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Review

Photovoltaics, Storage, Direct Current, and Flexibility in Building Energy Systems: A Review of Technologies, Coordination, and Grid Interaction

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Abstract

Buildings are increasingly required to accommodate distributed renewable generation while providing flexible demand and supporting power system operation. However, the existing review literature remains fragmented across photovoltaic (PV) systems, energy storage, direct current (DC) distribution, building energy flexibility, and energy management research. This review uses photovoltaics, storage, direct current, and flexibility (PSDF) as a building-centered analytical framework for synthesizing international research conducted under diverse terminologies. Following a PRISMA-based screening process, the selected literature was analyzed through bibliometric and thematic synthesis. The literature is organized through a three-layer framework comprising component technologies, coordination mechanisms, and interaction/application pathways. The review shows that PV and conventional battery storage are comparatively mature at the building scale, whereas DC system standardization, protection, interoperable converters, and scalable flexible load integration remain important engineering barriers. Demand-side management, demand response, and energy management systems are identified as the coordination layer that converts physical flexibility into economic, operational, and grid-support services. At the application level, coordinated buildings can contribute to renewable self-consumption, peak management, voltage regulation, resilience, and community energy sharing, although reported quantitative benefits are strongly case-dependent. Future research should prioritize interoperable and safety-oriented DC architectures, uncertainty-aware and cyber-resilient coordination, life cycle and multi-objective assessments, occupant-centered flexibility, and validation from single-building demonstrations to building–community–grid applications. These findings position PSDF as an integrative framework for flexible and grid-interactive building energy systems rather than as a fixed combination of four technologies.

Keywords: photovoltaics, storage, direct current, and flexibility (PSDF); building energy flexibility; direct current (DC) distribution; demand-side management; energy management systems; building-grid interaction; grid-interactive buildings; resilience

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1. Introduction

Rapid urbanization, climate warming, and the continued electrification of end-use sectors are increasing peak electricity demand and cooling-related energy consumption in buildings while also intensifying challenges related to occupant thermal comfort [1].

Improving energy efficiency and reducing energy demand are therefore widely regarded as essential, cost-effective, and reliable pathways for climate change mitigation [2]. At the same time, the rapid expansion of distributed renewable energy requires buildings to move beyond conventional efficiency-oriented operations toward more adaptive interactions with local generation and the power grid. In China, this transition is closely linked to the national goals of carbon peaking and carbon neutrality under the broader objectives of the Paris Agreement [3]. Accordingly, attention is increasing on integrated building energy systems that combine distributed photovoltaics, energy storage, flexible demand, and advanced power distribution technologies to improve renewable-energy utilization, grid hosting capability, operational flexibility, and building adaptability [4–6].

Against this background, the "Photovoltaics, Storage, Direct Current, and Flexibility" (PSDF) building concept was introduced in China's Action Plan for Carbon Dioxide Peaking Before 2030 (State Council Document No. 23, 2021) [7]. A PSDF building integrates building-integrated or building-attached photovoltaics (P), distributed energy storage (S), direct current power distribution (D), and flexible demand or loads (F), thereby transforming buildings from relatively rigid electricity consumers into controllable energy nodes [8]. In this architecture, photovoltaic generation provides local renewable supply; storage decouples generation and consumption across time; direct current distribution provides an efficient interface for many distributed sources, storage devices, and native DC loads; and flexible loads enable demand to respond to local generation, user requirements, electricity prices, and grid signals. The value of PSDF therefore lies not simply in combining four technologies, but in coordinating them as a building-scale energy architecture with both internal energy management and external grid interaction functions.

Such coordination is increasingly important because renewable intermittency, electric vehicle (EV) charging, battery operation, heating, ventilation, and air conditioning (HVAC) systems, and other controllable loads create coupled design and operational problems in buildings [9–16]. Demand-side management (DSM), demand response (DR), and energy management systems (EMS) provide the coordination layer for these resources. Existing studies have investigated photovoltaic-storage configurations [17], flexible load management [18], EV charging and discharging [19], virtual power plants (VPPs) integrating distributed resources [20], and microgrid operations [21]. As buildings evolve from passive consumers to "prosumers," optimized coordination between buildings and distribution networks can simultaneously reduce building operating costs, preserve occupant comfort, reduce distribution losses, and support voltage regulation [22–25]. Therefore, PSDF should be considered not only as an internal building energy system but also as a potential platform for grid-interactive buildings.

The terminology used to describe related systems is not internationally unified (see Table 1). In the Chinese literature, Photovoltaics, Energy Storage, Direct Current, and Flexibility is commonly discussed under the PEDF/PSDF framework [8,26]. In Japan, Werth et al. [27] proposed a DC-based Open Energy System (OES) in which residential DC nanogrids equipped with photovoltaics and batteries are interconnected through a shared DC network for local energy exchange. Other research streams use concepts such as DC microgrids, VPPs, peer-to-peer (P2P) energy trading, home energy management systems, and energy communities to address parts of the same broader transition toward distributed, flexible, and interactive energy systems [28–31]. These concepts are functionally related but are not interchangeable: DC microgrids emphasize electrical architecture and control, VPPs emphasize aggregation and market-oriented coordination, energy communities emphasize collective energy sharing and governance, and OES emphasizes interconnected local DC subsystems. In this review, PSDF is therefore used as an integrative analytical framework rather than as a universally standardized international term.

