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A review of data-driven smart building-integrated photovoltaic systems: Challenges and objectives

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ABSTRACT

The smart building-integrated photovoltaic (SBIPV) systems have become the important source of electricity in recent years. However, many sociological and engineering challenges caused by temporal and spatial changes on demand-side and supply-side remain. In this paper, the barriers and traditional data utilization of SBIPV system causing the above challenges are summarized. Data-driven SBIPV was firstly proposed, including four aspects: Data Sensing, Data Analysis, Data-driven Prediction, and Data-driven Optimization. Data sensing goes beyond the technical limitations of a single measurement and can build the bridge between demand- and supply-side. Then, the demand-side response and electricity changes in supply-side under various environmental changes will also become clear by Data Analysis. Data-driven Prediction of load and electricity supply for the SBIPV is the basis of energy management. Data-driven Optimization is the combination of demand-side trading and disturbed system optimization in the field of engineering and sociology. Furthermore, the perspective of data-driven SBIPV, technologies and models, including all four data-driven features to make automated operational decisions on demand- and supply-side are also explored. The data -driven SBIPV system requiring much greater policy ambition and more effort from both supply and demand side, especially in the areas of data integration and the mitigation of SBIPV system.

1. Introduction

The energy system is changing from traditional fixed producers to mobile and distributed providers of high-proportion renewable energy supply. The photovoltaic (PV) equipment plays a critical role in the current transitional period and will contribute to the ongoing energy transition [1]. The PV system saves conventional energy and obviates the electricity generation by peaking power plant and the emissions from diesel generators [2]. Although the largest share of PV applications is held by utility-scale systems [3], which account for almost 62% of the total installed capacity, building-integrated photovoltaic systems (BIPV) have been identified as one of the main tracks for extensive market penetration of PV and the most promising applications [4,5].

Compared with the utility-scale PV systems, BIPV is gaining popularity due to the lack of wide space and the large availability of roof [6]. Space flexibility makes BIPV can be installed on the building skin, enabling the combination of electricity generation and other functions of the building materials. Potential room for growth means product technology can be merged with BIPV technology for better performance [7]. However, BIPV also faces challenges from the supply-side and the demand-side [8]. In demend side, the electricity demand response and

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Nomenclature

Abbreviations

PV	Photovoltaic
BIPV	Building-integrated photovoltaic
SBIPV	Smart building-integrated photovoltaic
PVT	Photovoltaic thermal
GIS	Geographic information system
P2P	Peer-to-peer

Abbreviations

CNN	Convolutional neural network
ANN	Artificial Neural Networks
LSTM	Long Short-term Memory Networks
BIPVT	Building-integrated photovoltaic thermal
MLP	Multilayer Perceptron
SVM	Support Vector Machine

management allow people to choose the time period and flexibly mode of electricity, so the competitiveness of BIPV systems needs to be further improved [9]. On supply-side, the variability of sunlight and climate difference bring more unprediction for PV power output [10].

The data-driven smart Building-integrated photovoltaic (SBIPV) systems is a concept we proposed which could meet future needs on both demand and supply-side. There have been many papers presented the recent progress of BIPV systems. However, many of them only focused on the development on the supply-side [11] and ignored the demand-side. Yu et al. [12] summarized the changes in optical, thermal, and power generation efficiency of the BIPV systems; however, the impact of demand-side data was not investigated. The possibility of further analysis of data obtained from equipment such as inverters was verified in the review of Alim [13], but the changes in demand-side data were not deeply analyzed. The progress of BIPV and the factors affecting energy system prediction were discussed by Singh et al. [14], but the demand-side data was still not taken into account.

Most reviews mentioned above proved the flexibility and resilience of the BIPV. However, in addition to the lack of demand-side data considerations, the increasing impact of explosive full-link data was also not explored, which is exactly the main driving force for the transformation of future energy systems. Debbarma et al. [15] made a detailed summary of buildings integrated with PV and confirmed the superiority of the BIPV systems, but the large-scale data brought by the BIPV promotion was not considered. Baljit et al. [16] reviewed the design, energy performance, and cost of BIPV for large-scale application, but no summary was made for data mining. A blueprint of the future BIPV was also presented in the review of Baljit [17], but the impact of the various data was not taken into consideration. Biyik [18] confirmed the possibility of further improvement in power generation of the BIPV systems, but the coupling data-driven optimization of BIPV and the energy system was always absent [19,20].

All these issues lead to difficulties and challenges in effectively achieving the utilization of the full data link in BIPV systems [21,22]. To address these issues, this paper aims to effectively reviewed the technology progress in SBIPV system from the view of data, and try to discuss the data-driven method beyond the traditional obstcales of BIPV system. The paper first briefly summarizes current data utilization situations on the BIPV systems and the barriers that prevent from BIPV systems to data-driven SBIPV system in supply- and demand-side. Afterwards, four aspects of data-driven smart building-integrated photovoltaic systems are firstly presented, including both supply- and demand-side. The data-driven SBIPV systems was identified should have the following four characteristics: Data Sensing, Data Analysis, Data-driven Prediction, and Data-driven Optimization. These four features can be described in detail as follows:

- Data sensing: collection of traditional supply-side data, including weather, roof angel, etc., and the demand-side data, involving daily demand, price, etc., also show massive growth. These directly measurable supply and demand data constitute the most basic feature of SBIPV.
- Data analysis: analyzation of data obtained from direct or indirect measurement of data Sensing constitutes the second feature of SBIPV. Data Analysis of SBIPV can not only mine the residential behaviors in demand-side but also reflect different shading and various electricity consumption in supply-side.
- Data-driven prediction: The information obtained from the data analysis and data sensing can be used to predict the future trend of the supply-side and the energy variation of demand-side. Data-driven prediction is affected by long-term and short-term output forecasts on the supply-side and load changes on the demand-side [23].
- Data-driven optimization: The optimization puts forward higher requirements for policy guiding, distributed energy system design, and peer-to-peer (P2P) trading. The SBIPV systems will be able to effectively connect the supply-side and demand-side as an interface through data-driven optimization.

After this, the perspectives of data-driven SBIPV systems including the important research directions and solutions for above dilemma are proposed. The structure diagram of data-driven SBIPV systems is shown in Fig. 1.

In the next parts of this paper, Section 2 represents the data utilization and barriers of traditional BIPV systems. Sections 3-6 show four features of data-driven SBIPV systems, including data sensing, data analysis, data-driven prediction, and data-driven optimization. All four aspects are explained based on supply-side and demand-side. Section 7 draws out the perspective of data-driven SBIPV systems. All features and views of data-driven SBIPV systems are summeraized in Section 8.

