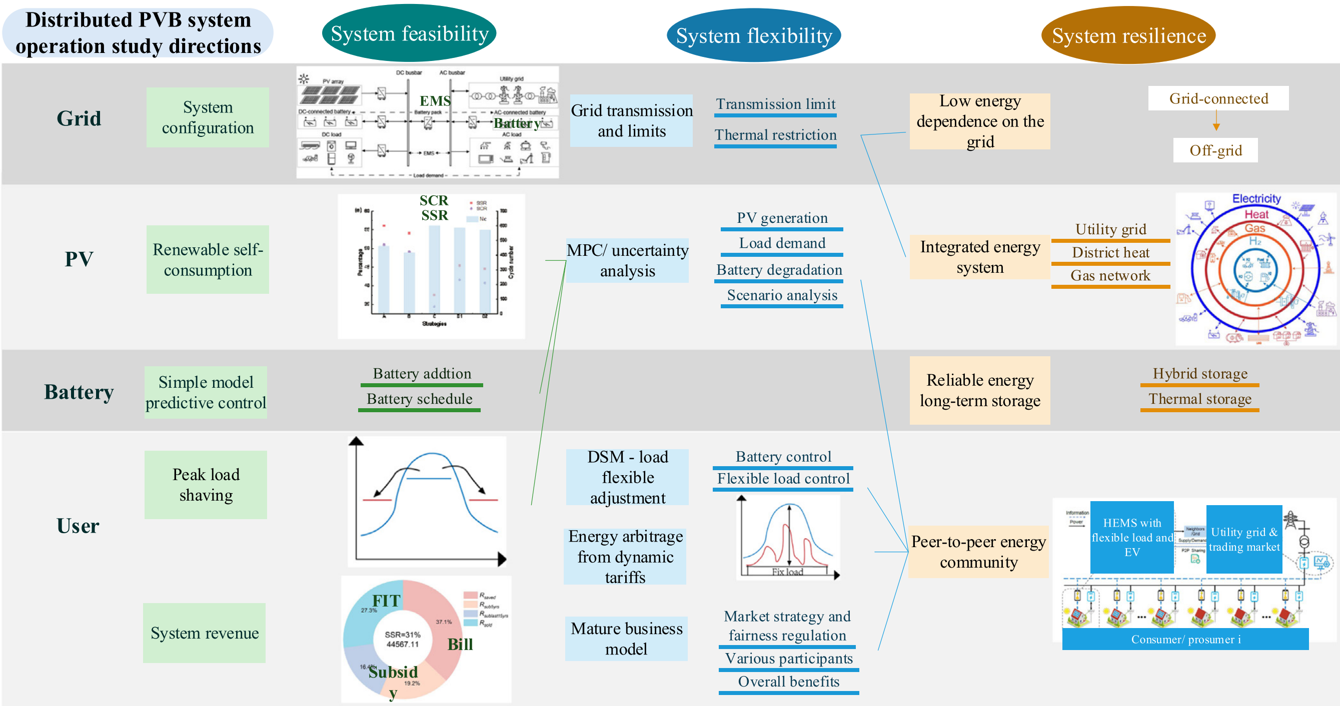

Fig. 7. PVB system operation optimization overview (business model sub-figure from Ref. [34]).

Table 5
Co-planning of system sizes and operation strategy.

Target	Location	Variable	Tariff	Key points	Year
Min total cost	Changsha, China	Battery size and schedule	FIT/TOU	The operation cost is sharply reduced by the PVB system. Grid import limit and peak FIT are more important than grid export limit.	2022 [122]
Max net profits	France	Battery size and operation	Not mentioned	The optimization for battery size and battery schedule based on MPC is conducted via global LP.	2016 [154]
Max SSR and NPV	Sweden	Battery size and rule-based schedule	TOU	The rule-based operation strategies are compared, including the conventional, dynamic price load shifting, and hybrid operation strategies, via multi-objective GA.	2017 [9]
Min system annual energy loss	Australia	CES site, size, and operation	Not mentioned	Separate optimization for three different targets. A modified center-of-gravity formulation to site CES. Size CES by a load following the control method. Schedule CES to flatten the daily demand profile and improve the voltage curve.	2017 [21]
Max total NPV	Australia	CES site, size, and operation	TOU	The CES size is optimized via GA with site allocation and load following the control strategy.	2017 [22]
Min annual electricity bill	Iran	Battery size and operation	TOU	Considering the uncertainties with the probability distribution function, Monte-Carlo simulation via MINLP with Meta-heuristic optimization techniques is used for net-zero energy.	2017 [95]
Max NPV	Australia	PVB size and EMS	TOU, demand	MILP is used. A large PV system with a small battery size is preferred. Peak grid consumption reduction is found under demand tariff.	2018 [10]
Max payoff of each player	Pakistan	Battery size and game theoretical EMS	TOU	Separate capacity optimization under different rule-based strategies. With PV prediction by the ARIMA method, the optimization could increase 30–40% payoffs.	2019 [155]
Min energy cost	Germany	Component size and operation strategies	Flat, FIT	Combine the operation strategy and component capacity optimization to achieve better economic performance for PVB with power-to-heat coupling.	2019 [114]
Max income	China	PVB size and system operation control	TOU	Separate capacity optimization under different rule-based strategies. High benefit, earning 36% investment, could be achieved with 23% revenue from energy saving and emission reduction.	2020 [156]
Min net electricity cost, CO_2 emission and max battery SOC limit	Taiwan, China	PV size, battery schedule, 2 electricity pricing, 6 strategies	Flat, Step, seasonal TOU	The differential evolution variant of multi-objective evolutionary algorithm (MOEA/D-DE) is used to find the optima with equal weighting for each objective. MPC-based operation strategy is shown to outperform conventional ANN and SVM-based strategies, while the temporal resolution is still limited to 10 min.	2021 [121]