Table 1. Definitions and conceptual boundaries of PSDF-related energy-system concepts.

Term	Full Name	Definition/Main Characteristics	Relationship to PSDF
PSDF	Photovoltaics, Storage, Direct Current, and Flexibility	A building-scale integrated energy framework combining photovoltaic generation, distributed energy storage, DC power distribution, and flexible demand/loads. The four components are coordinated to improve local renewable-energy utilization, demand flexibility, and interaction with the external grid.	Reference framework adopted in this review.
PEDF	Photovoltaics, Energy Storage, Direct Current, and Flexibility	A general power distribution system for buildings that integrates distributed photovoltaics, energy storage, and DC distribution and uses flexible control to provide energy flexibility services to the external power grid.	Closely overlapping concept that emphasizes building power distribution and flexibility services.
OES	Open Energy System	A DC-based distributed energy system composed of interconnected local subsystems/nanogrids, typically integrating PV and battery storage and enabling local energy exchange through a shared DC network.	Related DC-based distributed architecture emphasizing interconnected local DC subsystems and energy sharing.
DC microgrid	Direct Current Microgrid	An electrical distribution architecture in which distributed generation, energy storage devices, and loads are connected through a DC bus and coordinated through power and energy management strategies.	Primarily represents the DC electrical infrastructure component of PSDF.
VPP	Virtual Power Plant	An aggregation-oriented framework that coordinates distributed energy resources, storage, controllable loads, and other flexible resources for joint operation and participation in power system or electricity market activities.	Represents aggregation and grid/market coordination rather than a physical building topology.
Energy community	Energy Community/Renewable Energy Community (REC)	A community-scale energy arrangement in which multiple consumers and/or prosumers, such as households and public or commercial buildings, collectively coordinate local generation, storage, demand, and energy sharing. Energy communities may employ P2P trading, shared storage, sector coupling, and coordinated energy management to increase local renewable-energy utilization, economic benefits, and system flexibility.	Represents a multi-building/community application context for coordinated generation, storage, demand, and energy sharing.

A growing body of review literature has already examined important parts of this research landscape. Chen et al. [32] reviewed measures for improving building energy flexibility through DR, including photovoltaics, storage, HVAC, thermal mass, appliances, and occupant behavior. Azuatalam et al. [13] systematically compared energy management strategies for residential PV-battery systems, with particular attention to implementation practicality, forecasting, computational requirements, and battery degradation. Kumar et al. [33] reviewed DC microgrid structures, control, power management, and energy management. Tang et al. [34] further developed a systematic categorization of energy-flexible and grid-responsive buildings according to power grid requirements across multiple timescales. Thirunavukkarasu et al. [21] reviewed optimization techniques for microgrid EMS, while Liu et al. [8] provided a foundational PEDF-oriented review covering system definition, topology, control strategies, key technologies, and representative building applications. More recently, Chatzigeorgiou et al. [35] reviewed end-user PV-BESS installations with an emphasis on techno-economic analysis, operational control, sizing, and demand response. These studies demonstrate that the individual research streams related to PSDF are already well developed; however, their analytical boundaries remain different, as summarized in Table 2.

As shown in Table 2, the research gap addressed by the present review is therefore not the absence of studies on individual PSDF components, building flexibility, DSM, DC microgrids, or even the PEDF architecture itself. Rather, the existing review landscape remains fragmented across technology-centered, flexibility-centered, control-centered, and architecture-centered perspectives. Building flexibility reviews provide a detailed treatment of flexible loads and grid responsiveness but generally do not consider DC distribution

as a core infrastructure layer; DC microgrid reviews emphasize topology, converters, and control but provide less systematic treatment of building-specific flexible demand and occupant-related constraints; PV-battery reviews focus primarily on self-consumption, techno-economics, and HEMS; and PEDF-oriented reviews establish the integrated P–S–D–F concept but place less emphasis on systematically connecting this architecture with the wider international research streams of DSM, building–grid interaction, multi-building/community applications, resilience, and emerging digital technologies. Consequently, a building-centered, cross-domain synthesis linking subsystem technologies, coordination strategies, grid interaction, and broader application scenarios remains limited.

Table 2. Comparison of representative review studies related to integrated PSDF building energy systems.

