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Review

Overview and Comparative Study of Energy Management Strategies for Residential PV Systems with Battery Storage

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Abstract: PV and battery systems have been widely deployed in residential applications due to increasing environmental concerns and fossil energy prices. Energy management strategies play an important role in reducing energy bills and maximize profits. This paper first reviews the state of energy management problems, including commonly used objectives, constraints, and solutions for PV and battery applications. Then, a comparative study of different energy management strategies is conducted based on a real applied product and household profile. Moreover, results are discussed, and suggestions are given for different scenarios. Finally, conclusions and insights into future directions are also provided.

Keywords: solar energy; battery storage; energy management; comparative study; residential application

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1. Introduction

Photovoltaic (PV) energy has grown rapidly in the last decade due to increasing global environmental awareness and decreasing manufacturing costs of PV panels. As shown in Figure 1, the global PV capacity has grown from 70 GW in 2011 to 942 GW in 2021, and the annual addition has maintained a steady growth over the last few years [1]. However, because of the stochastic and intermittent behavior of solar energy, there are some mismatches between power generation and load consumption in residential applications. For example, Figure 2 shows a typical electricity demand of a household in one day. PV generates power during the daytime, but the load demand stays at only a low level. In the morning and evening, household appliances (e.g., water heaters, dryers, microwave ovens, electric vehicles (EV)) consume the majority of the daily energy, yet PV production is insufficient. As a consequence, the mismatch between generation and consumption may lead to power shortage or the overloading of distribution power networks and worsen the power quality [2,3].

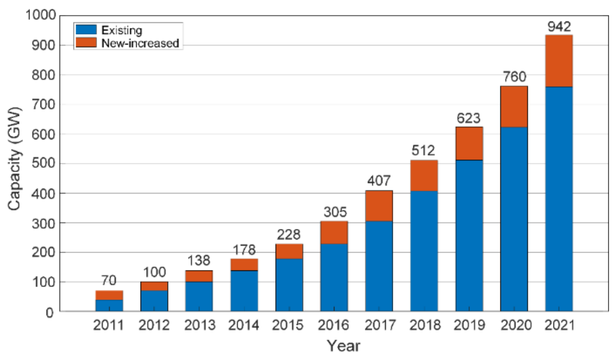

Figure 1. Global PV capacity and annual additions.

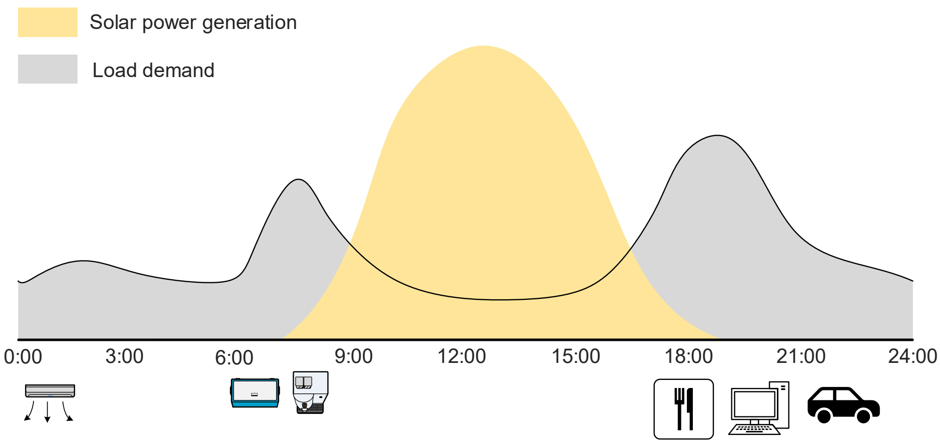

Figure 2. An illustration of mismatch between PV generation and load consumption.

As a promising solution, energy storage systems (ESS) have been integrated with many PV applications, where ESS can store excess PV energy during sunny periods and release it to cover the load demand when generated PV power is insufficient. Figure 3. shows a typical hybrid PV–battery system (HPVBS) for residential applications, where the PV, battery, and DC loads (e.g., televisions and computers) connect to the same DC bus [4]. At present, Li-ion batteries are the prime candidate in residential cases due to their versatility, flexible installation, and decreasing prices [5]. Through a bidirectional interlinking converter, the DC bus is connected to the AC bus, which connects the AC loads and the utility grid. Grid-connected HPVBSs are the intermediary between distributed power generations and the utility grid, which can distribute and buffer the energy between PV energy sources and the grid. On the demand side, HPVBSs can guide consumers to reasonably use electricity and reduce their energy costs. On the grid side, HPVBSs can realize the intelligent dispatching of the power grid system, which might not only increase the allowed PV capacity in the power grid, but also use the energy storage system to shift the peak loads, hence, improving the reliability of the grid and creating a better economic situation for the household. Therefore, energy management strategies are essential to reduce the impact of randomness and fluctuation of PV power generation on the operation of the distribution power system.

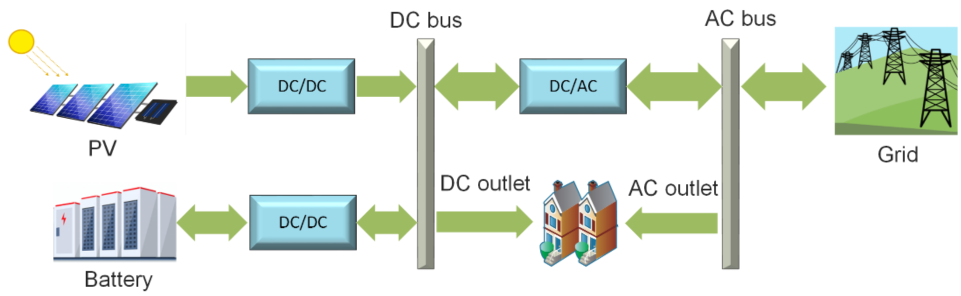

Figure 3. PV–battery grid-connected system.