2. Traditional data utilization and barriers of BIPV systems

2.1. Traditional data utilization

The number of BIPV systems in the energy girds is growing at an unprecedented speed, which bring various data [24]. General approach to achieve building integrated photovoltaic systems and implementation barriers of current method has been reviewed in many papers [25,26]. From data collection [27], processing [28], to optimization [29], they all face huge challenges. Options for current data utilization can be classified into supply-side and demand-side. In supply-side, data are always collected through meteorological instruments, temperature recorders, inverters, and other equipment to monitor photovoltaic equipment [30]. Various sensors make data collection not only fragmented, but often in different formats and lacking effective management. Besides, the availability of meteorological data and the lack of sensing data limit the accuracy and application range of related prediction methods [31]. A considerable amount of useful data is discarded due to lack of effective planning and policy guidance, which could have been used to further improve service quality and power supply.

In demand-side, the data collection is usually done by the residential meter. The data collected by sensors inside the buildings are usually less concerned. Besides, most of the demand-side electricity meters usually have data loss and missing, which makes the availability of collected data is poor [32]. The way of analysis the collected data is relatively direct and can be devide as: monitoring the current status of BIPV systems to ensure the safety and reliablity [33] and making predictions about the future trends of BIPV systems. Many AI method is introduced for data utilization including CNNs [34], Long Short-term Memory (LSTM) Networks [35], Gated Recurrent Unit (GRU) [36], Artificial

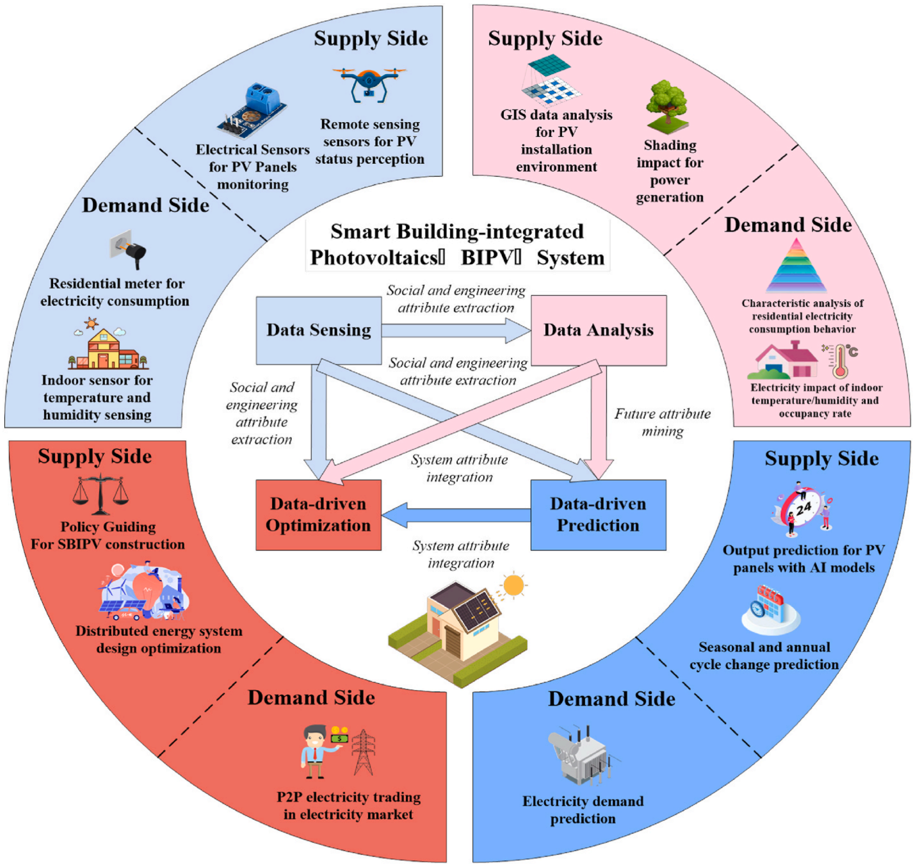

Fig. 1. Structure diagram of data-driven SBIPV systems.

Neural Networks (ANNs) [37], Multilayer Perceptron (MLP) [38], Support Vector Machine (SVM) [39], etc. Data analysis that takes into account the residential comfort and electricity economy is very rare, and traditional data analysis is difficult to use the interaction between users and the grid to promote photovoltaic consumption [40].

Except for the weak data sensing and analysis, global prediction and optimization from the modules level, PV equipment level, to BIPV systems level is also an important aspect to make full use of the full-link data and minimize the irreversible loss [41]. However, most optimization methods to improve system efficiency always emphasize the data on single supply-side and data-driven BIPV flexibility services are still lacking.

2.2. Barriers of current BIPV systems

Current status and barriers of BIPV systems has been effectively explained in many papers [42], but none of analysis has been made from the view of data. For supply-side of BIPV systems, the Geographic Information Systems (GIS) data for early evaluation, grid-side data during operation monitoring, post-installation maintenance data, and other data usuful for BIPV systems have not effectively collected. For demand-side, internal sensor data including indoor temperature, house occupancy and other data that can effectively coordinate building flexibility are absent. Besides, the lack of effective analysis and limitations of prediction and optimization methods make the data-driven SBIPV systems is hard to choose the best technical option. Lack and discard of data; poor quality of data analysis; limitations of prediction; variability of optimization. These disadvantages made the realization of the data-driven SBIPV systems at the current stage is still a big challenge. The comparsion of BIPV/Photovoltaic Thermal (PVT) reviews in recent 10 years has been shown in Table 1.

The barriers that prevent from the promption of SBIPV can be summarized as: (1) There is lack of wider collection and sensing data for the supply-side and demand-side when BIPV systems is concerned. (2) Limitations of data analysis between the sensing data and the user demand on time, space and energy grade. (3) Mismatches between the load and source prediction at various time scales limit the potential of BIPV systems. (4) Geographical obstruction of microgrid, lack of guiding policy and communication barriers of combinatorial optimization.

The detailed solutions of these barriers and the corresponding features of data-driven SBIPV systems will be presented in section 3-6. The solutions can be expressed as four aspects as following: (1) Data Sensing: collection of both supply-side data and demand-side data, especially advanced Sensors for PV panels, GIS data, smart residential electricity meters, and indoor sensors data. (2) Data Analysis: analyzation of data obtained from direct or indirect measurement of data Sensing, including shading impact, roof area, electricity consumption behavior, and indoor information (3) Data-driven Prediction: long-term and short-term output forecasts on the supply-side and load changes on the demand-side. (4) Data-driven Optimization: effective policy guiding, better distributed energy system design, and P2P trading.