and then combine the optimization together at the longer simulation period, e.g., optimize the system operation daily at 1hr resolution and size the PVB system based on year-long optimization at 1hr resolution as well.

The battery capacity and operation are emphasized in controllable variables in most studies [9,21,22,111,113,125,139], and the targets include maximum NPV [22]/ SSR [9]/ SCR, LCR [89]/ IRR [113], minimum electricity bill [96,125,139]/ energy loss [21]/ O&M cost [111]/ net grid transmission [89]. Smart algorithms like GA, PSO, and ANN are utilized more than MILP problems solved in CPLEX in the system size or operation design mentioned in Section 3.5 and Section 3.6 and conducted in previous years. The Pareto front is still useful when dealing with multi-targets in technical and economic aspects [9]. The location of the study comes from different countries in the world with high renewable energy penetration, and most of them are residential architecture, but the building type will be less limited if more smart algorithms are applied.

The key findings could be summarized as follows: The battery profitability in 2017 was not achieved in the residential part, and flat tariff brings more benefits due to the expensive battery addition [9,139], the intraday community energy transaction could increase the battery profits [113], noticeable technical and economic performance improvement could be achieved by CES system scheduling with 47% more load factor, 11.1% electricity cost reduction and 36.88% energy loss decrease [21,22], load shifting integration could significantly reduce battery capacity by 30% [125], the combination of MPC is also considered and annual cost cut down is obvious by more than 36% [96,111]. The simultaneous optimization of system size and operation is paid attention to in further study with smart algorithms, and more valuable results and findings on larger-scale systems with various energy flows are expected.

Conclusions

Under the carbon targets, renewable energy applications, especially photovoltaic (PV), play a crucial role. With battery installation to cope with the intermittent and fluctuating PV generation, the distributed photovoltaic battery (PVB) system is a typical prototype for distributed energy systems, and its design optimization is paid more attention to. This study provides a critical review of PVB system design optimization, from system modeling, evaluation system establishment, feasibility study, capacity optimization, operation improvement to co-planning of size and strategy.

The recent PVB system study includes system component variations like DC distribution load substitution for AC systems, system novel control schemes with demand side management and model predictive control, and electricity market tariffs. The PVB system study development globally is discussed with east Asia, the US, and Western European areas focusing on strategy improvement in recent years. The modeling of the PVB system is shown in three methods, mathematical establishment, software use or model-free simulation. The basic system mathematical model of distributed PVB system is shown in this study. Four battery degradation models with calendar and cycle losses are summarized. Several simulation software or established models are recommended for PVB system study, including HOMER, SAM, PVsol, PVsyst and RETscreen as mature practical model with relative publications and evaluations listed in detail, while the programmable function makes TRNSYS more widely used. The model-free simulation is also a novel direction based on the stochastic and reinforcement learning methods, which is suitable for complex distributed system especially with forecast-based controls.

The evaluation indicators are summarized from various aspects, especially SCR and SSR for technical performance, LCOE and NPV for economic analysis, and CO_2 emission reduction for environmental performance. Three prototypes are summarized for the evaluation system development, including cost-effective, techno-economic with different highlights like user load shifting, grid frequency, PV usage and battery aging, and techno-economic-environmental with multi-objective optimization, especially Pareto front. Although the single-objective optimization in household systems accounts for most of the studies, the multi-objective one on a larger system scale is necessary in future studies.

The PVB system feasibility study is analysed from system configuration variation, key technical and economic parameter analyses, basic rule-based operation strategies to future expectations, large system scale, grid parity, and energy community trading platform. Moreover, the targets, methods, tariff and time resolution influences, and design recommendations of PVB system capacity optimization are summarized. With the battery size as the major size optimization target via deterministic optimization method, the peak shifting TOU strategy is the mainstream and the multi-objective algorithms based on Pareto optima, especially NSGA-II, is emphasized. The temporal resolution affects the system size design, though not no obvious compared to PV alone system, with 60 min resolution is acceptable for coarse PVB system capacity optimization and 5 min for specific design. The time-based tariff, subsidy, feed-in tariff are influential to the system cost-optimization due to the energy arbitrage from higher system flexibility based on battery storage and user load management, and the tailored tariff is recommended with the future large-scale energy trading community for fairness and economic efficiency. Besides, several research directions for system operation development are proposed from system feasibility, flexibility, to resilience. Also, the co-planning of PVB system capacity and operation design optimization remains challenging, though basic resolutions, separate optimization and different time period for size and operation optimization, are raised. This study provides useful guidance and references to researchers and developers of distributed PVB systems for future design and optimization studies.

Declaration of Competing Interests

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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