Several overview papers address different aspects of energy storage and renewable energy-based systems. In [6], the authors summarize the recent grid codes in different countries for grid-connected PV applications. In [7], the impacts of different technologies and applications are discussed and compared. Power generation forecasting methods and system protection methods are summarized in [8,9], respectively. Some researchers also discuss the control methods at the converter level. Ko et al. in [10] investigate the commonly used maximum power point tracking (MPPT) methods for PV systems used in microgrids. Control strategies for PV and wind sources are examined in [11], and the cost-effectiveness of different ramp-rate methods to smooth the power output power is compared in [12]. In addition, there are some reviews about the energy management strategies for renewable energy-based systems. The energy management problems, objectives, constraints, and strategies are summarized for microgrids [13,14], isolated microgrids [15,16], and smart grids [17]. Unlike these review papers, this paper only focuses on hybrid PV and battery systems for residential applications. Some highlights of this paper are:

- Energy management strategies (including objectives, constraints, and optimization methods) are reviewed based on the state-of-the-art literature;
- Three mostly commonly deployed strategies in real cases are compared based on a real mission profile of a typical Danish household;
- The effects of spot price are analyzed, and suggestions and future directions are also provided.

The remainder of the paper is organized as follows: Section 2 provides an overview of control strategies based on different objectives for HPVBS. In Section 3, a comparative study is conducted based on a typical Danish household to compare different energy management strategies regarding the profit self-consumption degree, etc. The results analysis and future trends are discussed as well. Section 4 concludes this paper.

2. Energy Management for Hybrid PV Systems

As the brain ensures the economic and stable operation of the system, the energy management system (EMS) determines the working state of each component in an HPVBS. Therefore, proper EMS strategies are essential to achieve specific objectives in different scenarios.

According to the International Electrotechnical Commission (IMC), an EMS is "a computer system comprising a software platform providing basic support services and a set of applications providing the functionality needed for the effective operation of electrical generation and transmission facilities so as to assure adequate security of energy supply at minimum cost" [18]. In residential applications, an EMS usually consists of modules of forecasting, data acquisition/analysis, human–machine interface (HMI), and optimization/control. An illustration of a hybrid PV–battery system is shown in Figure 4. According to the forecasting results of the PV generation, load consumption, and the acquired energy market prices, the EMS can schedule and optimize the system operation to satisfy the technical constraints.

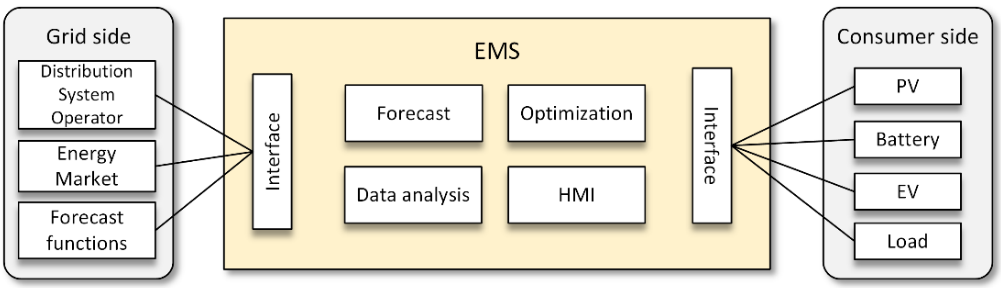

Figure 4. An illustration of a hybrid PV–battery system.

2.1. Objectives and Constraints

The energy management strategies for HPVBS can have different objectives. These objectives are based on user comforts and preferences, installed equipment, regulations and tariff, generation and consumption, etc. In state-of—the-art research, the variables regulated by the EMS are expanded from the adjustable power supply to the demand side management, and the control objectives are expanded from economics to the environment [19]. In this regard, Figure 5 shows different types of optimization objectives, which can be briefly divided into four categories: capital costs and profits, energy storage costs, environmental costs, and other objectives. Among them, the capital costs/profits consider the initial investment, energy costs (buying/selling energy), maintenance and operation costs (e.g., start-up/shut-down costs), allocation cost, total costs, annual costs, etc. Energy storage costs include the costs during the charging/discharging periods, storage degradation costs, and annual levelized battery costs. Environment costs are about carbon and pollution emission, and penalties for emissions or subsidies for emission reduction. There are some other miscellaneous objectives, which are hard to categorize, including consumers' comfort/satisfaction, reliability, load-shedding costs, demand response costs, etc.

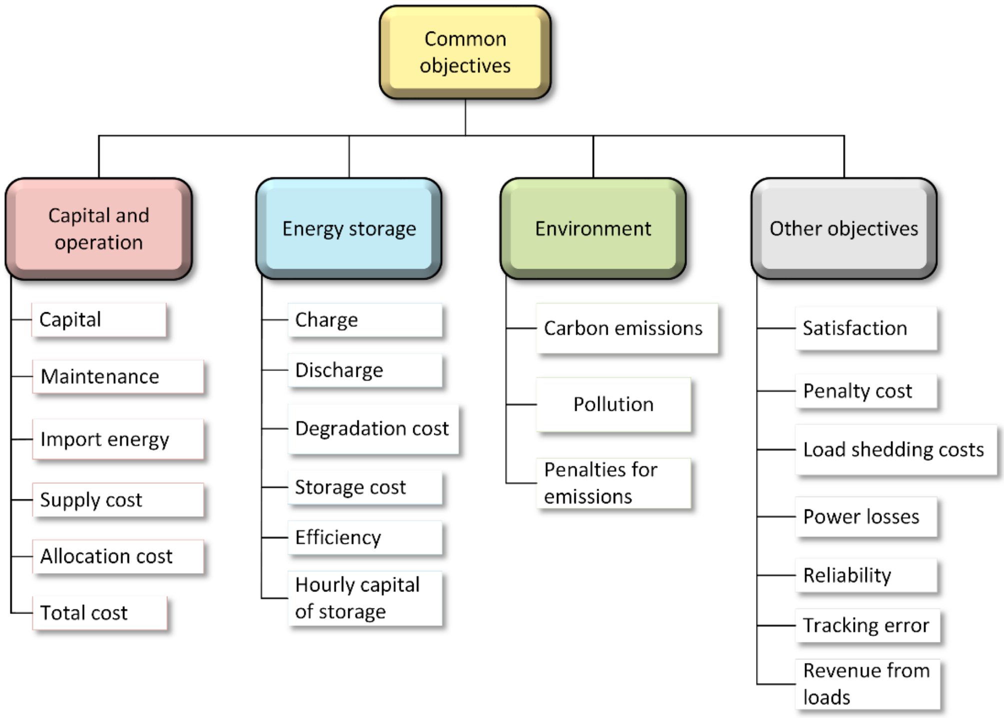

Figure 5. Different types of objectives for HPVBS.