3. Data sensing of SBIPV systems

Achieving effective sensing of data will be the first step to effectively play the role of the data-driven SBIPV systems [58]. For future perspectives of SBIPV systems, the data sensing is the cornerstone, further analyzation and effective prediction of large-scale supply-side and demand-side data will build a bridge for the coupling of various energy systems [59]. The data-driven optimization of the SBIPV systems will help realize an optimal solution for the demand and supply-side. On the supply-side, data sensing can mainly be achieved by data acquisition equipment; on the demand-side, the data sensing can reflect through smart meters and indoor sensors. The data sensing process in SBIPV

Table 1
The comparsion of BIPV/PVT reviews in recent 10 years.

Research/studies	Year	Main points	Supply-side		Demand-side	Full-link data
			Electricity	Heat		
Zhang et al. [43]	2012	(1) The global market potential of (PV) and (PV/T). (2) The main characteristics, current situation, research priorities, and difficulties/barriers. (3) The experimental/theoretical studies applied to PV/T. (4) The results and problems in each research method category.	✓	✓	×	×
Mellit et al. [44]	2014	(1) AI-based methods for MPPT. (2) Special attention on the cost, complexity, efficiency and possible realization. (3) Future trends and challenges of MPPTs into FPGA.	✓	×	×	×
Aste et al. [45]	2014	(1) PVT configurations and related performance parameters. (2) PVT was subdivided according to the main elements. (3) The major developments of BIPV systems.	✓	✓	✓	×
Baljit et al. [16]	2016	(1) BIPV/T technology optimization. (2) BIPVT was compared with BIPV in terms of design, energy performance and economy. (3) Different working fluids for BIPV/T on roofs/walls. (4) On-site installation examples according to climatic conditions.	✓	×	×	×
Agathokleous et al. [46]	2016	(1) The optimum air gap between for a BIPV system. (2) heat transfer analysis of double skin facades and air flow (3) Nu number in double skin facades and heat transfer coefficients.	✓	✓	×	×
Yang et al. [47]	2016	(1) Major developments, experimental and numerical studies of BIPV/T technology. (2) The research, development, application and current status of BIPV/T systems and modules.	✓	✓	×	×
Rajoria et al. [48]	2016	(1) BIPV systems was analyzed by heat load leveling. (2) Translucent BIPVT has higher efficiency.	✓	✓	×	×
Debbarma et al. [15]	2017	(1) Current applications of BIPV and BIPV-T technology. (2) BIPV and BIPVT systems discussion from thermal modeling, energy and exergy analysis. (3) The latest development on a global scale.	✓	✓	×	×
Biyik et al. [18]	2017	(1) A comprehensive review of BIPV in terms of power generation, nominal power, efficiency, types, and performance evaluation methods. (2) The feasibility of improving the efficiency of BIPV.	✓	×	×	×
Debbarma et al. [49]	2017	(1) Various technologies involved in BIPV and BIPVT and their functions. (2) BIPV and BIPVT device applications were analyzed in terms of cost and aesthetics. (3) The significant advantages and potential for BIPV.	✓	×	✓	×
Shukla et al. [2]	2017	(1) BIPV products and their market potential. (2) International standards and specifications for BIPV (3) The progress of BIPV materials. (4) A life cycle assessment of BIPV.	✓	×	×	×
Sultan et al. [50]	2018	(1) Photovoltaic/thermal energy (PV/T) technology progress and application. (2) Recent work in PV/T technology. (3) Various types of BIPV systems are described in performance, design, fabrication, simulation and experimental evaluation.	✓	✓	×	×
Alim et al. [13]	2019	(1) Australia is behind in the solar power race. (2) The typical energy payback period for solar panels is around 10–15 years. (3) Most of the energy was wasted due to low quality inverters. (4) The selection procedure should be followed to select a BIPV system. (5) Lower initial capital costs and increased public awareness were necessary.	✓	×	✓	×
Ravyts et al. [51]	2019	(1) A potential BIPV electrical architecture. (2) System-level standards for BIPV installations, providing a frame of reference for comparing electrical architectures. (3) Modularity is achieved and engineering costs are minimized.	✓	×	×	×
Agathokleous et al. [42]	2020	(1) Status of BIPV systems applications. (2) Technical barriers of BIPV. (3) Future perspectives and recommendations for BIPV systems promotion.	✓	×	✓	×
Ghosh et al. [17]	2020	(1) A comprehensive review of progress on BIPV. (2) Different possible photovoltaic applications. (3) Potential future BIPV applications.	✓	×	×	×
Sarkar et al. [20]	2020	(1) A brief overview of developments and recent trends in BIPV systems and their technologies. (2) The power-voltage (PV) characteristics of various BIPV products at different solar radiation values. (3) Replacing with BIPV photovoltaic array modules, architectural or residential components can reduce the cost.	✓	×	×	×
Yu et al. [12]	2021	(1) The development of BIPV windows and shading shutters. (2) The power generation, thermal properties, and optical properties of BIPV windows were discussed. (3) The development and performance of BIPV blinds.	✓	✓	×	×
Kuhn et al. [7]	2021	(1) A structured overview of BIPV technology design options. (2) The analysis of the German BIPV market. (3) Design options for complete electrical systems from sub-module level design parameters to building energy systems.	✓	×	✓	×
Yu et al. [52]	2021	(1) The design and performance of BIPVT systems. (2) BIPVT systems were devided according to thermal energy utilization and various design. (3) Power output, thermal performance, and effects on building loads.	✓	✓	✓	×
Rounis et al. [3]	2021	(1) Overview of PVT and BIPV systems (2) Wind-driven convection was simulated and measured. (3) Testing and modeling of BIPV systems.	✓	✓	×	×
Rajoria et al. [53]	2021		✓	✓	×	×

(continued on next page)

Table 1 (*continued*)

Research/studies	Year	Main points	Supply-side		Demand-side	Full-link data
			Electricity	Heat		
		(1) Progress of BIPVT systems was reviewed. (2) Technical developments, experimental and numerical studies, and parametric effects.				
Chinnaiyan et al. [19]	2021	(1) The application of phase change materials in BIPV system. (2) The reduction effect of the surface temperature of the photovoltaic system. (3) Passive methods employing phase change materials for BIPV.	✓	✓	×	×
Singh et al. [14]	2021	(1) Various factors that affect the design and performance of BIPV system applications, such as air gap, ventilation rate, and tilt angle of PV shading devices, etc. (2) The results of possible factors with the building location.	✓	×	×	×
Akram et al. [54]	2022	(1) Failure detection methods and recent advancements in BIPV. (2) Automatic or AI based methods, their implementation and applications are discussed.	✓	×	×	×
Nuria et al. [55]	2022	(1) The features of BIPV modules, a reference for BIPV manufacturers, and BIPV designers. (2) Optical properties of BIPV modules, such as light transmittance or color rendering	✓	×	×	×
Tamer et al. [56]	2022	(1) Current weather metrics as predictors of future weather metrics (2) Lifetime GWP and cost of energy (3) Current weather metrics as predictors of future weather metrics and energy generation/consumption	✓	×	×	×
Ghosh et al. [57]	2022	(1) Three different generations PV based fenestration integrated photovoltaics (FIPV) (2) Benign energy-generating components and passive energy-saving are both concomitantly possible using photovoltaic (PV) window fenestration	✓	×	×	×
This paper	2022	Traditional data utilization and barriers of BIPV systems. (1) Four features of data-driven SBIPV system: Data sensing; Data analysis; data-driven prediction; data-driven optimization. (2) Perspective of data-driven SBIPV systems.	✓	✓	✓	✓

systems is shown in Fig. 2.