In order to achieve multiple objectives and obtain the optimal trade-off between competing objectives, different multi-objective optimization strategies are proposed [18–61]. In [21], the authors create a multiple-objective function to minimize the fuel, maintenance, and start-up costs. Houshmand et al. [22] use a multi-objective to minimize the energy costs and maximize the battery lifetime. In [18], a smart schedule is conducted to minimize energy costs and improve the self-consumption of the PV system, which maximizes the economy of the household power system and improves the power flexibility. Although the above research considered the economic benefits of microgrid operation, they lack the analysis of its environmental benefits. In this context, many scholars studied energy management optimization strategies considering both economic and environmental benefits. The work in [37] sets the operation cost and emissions reduction as optimization objectives, constantly adjusting the weight coefficients of the two objectives, and analyses the impact of different weights on the economic and environmental benefits of the microgrid. The authors of [56] propose a microgrid dispatching strategy for a hybrid system consisting of PV arrays, a wind turbine, a battery, and a diesel generator. By optimizing the system operation and power flow, the operation cost and carbon emissions can be minimized simultaneously. In [38], a novel home energy management system is proposed, where peak power smoothing and carbon emissions are considered. By using wireless communication technologies, different components in this system can quickly coordinate with each other and respond according to the demand, and carbon emissions can be reduced greatly. Furthermore, some scholars also consider the system's reliability and users' comfort and satisfaction. In [57], a techno-economical objective function is formed, which includes maximization of profits, self-consumption, and reliability. The proposed electricity market strategy and energy transaction method can dynamically dispatch power between the grid and each sub-grid, which improves energy profits and enhances system reliability. In [58], the authors study the impacts of the proposed energy management strategy on the reliability of distribution networks when considering customers' satisfaction. The results show that the proposed strategy can maintain the system's reliability when conducting load shedding and curtailment. Shafie-Khah et al. [59] propose a home energy management strategy considering the uncertainty of EV charging behaviors and PV output power. The proposed strategy can reduce "response fatigue" in long-term periods and improve consumers' satisfaction.

When conducting energy management optimization, many constraints should be considered. In real applications, almost all optimization strategies for energy management include a series of constraints that describe the physical and economic limitations of the system. A system must work within these constraints to ensure an economic and stable operation. For example, as a hybrid PV system, PV arrays have upper power limits to generate solar energy, and batteries or other energy storage devices have state of charge (SOC) limits and current rate limits for charging/discharging. In addition, some loads cannot be shifted or cut down, which forms the demand constraints. Operational constraints are used for ramp-rate limits, power balance, and shut-down and start-up limits. Converters in the HPVBS also have power limitations, which means only a certain amount of power can be fed into the grid and the energy storage system. When the diesel generators are integrated, carbon emissions can be a constraint, too. Table 1 presents the commonly used constraints related to the PV and battery systems.

Table 1. Summary of commonly used constraints.

Ref.	Generation	Demand	Storage	Operation	Price	Emissions
[20]	√		√			
[60]				√		√
[61]	√	√	√			√
[62]	√		√	√	√	√
[63]		√	√	√		
[64]			√	√	√	√
[65]		√		√	√	
[66]		√		√		
[67]	√	√	√		√	
[68]	√	√	√			

2.2. *Solution Approaches to Energy Management Problem*

To achieve optimal operation of HPVBS, various solution approaches have been used to solve energy management problems. Figure 6 presents the commonly used optimization approaches, which are discussed below.

Linear programming and non-linear programming are classical methods to solve static optimization problems. When the constraints are linear equations or inequations, linear programming approaches can solve the maximum or minimum value of the linear objective function. Non-linear programming should be applied when there are one or more non-linear functions in the objective function or constraint conditions. In this regard, [69] proposes a two-stage resilient energy management strategy, where the first stage concentrates on the forecast and the second stage is about the flexible operation. Linear programming is used to solve this energy management problem and the results show that the proposed strategy can tackle extreme weather conditions without increasing the system capacity. In [70], the authors model and design modular energy management for the hybrid PV–wind–battery–grid system. Considering the on/off state of the energy storage unit, the energy management optimization is seen as a mixed integer linear programming problem. Through the hierarchical control structure, the hybrid system can work in different modes with avoiding damage to the battery; meanwhile, the operation costs are minimized, and self-consumption is promoted. In [71], a complex mixed non-linear integer model is proposed in a residential scenario. The optimization approach, which consists of particle swarm optimization (PSO) and sequential quadratic programming (SQP), is used to solve this non-deterministic polynomial-time hard problem. The results show that the proposed hybrid algorithm is more effective to search for the global optimum considering the demand response function.

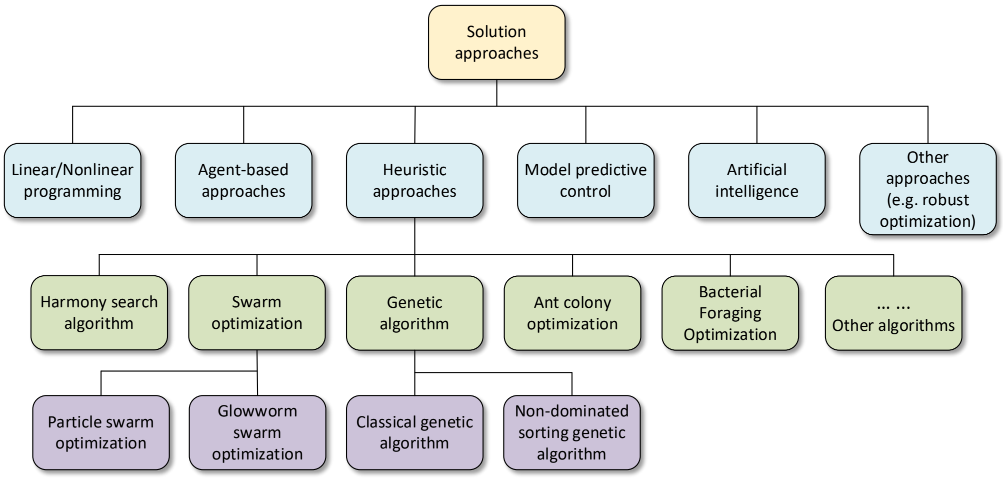

Figure 6. Commonly used solution approaches.

Heuristic approaches are defined as: an algorithm based on intuition or experience that provides a feasible solution to each instance of the combinatorial optimization problem to be solved at an acceptable cost (computing time and space), and the deviation degree between the feasible solution and the optimal solution is generally unpredictable. Many heuristic algorithms have been developed, and the commonly used heuristic approaches include genetic algorithm (GA), ant colony optimization algorithm, swarm optimization algorithm, etc. In [72], PSO is adopted to solve a Pareto energy management optimization problem. Considering that lower utilization of a battery can decrease battery health degradation yet increase energy consumption, the PSO algorithm is used to compromise the weight coefficient. The results show the proposed strategy can greatly reduce the battery lifetime degradation without increasing the energy consumption much. The work in [73] predicts photovoltaic output power and optimizes the weights and thresholds of neural network using GA to obtain photovoltaic power prediction output. This method can avoid local optimal values and has higher prediction accuracy than traditional neural network algorithms, hence, improving the economic operation and efficiency of the energy management strategy. In [74], based on a standalone renewable energy-based system in India, the model of each component (e.g., the total cost, output power, and battery SOC) is established. Taking the continuity of load demand as the objective function, the ant colony algorithm is used to solve the problem, and the optimal capacity configuration of photovoltaic and energy storage equipment is obtained.

Agent-based approaches can obtain information individually and make independent decisions according to the information. Through negotiation among multiple agents, the agent cooperates to complete the overall task to achieve global optimization. The authors in [75] propose a multi-agent-based management structure, where each component can communicate with each other. By using an adaptive multi-input and single-out fuzzy controller to dynamically regulate the control parameters, the generation cost of the system can be minimized. In [76], a three-layer multi-agent architecture is proposed, which includes three mechanisms: day-ahead planning, day rolling, and real-time scheduling. The whole system realizes the coordinated operation of microgrids through cooperation between time scales.

Model predictive control (MPC) is a rolling horizon optimization method, which is robust to disturbances from outside the system. Tobajas et al. propose a stochastic MPC optimization strategy in [77] to control the hybrid energy storage system by considering the two operating modes of standalone and grid-connected modes. Through the power complementation of each subsystem, the battery degradation can be minimized, and the energy purchase cost is reduced. In [78], a SOC-based charging scheme is proposed to control the battery and smooth the PV power fluctuation. In islanded mode, voltage MPC is applied to control the interlinking converter to stabilize the voltage. In grid-connected mode, power MPC is applied to control the grid-feeding power to provide grid support.

Artificial intelligence approaches are increasingly used to predict PV and wind generation, and load consumption due to their capacity of handling massive data. Traditional strategies rely on the accuracy of the day-ahead forecast, which may lead to the low economy of distributed renewable energy (DRE) systems [19]. Shimotakahara et al. [79] propose a coordinated resource allocation method between devices based on the multi-agent principle. A Q-learning-based algorithm is introduced to optimize the long-term communication process, which reduces the communication pressure and improves the quality and accuracy, hence, resulting in a reduction in power oscillations in the demand response. In [80], an artificial neural network (ANN) controller is employed to perform the energy management strategy, and the cooperation among different sources and loads is based on a multiple-agent system. Through real-time energy dispatch, the power source can operate in MPPT mode, which maintains the power quality of grid-feeding power and improves the utilization of renewable energy.

There are also some other approaches to handle the energy management problems. In [81], the game theory approach is used for demand response programs with a microgrid. Applying the game theory approach, demand response is implemented by scheduling the shiftable loads, which greatly reduces the operation costs, and the technical and security constraints can be satisfied as well. A robust optimization method is evaluated in [82] for a grid-connected PV–wind–battery system, where the uncertainty of the pool market price challenges the energy dispatch and leads to increases in procurement costs. A robust optimization technique can reduce the effects of uncertainty on decision-making, hence, reducing the purchasing cost from the grid.

3. Comparative study of Different EMS Strategies in Real Applications

An EMS strategy is essential in residential applications because consumers are very sensitive to operations costs. In this section, different EMS strategies are compared from different perspectives based on a real PV–battery grid-connected commercial product.

3.1. Data Profiles

Figure 7 shows the data profiles for the PV–battery grid-connected system. In Figure 7a, the ambient temperature and solar irradiance are represented by a blue curve and orange curve, respectively. These data are recorded for a full year with a one-minute resolution in Aalborg, Denmark, located at 57° N, 9° E. The load profile of a typical Danish household is shown in Figure 7b, whose annual electricity consumption is about 3 MWh. Figure 7c,d are the spot price of west Denmark (DK1) in 2020 and the first half year of 2022 [83]. The data of load and spot prices are based on one-hour resolution.