3.1. Supply-side: sensors for PV panels and GIS

To collect more data from PV panels and environment, data-driven probabilistic net load monitoring methods and sensors should be applied [32]. Different types of sensors shoul be widely installed on PV panels to monitor common power output, including real-time power, output voltage, and transmission current [60]. For SBIPV systems, devices including inverters and boost valves are often equipped with various sensors to monitor the active power [61,62], reactive power, harmonic frequencies, node voltage waveforms and other common power quality on the supply-side [63]. Besides, the environmental parameters of PV penels would include meteorological data, such as wind direction, wind speed, air temperature, humidity, air pressure and other data. Through the sensors in PV panels, different paraments of PV panels can be effectively collected and transferred to terminal of users, which can be used to the decision-making of residents. Based on the online prediction method and feedback from sensors, many control strategies have been improved and proved [64,65].

Besides, because of the GIS data has demonstrated its principal role in exploiting geographical information to develop a spatial decision support system so as to locate solar facilities [66]. The utilization of GIS data can detect the potential of solar power generation in the early planning of the construction. The value of its data collection has been verified in South Korea [67], Iran [68], Italy [69], Australia [70] and other countries. Most GIS data will be presented in the form of images. The cameras in drone and satellite can clarify the house inclination, house area, house type, the potential area, and the location of the cloud layer. So the GIS data should undoubtedly be included in the data sensing to achieve effective scheduling and reasonable distribution of PV panels in roof.

3.2. Demand-side: residential electricity meters and indoor sensors

The multi-source information on both demand and supply-sides are useful to evaluate opportunities and challenges for SBIPV systems [71]. Resident data represent the distribution and habits of electricity

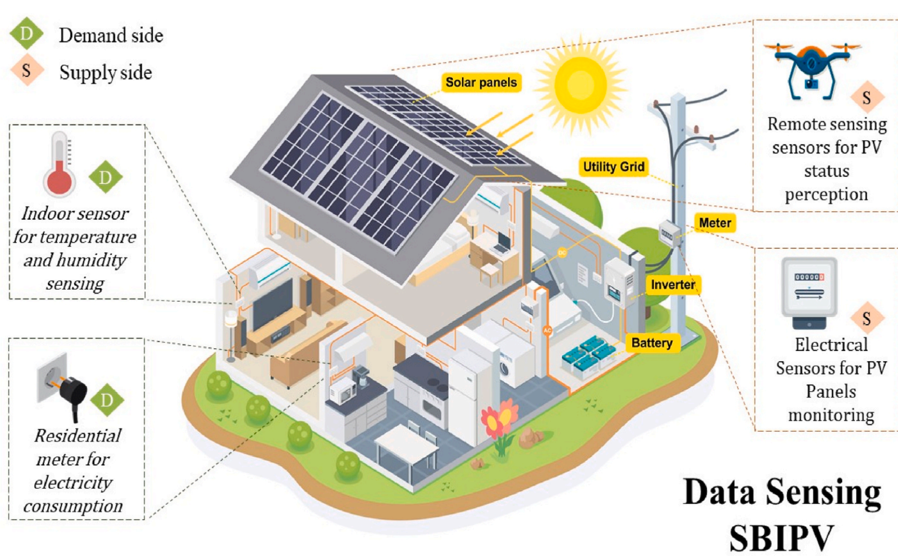

Fig. 2. Data sensing of SBIPV systems.

consumption of individuals and are of great significance for the SBIPV systems to achieve effective scheduling and reasonable distribution of PV panels. In addition, the measured data can be used in SBIPV systems to reduce peak loads (peak clipping or peak shaving), shift load from on-peak to off-peak (load-shifting), increase the flexibility of the load (flexible load shape), and reduce general energy consumption (strategic conservation). The aggregation and collection of these data is of great significance for further improving user experience, improving service quality, and improving building energy flexibility [72]. The applications and designs involved in this process have been confirmed by a number of studies to be possible and reproducible [73].

The data of resident electrical consumption is mainly collected by residential meters, which can effectively help deploy BIPV systems in next step: data analysis. The improvement of the power market, widespread application of intelligent communication, and smart meters have made it possible for the demand-side to participate in the optimal operation of the distribution network [74]. The data gotten from meters can provide a reference for PV installation height determination, manpower maintenance, boost location selection and inverter selection for the BIPV systems [75,76]. Weak PV technology conditions (including low conversion efficiency and reliability) and low PV electricity penetration levels would result in insufficience of data sensing in SBIPV systems [77,78]. The indoor sensors can realize the monitoring of the room occupancy and effective measurement of temperature and humidity. These indoor data usually affect the user's subsequent electricity consumption behavior, which would play important role in improving the electricity services of the buildings. Baran Yildiz et al. conducted an effective evaluation [79] on the excess power generation of BIPV systems and domestic electric hot water systems based on Australian electric/heating data of demand-side. The experiments on Sweden also confirmed the potential of demand-side [80]. Because of the thermal inertia of buildings, the data of indoor sensors would undoubtedly play more important roles in demand-side management.

Data sensing is the primary feature of the SBIPV systems. The measured and conneted data are significant for PV equipment and provide insights into a new structure to create a connected infrastructure. However, not all data can be measured. Using the data already measured to obtain potential information is the second feature of the SBIPV systems: Data analysis.

4. Data analysis of SBIPV systems

After data sensing, the data can be further analyzed to explore potential value and guide the operations of SBIPV systems. During all methods of data analysis, the GIS is always ignored. Actually, the GIS can function as a tool in finding resource and system-efficient locations for SBIPV systems, and created a more refined observations [81,82]. This technology can enable the data analysis of the SBIPV systems by collecting data of various sensors. and it has helped decision maker achieve refined observations under a great penetration rate of SBIPV. The data analysis of SBIPV systems is shown in Fig. 3.