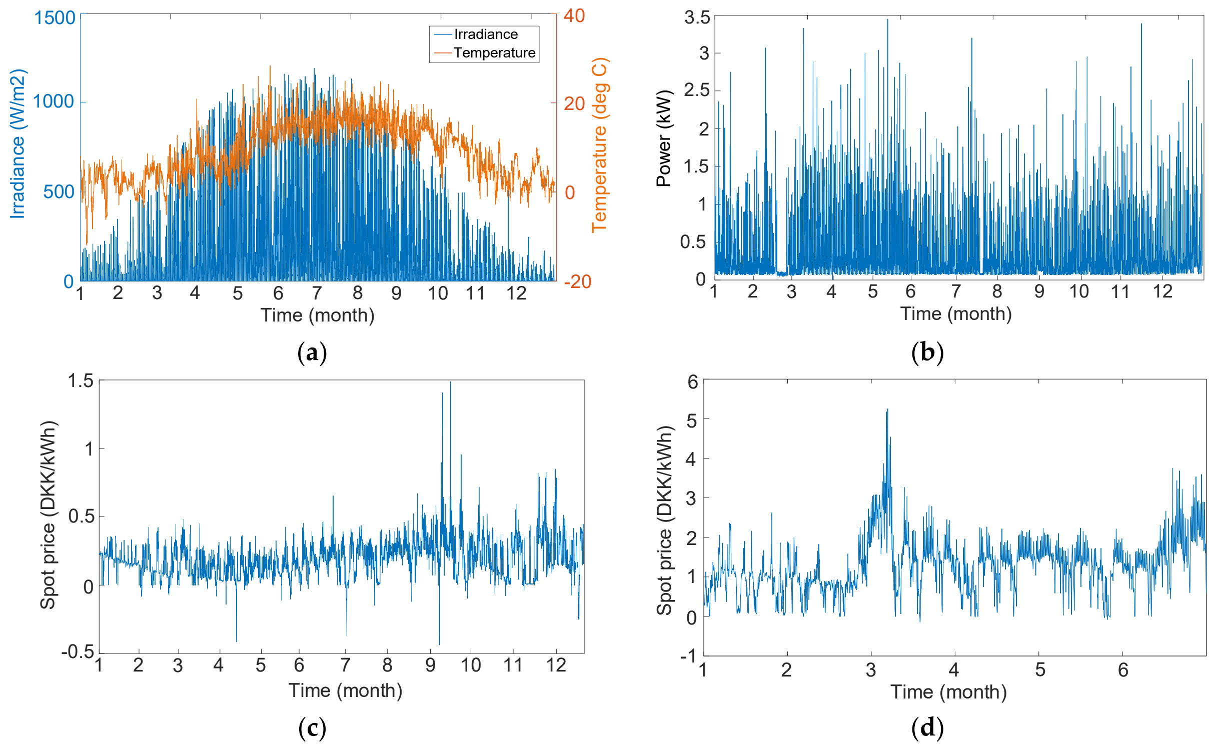

Figure 7. Data profiles: (**a**) PV data; (**b**) load data; (**c**) price data in 2020; (**d**) price data in 2022.

The PV–battery system is based on Huawei LUNA2000-(5-30)-S0 [84]. The system structure is shown in Figure 3, and the system parameters are shown in Table 2 below.

Table 2. Objectives for minimization of environmental costs.

Parameter	Value	Unit
PV capacity	5	kWp
Battery capacity	5	kWh
Inverter capacity	5.5	kVA
Max battery power	5	kW
Efficiency of converters	95	%
Upper limit of battery SOC	90	%
Lower limit of battery SOC	10	%

3.2. Different Strategies

In order to compare and illustrate the impacts of different energy management strategies on the system operation costs, self-consumption, and self-sufficiency, two simple cases (with PV only and without PV or battery) are also taken into account. Self-consumption is defined as the ratio between consumed PV energy (including energy directly used by loads and charged to the battery) and the total PV generation, which describes the utilization rate of the PV energy. Self-sufficiency is defined as the ratio between the energy supplied by the PV–battery system (including energy directly used by loads and discharged from the battery) and the load demand, which is used to qualify the energy independence of the PV system. The degree of self-consumption (*sc*) and self-sufficiency (*ss*) are represented as follows:

$$sc = \frac{E_{DC} + E_{BC}}{E_{PV}} \tag{1}$$

$$ss = \frac{E_{DC} + E_{BD}}{E_L} \quad (2)$$

where E_{PV} and E_L are the produced solar energy and total demand, respectively. E_{DC} is the directly consumed energy by the load. E_{BC} and E_{BD} are battery charged and discharged energy, respectively.

3.2.1. Strategy 1: Maximum Self-Consumption

In this mode, the strategy aims to maximize the self-consumption of the HPVBS. The flowchart of the maximum self-consumption is shown in Figure 8, and the principle can be described as follows:

- When the sunlight is sufficient, the PV energy first covers the load demand, then charges the battery, and feeds into the grid lastly;
- When the sunlight is insufficient, the PV energy first flows to the load, and then the battery discharges. The power shortage (if any) will mean electricity is purchased from the grid lastly.

Figure 9 shows several scenarios when the HPVBS conducts the maximum self-consumption strategy.

(a) When the sunlight is sufficient, the PV output power is 8 kW, and the load demand is 4 kW, the remaining power flows to the battery;
(b) When the PV output power is 8 kW, and the load demand becomes 2 kW, the battery is charged to the maximum, and the remaining power flows to the grid;
(c) When the sunlight becomes weak, the PV output power is 3 kW and load demand is 4 kW, the battery discharges to cover the shortage;
(d) When there is no sunlight at night and the load demand is 8 kW, the battery discharges at its maximum output. The power shortage is covered by the grid.

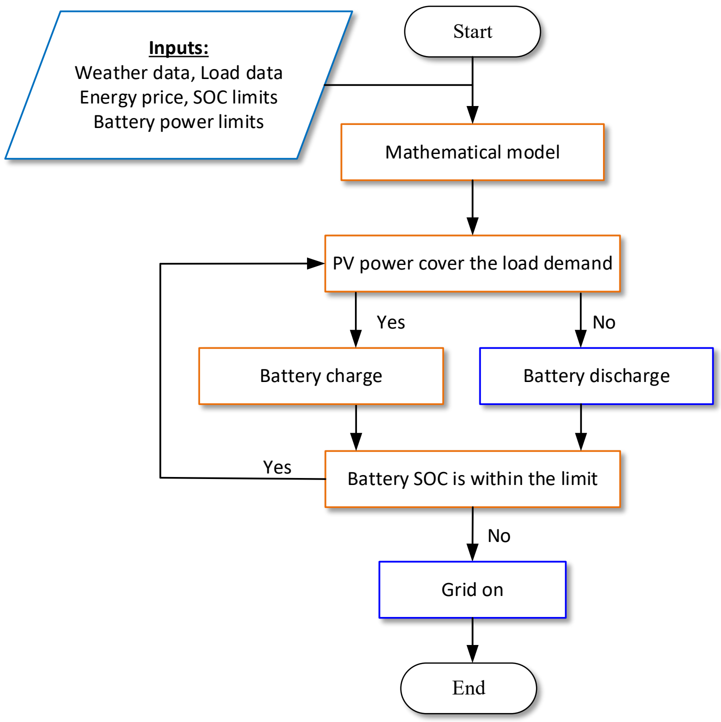

Figure 8. Flowchart of maximum self-consumption strategy.