4.1. Supply-side: shading impact and roof area

One of the most critical problems which affect the performance of BIPV systems is shading. Shading may result from soiling, trees, buildings [83], or chimneys [84]. Some results [85] shown that soiling seriously affects performance of PV panels. Winter rains are adequate to keep surfaces cleaned. The PV arrays always get entirely or partially shaded by the passing clouds, neighboring buildings and towers, trees, and utility and telephone poles [86,87]. Complicated shading causes the photovoltaic panels to be affected differently by shadows. When the shading covers all the photovoltaics, the power generation efficiency is almost zero. At this time, the photovoltaic effect stops and the photovoltaic panels no longer operate [88].

Under partial shading conditions, the PV characteristics get more complex with multiple peaks. The partial shading can lead to more than 10–20% of annual reduction in power production in residential applications [89]. For such problems, there exist different solutions. Detection and classification of shading [90] and adjustment of the PV arrays [91] can increase both power generation and PV reliability. This the most usual method. But for other situation, eapecially cities, situations will become various. In cities, the high-rise buildings and vegetation [92,93] are also the main reasons for output reduction. For this delimma, the meteorological data will effectively help the data analysis on the power generation [94–96]. The GIS data analysis including roof angle, shading impact, roof area, house type, ground inclination, occlusion classification [54], guano, snow, and smog [97]. Recent research progress in these directions is crucial for future SBIPV systems [98]. When extreme weather happening, residents can clean up the PV panels earlier to reduce grid dependence baseds on the weather data.

The GIS detection involves roof angel classification, gross area calculation, roof, and orientation analysis [99,100]. The data analysis needs to consider complex geometries [101], non-uniform irradiance conditions, and partial shading [102,103]. Only by using GIS detection, PV systems can be installed at the optimum inclination angle [104,105] and achieve the best performance of power generation [106]. The successful development of solar markets relies heavily on the

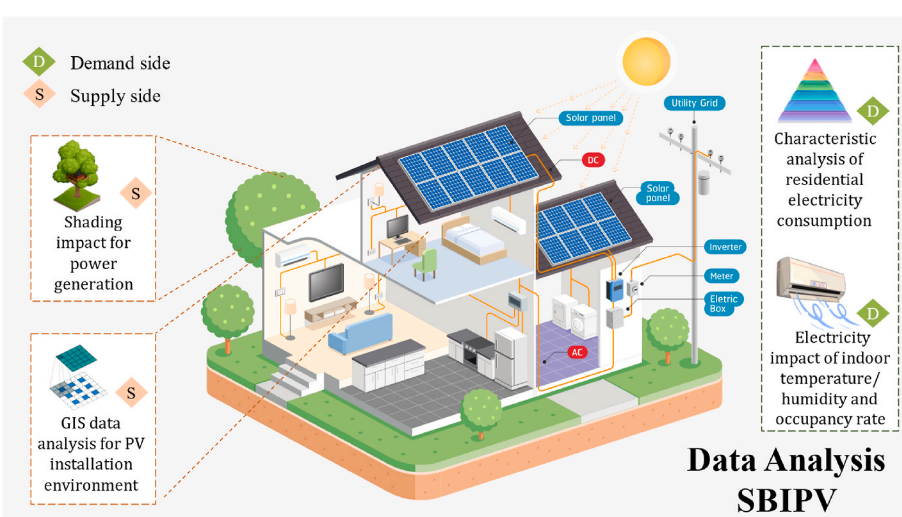

Fig. 3. Data analysis of SBIPV systems.

GIS-assessment of the roof surface area available before equipment installation, and area (including potential area) of the buildings have a profound impact on the BIPV systems [107]. Robustness of the GIS-assessment of the BIPV systems has been verified successively in China [65], the United States [108], Sweden [109] and South Korea [110]. The suitability of each roof for PV deployment and the characteristics can be analyzed for a minimum SBIPV systems [111,112]. It is worth mentioning that the construction costs of BIPV systems are usually different for different types of land and buildings. The installation area of different types of buildings varies, with suburbs generally having more potential areas than cities. Land acquisition costs for public infrastructure such as airports and hospitals are also very different from slums. This must be noted during the analysis.

The combination of GIS and semantic segmentation is another novel method characterized by cost-effectiveness and data consistency. The semantic segmentation for PV panels includes the analysis of homogeneous texture and heterogenous color of PV panels and image data of buildings [113]. Although the data of the area of houses and rooftop PV panels in local areas can be obtained through cameras, the detection and analysis of satellite/aerial imagery is a more appropriate approach. The highly similar texture of PV panels in most BIPV systems and different colors under various optical conditions are the key to identifying PV panels. The automatic detection of PV panels using support vector machine (SVM) [114], deep learning [106], and convolutional neural network (CNN) [115] have also been verified in data sets of many cities. The GIS analysis will be an economical solution for BIPV detection in future.

4.2. Demand-side: electricity consumption behavior and indoor information

Through the analysis of the power data and load type, the division of electricity consumption labels can be realized to achieve accurate power transmission and intelligent load shedding [116]. The labels of residents could further reduces power consumption and heat loss. In addition, the division of labels facilitates the integrated control of storage and loads in PV and residential buildings [117]. For users, on the one hand, electricity consumption data can be used to further coordinate the power grid with building-integrated photovoltaics, which will suppress the generation of harmonics and improve the power quality. On the other hand, the behavior of users can promote optimal utilization of electrical and thermal energy storage devices. The data analysis derived from eletricity consumption will be fed back to the strategy on user and realize the information cycle. Different strategies on users would creat diversified electricity consumption habits and satisfaction degrees [118] with the BIPV systems.

Besides, for energy companies, the consumption behavior of users will be more complex and diverse in the future [119]. The trend of this complexity may bring more uncertainty on the combination of power supply solutions. So the data analysis will be more necessary for business company. In the SBIPV systems, the user load data will be affected by demand-side pricing, indoor temperature, humidity, resulting in changes in housing occupancy and load [120]. However, demand-side data is still mainly affected by the subjective will of users, which is affected by the environment. Some researches have proven that passive behavior of existing buildings can be improved through the integration of active BIPV systems [121]. The analysis of indoor information opens a window for researchers to formulate more effective energy strategies. Through the indoor sensors, it is possible to evaluate the electricity consumption changes in advance. In fact, it is increasingly evident that data analysis [122,123] by artificial intelligence (AI) can greatly contribute to the flexible electricity response in SBIPV systems by automating processes while analyzing the data of indoor sensors [124].

Data analysis is another major feature of SBIPV systems. The BIPV systems generates various data in production, sales, and utilization. The analysis of these skyrocketing data may mining unexpected value in energy markets. The analysis of these data allows people to examine the whole system more macroscopically and provides novel solutions for the sites where the data cannot be directly measured. However, the data sensing and analysis are only applicable to the existing data, and the future prediction is still difficult [125]]. Using the data sensing and data analysis to predict the future is the third feature of the SBIPV systems: data-driven prediction.