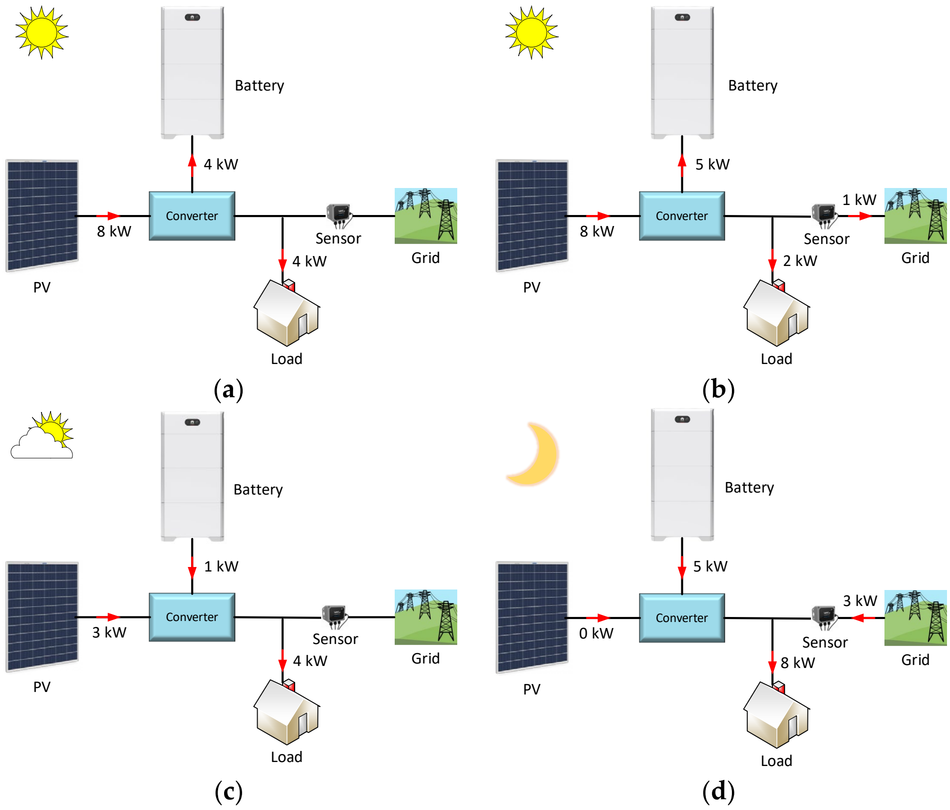

Figure 9. Examples of the maximum self-consumption strategy.

3.2.2. Strategy 2: Time of Use (TOU)

In this mode, the charge period and discharge period should be set manually or automatically. There can be more than one charge/discharge segment across one day, and each segment is hour-based. The flowchart of this strategy is shown in Figure 10, and the principle of this mode is described as:

- The battery does not discharge in the charge period, and does not charge in the discharge period. Each time segment should be set as charge mode or discharge mode;
- During the charge period, the battery is charged to a certain SOC. The grid provides power to cover the load demand and charge the battery;
- During the discharge period, PV and battery energy are used to cover the load demand. When PV energy is insufficient or the battery is fully discharged, the grid provides extra power to cover the load.

Consider that the spot price has two valleys, at night and in the afternoon. It is assumed that 0:00–6:00 and 12:01–18:00 are charge periods, and 6:01–12:00 and 18:01–24:00 are discharge periods.

Figure 11 presents several examples of this strategy:

(a) During 0:00–6:00 (i.e., charge period 1), the grid provides power to cover the load demand and charges the battery at half-rate power of 2.5 kW;
(b) During 6:01–12:00 (i.e., discharge period 1), the PV output power is 5 kW, and load demand is 4 kW, the remaining power of 1 kW feeds into the grid;
(c) During 12:01–18:00 (i.e., charge period 2), the PV output power is 5 kW, and load demand is 3 kW, the excessive PV power and the grid together charge the battery at half-rate power of 2.5 kW;
(d) During 18:01–24:00 (i.e., discharge period 2), the PV output power is 0 kW and the load demand is 4 kW, the battery discharges to cover the power shortage.

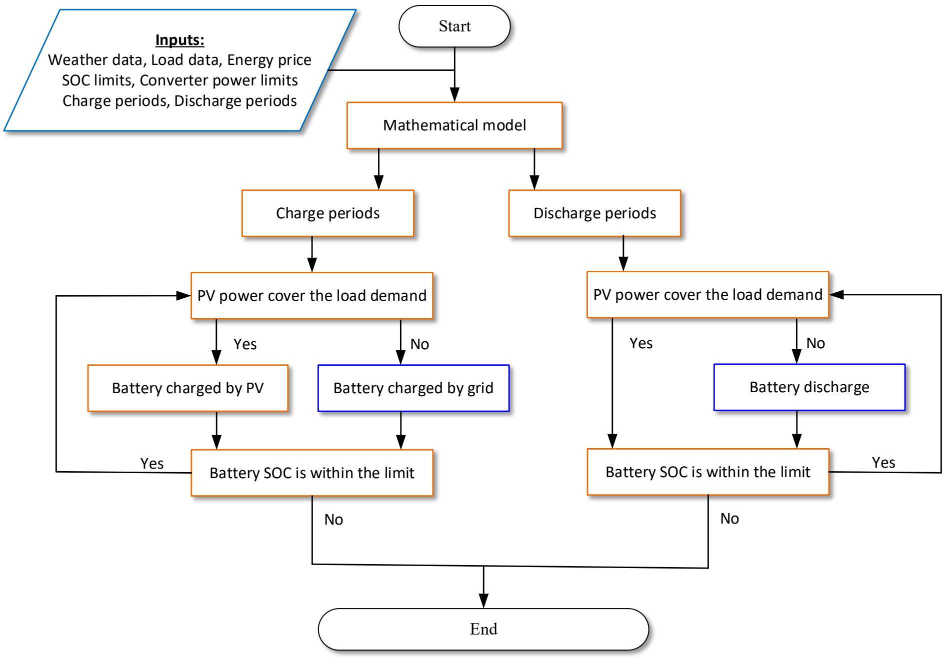

Figure 10. Flowchart of time of use strategy.