5. Data-driven prediction of SBIPV systems

The high penetration rate of the BIPV systems introduces randomness and uncertainty to the distribution system [126,127], and therefore its future may show various possibilities. The data-driven predcition is an another feature for various future possibilities. Traditional prediction may always use physical models which requires complex calculations to estimate the parameters. So the environmental uncertainty limit the integration of physical model promotion. In the future, the Data-driven Prediction of the SBIPV systems will be more popular and the data-driven prediction of SBIPV system is shown in Fig. 4.

5.1. Supply-side: power output prediction of PV and cyclical changes

Basically, the PV generation output prediction can be conducted with AI algorithms and physical modeling. Physical models and machine learning technologies are also gradually merged for higher reliability. Regardless of how the prediction horizons are defined, the time scale of the models must be clearly defined. Output forecasts are usually at the millisecond, second, minute, hour, and day level. At this level, Artificial intelligence (AI) models, such as CNNs [128] and recurrent neural networks (RNNs) [129,130], have already produced promising results in PV generation prediction based on historical data analysis. The prediction by AI can effectively map the complex interdependence between short periods. These data-driven short time prediction models are mostly divided into three categories: time series [131,132], numerical weather prediction (NWP) [133] and sky imaging [134]. Although the accuracy of the time series models is ideal, the meteorological data and historical may not be available at remote locations [135]. Numerical weather prediction and sky imaging will also play more important roles in some places where weather data are not accessible [136]. Energy system is moving towards an active, more flexible, smarter and decentralized system. This transition requires SBIPV systems operators to dynamically predict power flow [137,138]. Accurate prediction of the future can help to effectively avoid possible accidents [139] and achieve efficient dispatch of electrical energy in SBIPV systems [140,141]. From the existing research, the combination of AI models, physical methods, and empirical formulas may be a better way and have more possibilities [142,143].

In terms of long-term forecasts, seasonal and annual cyclical changes are important references for achieving power supply stability. In the annual and quarterly forecasts, the regularity is more prominent [144]. Photovoltaic power presents volatility, annual periodicity, and adjacent similarity [145], which are usually determined by the regularity of climate change, like plum rain [146], and the periodicity of local economic development. Usually, rapid economic development, influx of people, and expand of immigrants usually show an increasing trend in annual electricity consumption. Whereas the population is severely aging and the economy is in recession, the annual power consumption usually shows a decreasing trend. In addition, the power consumption also shows regularity [147], which should be considered when deploying the BIPV systems [148], the planning of the position of energy storage stations, and the size of the SBIPV systems [149,150]. The energy storage stations in suitable locations can effectively reduce power transmission losses, ensure the technical and economic balance of demand-side response, and avoid power interruptions in extreme weather conditions. Robust optimization, convex optimization, sequence learning, etc., are usually introduced to determine the size of

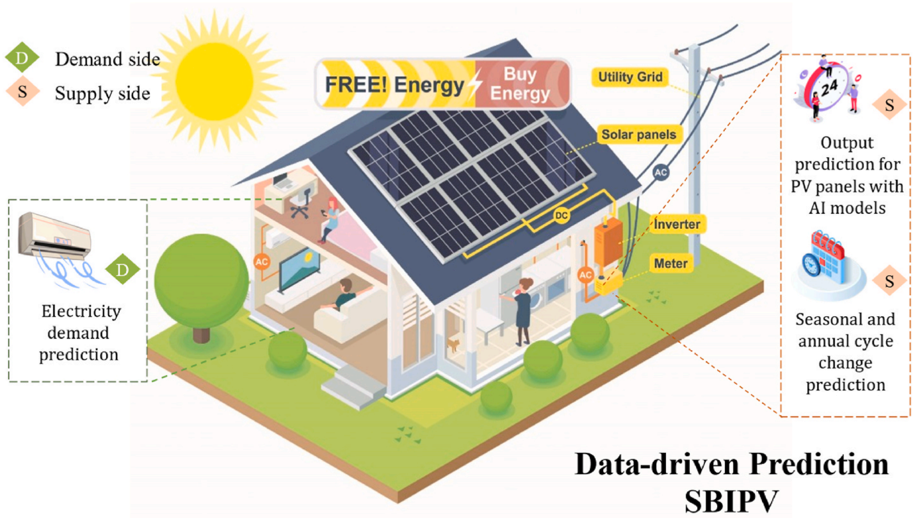

Fig. 4. Data Prediction of SBIPV systems.

the SBIPV systems [151,152].

5.2. Demand-side: load prediction

The urban electricity load is changing with the promotion of renewable energy. Changes of load in the United States [153], China [154] and India [155] have been proven the huge impact on city-level load. For the SBIPV systems, it will be important to reasonably predict the load changes. It is worth mentioning that the electricity load variation during the COVID-19 leads to more diversity in the load type [156]. The shutdowns caused by Covid-19 are likely to increase energy consumption by home office users. At high voltage levels trading mechanisms like contracts for ancillary services [157] and balancing markets [158] can predict the economically efficient supply of system flexibility services [159]. But for medium and low-voltage levels, with real-time load prediction of the SBIPV systems, arrangements for power consumption [160], energy storage [161], and electricity price [162] could be enabled for medium and low-voltage levels. The AI prediction models would play an important role in this process, which can tackle various challenges [163]. Based on the consumers load change, the

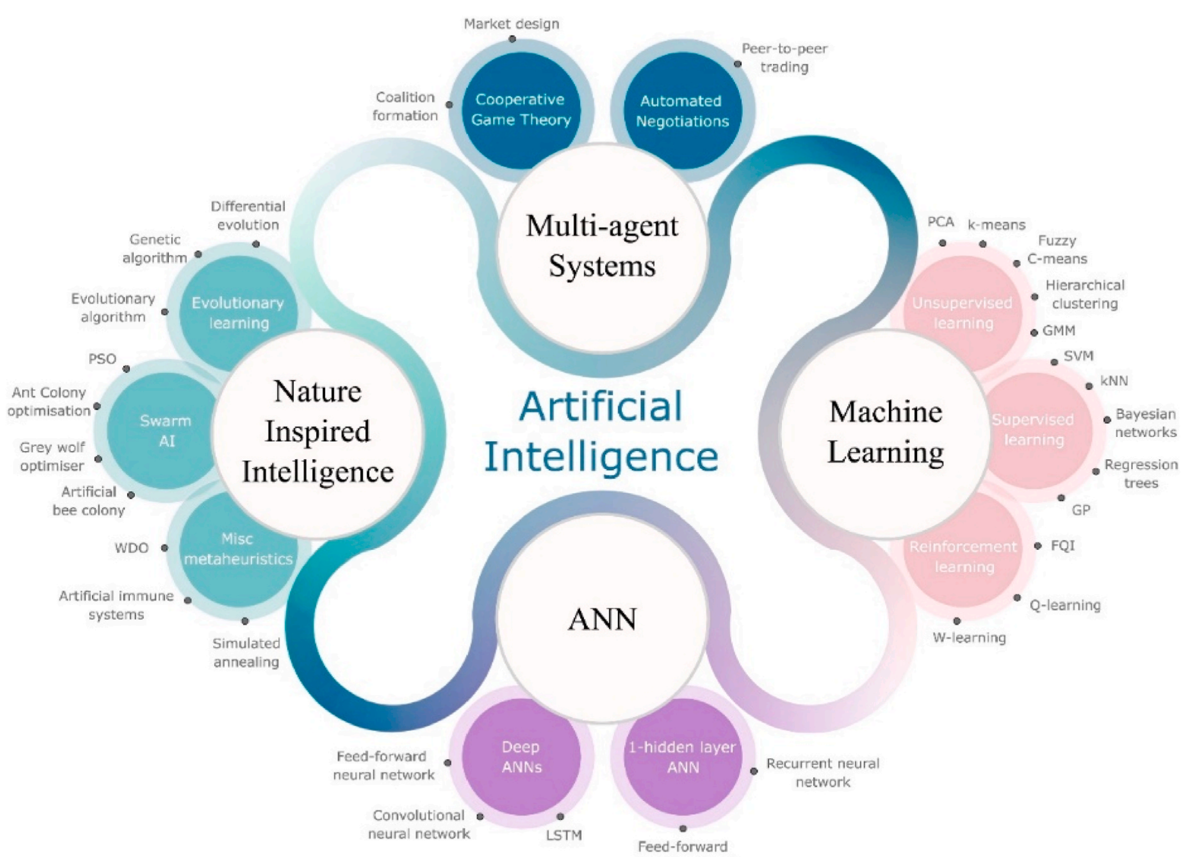

Fig. 5. Classification of AI approaches for demand prediction [122].

acquisition of user's attributes and preferences can be got. After the dynamic pricing [164], scheduling and control of devices [165], the SBIPV systems can find the way to incentivize participants or reward in a fair and economically efficient way. The AI techniques used for load prediction are shown in Fig. 5.

Data-driven Prediction is another major feature of SBIPV systems. The prediction on the demand-side and supply-side can allow people to make reasonable predictions, make sufficient preparations for the evolution of the entire system and provide an interface for the coupling of the SBIPV systems. The prediction on the demand-side and supply-side can allow people to make reasonable predictions, make sufficient preparations for the evolution of the entire system and provide an interface for the coupling of the SBIPV systems. Optimizing the current energy system by data-driven prediction and achieving systematic optimization will be another major feature of the SBIPV systems: data-driven optimization.

6. Data-driven optimizations of SBIPV systems

The data-driven optimization of the combination of the SBIPV systems and the energy system is diverse. Due to the diversity of renewable energy, energy storage methods, and user demand energy types, data-driven optimization often has various methods. With the development of the microgrid [166], policy planning [167] and P2P trading, the future optimization coupling of the SBIPV systems and energy system have being show more complexity and flexibility. The data-driven optimization of the SBIPV systems has been shown in Fig. 6.

6.1. Supply-side: policy guiding and distributed energy system design

The flexibility of combining power generation with buildings still lacks regulations and standards to manage the energy system is the next perspective of data-driven optimization in supply-side. Many countries have formulated the goal of using solar PV in construction [168,169], but compared with various application scenarios [170], solar PV policy guiding is still not enough [171]. The performance metrics of the BIPV systems established based on energy policies or industry standards have a profound impact on the construction planning of the building [172, 173]. These effective guidance on the supply-side is of great significance for alleviating the pressure of power supply and energy storage, which can realize the economical utilization of energy. Various distributed system design has different effects on building exterior, system efficiency and energy storage [174]. Although China [175], Europe [176], the United States [177], the Middle East [178], and other countries have successively issued various laws and regulations. The implemented pilot projects and case studies have also reached a level that can be commercialized, but due to the uniqueness of the building and the cost constraints of photovoltaics, most policies and legal guidance measures have significant time and space limitation [179]. Effective policy guiding of the supply-side will affect the willingness of SBIPV systems users to choose PV equipment. Most of the policies still remain on the construction, operation, and maintenance of BIPV, and the rules of relevant guidance for users' energy management are not enough. More useful measured data for technology and policy planning should be taken into consideration [180]. At the same time, for cogeneration systems, the thermal inertia of the building can promote the intelligent building services. At this level, quite a few cases have been performed [181], giving valid verification of the reproducibility of the SBIPV system [182, 183]. However, because of the different climatic conditions and economic development in different places, the rules made are generally often geographically limited [184].

In addition to the policy guidance, how to reasonably carry out distributed energy planning and design depends on whether the coupling of the SBIPV systems and other energy systems can achieve a stable power supply. The changes in data collection and utilization methods will show big potential in this data-driven optimization [185]. In all disturbed energy system, the combination of PV panels with the microgrid shows huge superiority [186]. Due to the variety of combinations of individual microgrids, it usually includes Wind-solar hybrid systems, PV-geothermal systems [187,188], PV-electric vehicle systems [189], etc. The residual power of these microgrids can still be spontaneously connected to the grid or energy storage. The robustness of energy storage system using battery with BIPV through linear programming has been confirmed [190].

The effective combination of microgrid and photovoltaic will undoubtedly coordinate power supply and creat more income for residents in microgirds. The user has changed from a consumer to a prosumer. The biggest contribution of this data-driven optimziation is the large potential of microgrid transactive energy systems at the distribution level in reducing transmission losses, decreasing electric infrastructure expenditure, and improving supply reliability [191]. Through distributed energy system design, human beings can enhance the local energy use, cutt electricity bills, and realize the interaction of information flow and energy flow in the SBIPV network.