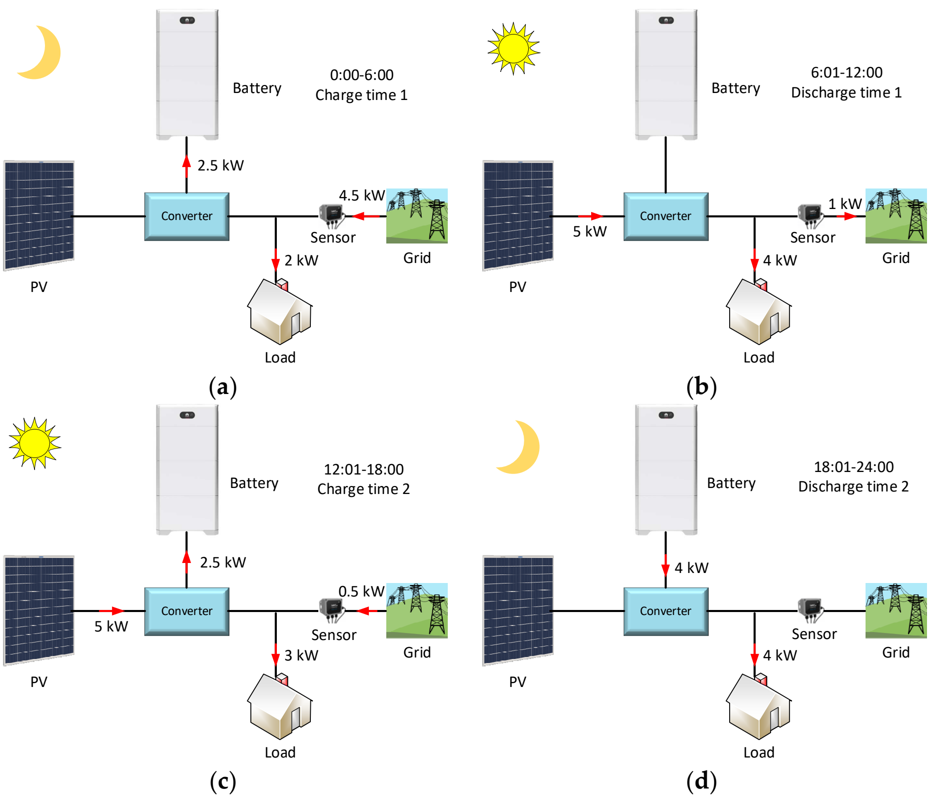

Figure 11. Examples of the time of use strategy.

3.2.3. Strategy 3: Fully Fed to Grid

This mode maximizes the PV energy for grid connection, and the flowchart is shown in Figure 12. The principle can be summarized as:

- When the generated PV energy is greater than the maximum capacity of the inverter, the battery is charged to store extra energy;

- When the generated PV energy is less than the maximum capacity of the inverter, the battery discharges to maximize the output energy of the inverter.

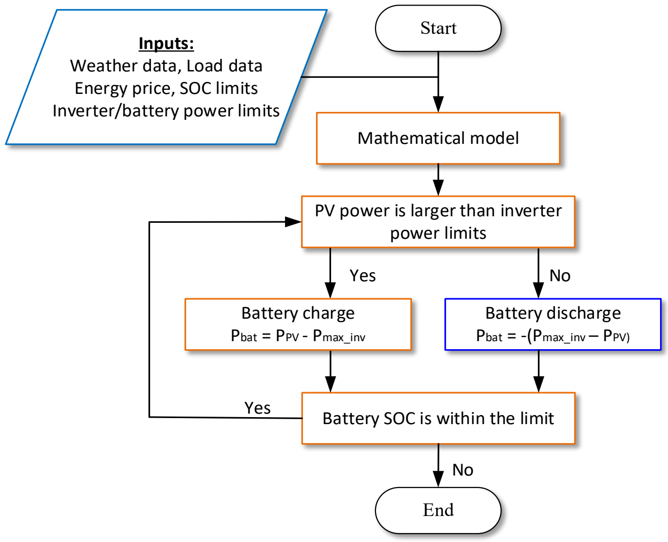

Figure 12. Flowchart of fully fed to grid strategy.

Figure 13 shows several examples of this mode:

(a) When the PV output power is 8 kW, the inverter outputs power at its maximum capacity of 5.5 kW, and the remaining power charges the battery;

(b) When the sunlight becomes weak and the PV output power is 3 kW, the battery discharges at the power of 2.5 kW to maximize the inverter output.

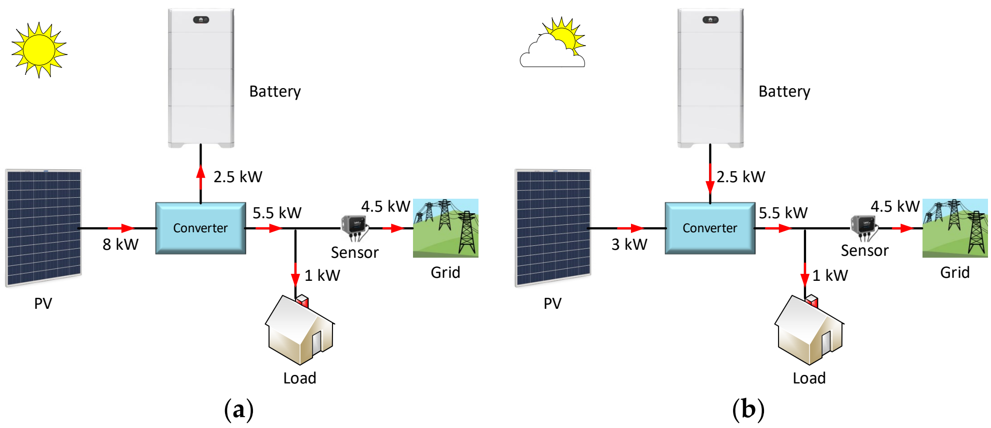

Figure 13. Examples of the fully fed to the grid strategy.

3.3. Results and Discussion

In Denmark, consumers can sell energy to the grid with "spot price" and buy energy with "spot price + tax + value added tax (VAT)". It is assumed that the tax is 1.5 DKK/kWh, and the VAT is 25%. The cost can be calculated by Equations (3) and (4), and the degree of self-consumption and self-sufficiency are calculated from Equations (1) and (2). Table 3 presents the results of different strategies based on the spot price in 2020.

$$Cost = \sum_{i=1}^{8760} \left[1.25 \left(P_{Load}^{i} - P_{PV}^{i} \right) \cdot \left(S_{p}^{i} + 1.5 \right) \cdot [1 - Q(i)] - \left(P_{PV}^{i} - P_{Load}^{i} \right) \cdot S_{p}^{i} \cdot Q(i) \right] \tag{3}$$

$$Q(i) = \begin{cases} 1 & P_{PV}^i \geq P_{Load}^i \\ 0 & P_{PV}^i < P_{Load}^i \end{cases} \tag{4}$$

In Equation (3), P_{PV}^i, P_{Load}^i, and S_p^i are the PV power, load power, and spot price in ith hour, respectively. $Q(i)$ is a binary state value, which is determined by the PV and load power in Equation (4). When PV power is larger than or equal to the load power, $Q(i)$ is 1, otherwise $Q(i)$ is 0.

Table 3. Simulation results of different strategies based on spot price in 2020.

Strategy		Cost (DKK)	Self-Consumption (%)	Self-Sufficiency (%)
Without PV or battery		6077	0	0
PV only		3449	14	24
With PV and battery	Maximum self-consumption	1560	34	58
	TOU	4462	25	43
	Fully fed to grid	3447	14	24

Energy prices in Denmark have risen greatly since the beginning of 2022 due to wars and the following energy crisis. In order to demonstrate the impacts of spot price on the operation cost, the spot price of the first half year of 2022 is taken into account. It is noted that weather and load profiles remain the same, which means the weather conditions and consumption patterns do not influence the results. Resulting comparisons of different strategies are presented in Table 4.

Table 4. Simulation results of different strategies based on spot price in 2022.

Strategy		Cost (DKK)	Self-Consumption (%)	Self-Sufficiency (%)
Without PV or battery		5446	0	0
PV only		1653	15	28
With PV and battery	Maximum self-consumption	615	32	62
	TOU	2417	24	46
	Fully fed to grid	1606	15	28

From results in Table 3, it can be seen that:

1. PV arrays can greatly reduce the cost of purchased energy from the grid, and improve the degree of self-consumption and self-sufficiency;
2. When the battery is installed, the energy costs can be further reduced to some extent, and the degree of self-consumption and self-sufficiency can be also improved;
3. Among the three strategies (i.e., maximum self-consumption, TOU, fully fed to the grid), maximum self-consumption can achieve the lowest cost, and highest degree of self-consumption and self-sufficiency, which means the household consumer can benefit from the economic operation. TOU has the highest cost, because the battery is mostly charged by the grid in charge periods, which increases the energy exchange between HPVBS and the grid, hence, increasing the cost and reducing the self-consumption/self-sufficiency. As for the strategy of fully fed to the grid, the results are similar to the case when only PV is equipped. This is determined by its principle, which requires the battery to discharge to maximize the inverter output. In this case, the battery is not fully utilized and keeps a low SOC in most time.

The results in Table 4 have the same trend with the results in Table 3. Comparing the results in Tables 3 and 4, it can be seen that:

1. When there are no PV or battery, the energy cost in the first half of the year of 2022 is close to the annual cost in 2020, due to the surging energy prices;
2. The degree of self-consumption and self-sufficiency in Table 3 is slightly different from that in Table 4, which means the PV generation and load consumption in the first half of the year are slightly different with that in later half of the year;
3. The energy costs of the three strategies in the first half of the year of 2022 is less than half of that in 2020. The consumption in the first half of the year is more than that in later half of the year, which means that PV–battery system can obtain more profits in high energy price cases.

Therefore, from the above results and points, it can be concluded that residential consumers can obtain more profits and energy independence with the installed hybrid PV and battery system. However, these strategies have quite different economic performance in the conducted household case, which means these strategies should be applied to different scenarios. Specifically, the maximum self-consumption strategy applies to the areas where the electricity price is high, and the higher the spot price, the more economical the scenario is. The TOU strategy applies to the areas where the peak price differs a lot with off-peak price, because in this mode, the grid charges the battery during off-peak price periods and discharges during peak price periods, which improves the energy exchange between HPVBS and the grid, and only a large price difference can cover the costs of charged energy and battery degradation. The strategy of fully fed to grid applies to the grid-connected scenarios where the battery needs to support the grid and works as a backup. In this case, the battery operates in a low SOC. In order to improve the utilization of the battery, the sunlight should be sufficient to charge the battery, which means this strategy is more economic in dry and low latitude areas.

4. Conclusions and Future Trends

An energy management system plays a vital role in reducing energy bills for consumers and reduce carbon emissions in hybrid PV and battery systems. This paper presents a comprehensive review on the developed strategies for the PV–battery-based systems, including objectives, constraints, and solution approaches. Moreover, three energy management strategies are compared and discussed based on a real household profile regrading different criterion. Even if evaluated by a criterion, the performance of a strategy can be different considering the latitudes, weather profiles, and energy prices. Therefore, energy management should be optimized according to specific application. This study will be useful for several groups of people, including developers or engineers of products from industry, distribution networks engineers, and residential consumers, and has good prospects for engineering.

With the development of mathematic techniques and calculation capability, the energy management strategies can be improved from the following aspects:

1. Optimization objectives. Single-objective methods consider just one aspect, which may not obtain the comprehensive performance. Hence, the optimization strategies turn to multi-objective optimization;
2. Adaptability of algorithm. The single strategy or fixed pattern is difficult to apply to all optimization problems. For example, the variable solar radiation or the performance degradation of PV arrays due to aging effects requires promoting the adaptability of the algorithm;
3. Reliability of algorithm. The randomness and convergence of the algorithm often conflict with each other. In order to reduce the influence of uncertain factors and better optimize the results, an artificial guidance strategy can be added, which also improves the self-learning ability of the algorithm;
4. Accuracy of mathematical model. In some cases, real-time control has more flexibility and can obtain a better performance, but the differences between the mathematical model and the real dynamics may increase the control difficulty and impair the optimization performance.

For future work, we plan to propose new strategies based on the real data and applications, and then evaluate and compare their performance and cost-effectiveness with the existing strategies. It should be noted that some existing strategies may not hold true due to the modelling assumptions and simplification. Thus, it is interesting and meaningful to compare and verify some of these strategies.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial neural network
DRE	Distributed renewable energy
EMS	Energy management system
ESS	Energy storage system
EV	Electric vehicle
GA	Genetic algorithm
HMI	Human–machine interface
HPVBS	Hybrid photovoltaic and battery system
IMC	International Electrotechnical Commission
MPC	Model predictive control
MPPT	Maximum power point tracking
PSO	Particle swarm optimization
PV	Photovoltaic
SQP	Sequential quadratic programming
SOC	State of charge
TOU	Time of use
VAT	Value added tax

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