6.2. Demand-side: P2P trading

For SBIPV systems, data-driven optimization not only means a

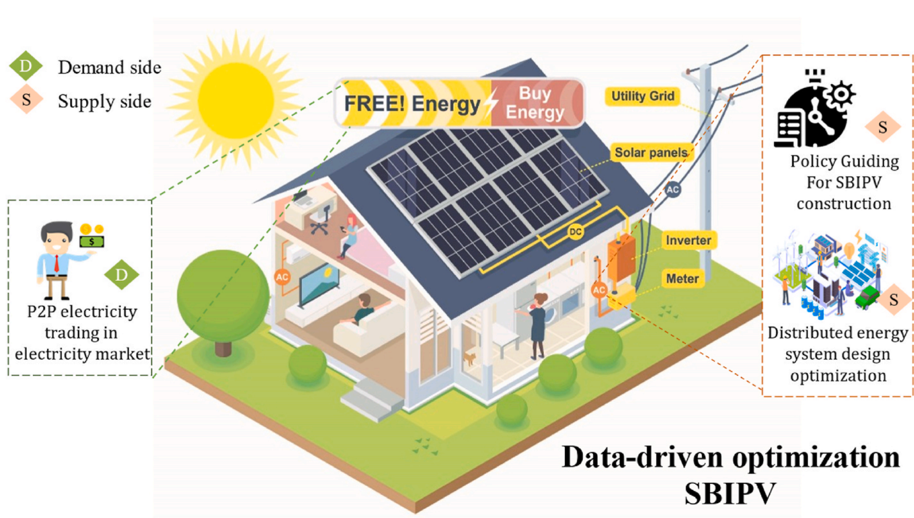

Fig. 6. Data-driven Optimization of SBIPV systems.

combination with multiple energy sources but also a cross-combination of the environment [192], economy [193], and policy [194] for SBIPV systems. Under the traditional paradigm, electricity trading is usually realized through a centralized energy trading system, which needs to actively organize consumers to participate in the electricity market. This type of centralized energy transaction not only has high transaction costs, but also has low management efficiency [195]. Therefore, attention should be shifted from panel production to electricity trading. In an open electricity market, the electricity price and the way of information dissemination significantly affect user choice. A key question that remains unresolved is how to coordinate various numbers of distributed energy resources, especially when each one with different owners and characteristics, and the P2P trading is considered as a possible solution [196].

The peer-to-peer energy trading enables between sharing economy of consumers within the local distribution network. P2P energy trading is decentralized, usually through direct end-to-end electricity trading. Different from centralized energy trading, the P2P trading model encourages multi-party transactions, and energy matching can be carried out according to user preferences. The advent of blockchain technology [197] and the increasing penetration of rooftop PV systems have presented a new opportunity for P2P energy trading. In electricity markets including the SBIPV systems, communities may enjoy cheap electricity prices and will support solar energy. However, there exists a considerable knowledge gap between market mechanisms and energy exchanges [198]. Challenges arise in the auction to ensure individual rationality, incentive compatibility, budget balance, and economic efficiency. The transition to a low-carbon future with a high proportion of renewable energy changes citizens from passive energy consumers to active energy prosumers [199,200]. Through the P2P trading, the transition to a low-carbon future would change citizens from passive energy consumers to active prosumers [201]. The P2P trading will further promote the transformation of demand-side management. Cooperating with demand-side microgrid optimization, P2P trading, and policy guidance. It can be predictably the SBIPV systems will have a new look after data-driven optimzation.

Current power networks and consumers are undergoing a fundamental shift. For SBIPV systems, data-driven optimization not only means a combination with multiple energy sources but also a cross-combination of the environment, economy, and policy for SBIPV systems. The four perspectives of data-driven SBIPV systems can break through the barriers of traditional BIPV systems, and the roadmap to the Data-driven SBIPV systems is presented in next section.

7. Perspective of data-driven SBIPV systems

It is foreseeable that the SBIPV systems will contribute to the energy transition and will play a vital role in shaping future energy systems. At the current stage, BIPV faces four major problems: (1) Lack of effective collection of massive data derived from classification under the high penetration rate of BIPV; (2) Limitations of data analysis between the sensing data and the user demand; (3) Mismatches between the load and source prediction at various time scales; (4) Geographical obstruction of microgrid, lack of guiding policy and communication barriers of combinatorial optimization. The roadmap to data-driven SBIPV systems for above dilemma should include the following important research directions:

- Great data sensing and excellent business model of distributed photovoltaics connected to the microgrid. The dynamic models of rooftop photovoltaic arrays and grid-connected systems, which should include the coupling effects of transient power characteristics of rooftop photovoltaics and distribution network transient characteristics. The building-integrated photovoltaic business model must considering the multiple investment entities, operating entities, and consummers.
- Data analysis of high-penetration building-integrated photovoltaic access capability. Evaluation of the ability of building-integrated photovoltaics to connect to the distribution network considering power supply capacity. Data analysis with comprehensive consideration of access capability, personal safety, and system efficiency in different application scenarios.
- Power supply and load coordinated control technology with smart building-integrated photovoltaic systems based on data-driven prediction. Technologies for distributed photovoltaic, energy storage, and controllable load optimization coordinated power regulation with balance boundary of source-load coordination in data-driven SBIPV systems; Optimal strategy for indoor and outdoor multi-scenario power supply and consumption system network with demand-side energy storage.
- Data-driven SBIPV system and other energy system collaborative operation and maintenance technology. Online fault diagnosis method and technology of photovoltaic modules (strings) based on artificial intelligence and P2P. An intelligent building-integrated photovoltaic operation, maintenance, and monitoring system that integrates demand-side and supply-side data.

The perspective of data-driven smart building-integrated photovoltaic (SBIPV) systems will be able to effectively coordinate data sensing, data analysis, data-driven prediction, and data-driven optimization.

8. Conclusion

SBIPV has become an important part of energy transformation. In this paper, recent papers related to SBIPV systems were comprehensively summarized from the view of data. The traditional data utilization and the barriers of current SBIPV systems were discussed. For data-driven SBIPV systems, related methods are divided into four aspects, including data sensing, data analysis, data-driven prediction and data-driven optimization. Furthermore, we proposed the roadmap for realizing the data-driven SBIPV systems. The main findings of this paper can be listed as follows:

(1) The traditional utilization of data sensing and weak analysis is the key to hinder the data-driven optimization and prediction of building-integrated photovoltaics. Excellent and substantial data should be further collected.
(2) After the detailed summary of barriers in traditional building-integrated photovoltaic systems, we firstly proposed the concept of data-driven smart building-integrated photovoltaics systems, and devided it as four aspects: data sensing, data analysis, data-driven prediction, and data-driven optimization.
(3) The data sensing is the cornerstone for data-driven SBIPV systems, effective analyzation and precise prediction will build the bridge for data-driven optimization of SBIPV systems. So far, the potential of demand-side data has not been fully developed, but GIS may provide a novel method for supply and demand coordination.
(4) The roadmap to data-driven SBIPV systems still need a lot of efforts in various technologies. But collective effect of technologies including P2P trading, artificial intelligence, and others would bring new possibilities to this evolutionary.

We hope this review would be helpful for researchers to make better utilization of solar energy, achieve flexible interaction between energy flow and information flow, and go far beyond what might be traditionally characterized as “energy” issues.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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