Main Scope	Technology Integration	DSM/EMS	Grid Interaction	Multi-Scale/ Application Breadth	Main Limitation Relative to the Present Review	Systematic/ International Synthesis	Ref.
Building energy flexibility and DR	PV–ESS–flexible loads	✓	✓		DC distribution is not treated as a core infrastructure layer; there is limited integrated P-S-D-F perspective.		[32]
Residential PV-battery HEMS	PV–ESS	✓			Focuses on residential PV-battery HEMS; there is limited treatment of DC infrastructure and broader community/grid applications.	✓	[13]
DC microgrid control	DC–ESS–DER	✓			Emphasizes DC topology, converters, and control; there is limited treatment of building-specific flexible demand and occupant constraints.		[33]
Grid-responsive building flexibility	Generation–ESS–flexible loads	✓	✓		Strong on grid-responsive flexibility, but DC distribution is not a core infrastructure layer.	✓	[34]
Microgrid EMS optimization	DER–ESS–loads	✓		✓	Algorithm/EMS-centered; there is limited treatment of building-specific physical architecture and occupant-related constraints.	✓	[21]
PEDF building architecture	P–S–D–F	✓	✓		Establishes the PEDF architecture, but gives less emphasis to broader international DSM, community/grid, resilience, and digital technology literature.		[8]
End-user PV-BESS and DSM	PV–ESS–flexibility	✓	✓		Focuses mainly on PV-BESS, tech-no-economics, sizing, and DSM; there is limited DC infrastructure and multi-layer building–grid synthesis.	✓	[35]
Integrated PSDF building systems	P–S–D–F	✓	✓	✓	-	✓	Present review

Note: ✓ indicates that the corresponding dimension is explicitly addressed as a major review scope; a blank cell indicates that it is not a primary focus.

To address this gap, the present review adopts PSDF as an analytical framework for organizing internationally distributed research that may use different terminology but addresses functionally related building energy problems. The literature is synthesized through a multi-layer structure consisting of: (i) a component layer covering photovoltaics, energy storage, DC distribution, and flexible loads; (ii) a coordination layer covering DSM, DR, EMS, optimization, and user-side participation; and (iii) an interaction and

application layer covering building–grid coordination, smart communities, resilience, emerging technologies, and policy-related deployment issues. This structure is intended to move beyond a sequence of technology summaries and instead clarify how the four PSDF components interact, how they are coordinated, and how their combined flexibility can support both building performance and external power system requirements.

Compared with previous review studies, the main contributions of this review are as follows:

(1) A building-centered conceptual framework is established to clarify the relationships and boundaries among PSDF/PEDF and related concepts such as OES, DC microgrids, VPPs, and energy communities, thereby enabling international research conducted under different terminologies to be compared within a common functional framework.
(2) A multi-layer taxonomy is developed that links PSDF component technologies with DSM/EMS coordination and building–grid interaction, allowing the review to connect physical system architecture with control strategies and demand-side flexibility rather than treating these topics independently.
(3) The review provides a critical synthesis of technology maturity, performance indicators, implementation conditions, engineering barriers, and major trade-offs, with particular attention to the differing objectives of building energy performance, user comfort, economic operation, renewable self-consumption, grid flexibility, and resilience.
(4) Future research priorities are derived from the limitations identified across the reviewed literature, including interoperability and DC system engineering barriers, uncertainty-aware and multi-timescale coordination, user participation, cybersecurity and digitalization, life cycle assessment, and the transition from single-building demonstrations toward scalable building–community–grid integration.

The remainder of this review is organized according to the above framework. Section 3 reviews the component layer of PSDF, including photovoltaics, energy storage, DC distribution, and flexible loads. Section 4 examines the coordination layer, with an emphasis on DSM/DR strategies, EMS, techno-economic optimization, control-based approaches, and user-side participation. Section 5 discusses the interaction and application layer, including smart communities, resilience and emergency operations, emerging intelligent technologies, and policy or implementation pathways. Section 6 critically summarizes the principal technical, methodological, economic, and deployment challenges and derives corresponding future research priorities, followed by the conclusions in Section 7.

2. Materials and Methods

2.1. Review Materials, Search Strategy, and Study Selection

Because PSDF/PEDF terminology is not used consistently across the international literature, a search based only on the term "PSDF" would omit a substantial body of functionally relevant research. Therefore, this study focuses on the four core functional domains of the framework, and the literature search primarily targets articles published from January 2010 to 31 July 2026 to ensure the inclusion of recent and scientifically relevant studies. Before determining the specific search terms, a preliminary review of articles related to the four main functions of PSDF technology in the Web of Science was conducted. This helped establish a broad understanding of current research trends and identify the detailed keywords to be used. Given the close relationship between PSDF technology and building energy systems, research on its four core functions within the building energy sector was examined. The preliminary search queries are listed in Table 3, and the resulting trends are shown in Figure 1. Since the early 2010s, the number of publications on photovoltaics, energy storage, direct current, and flexibility has shown an overall upward trend. The growth has been most pronounced in energy storage and

photovoltaics, which have also accounted for the largest share of publications. Research on flexibility has shown a notable increase in recent years, while publications on direct current, despite a smaller overall volume, have maintained steady growth. These patterns reflect an increasing research interest in the technologies and functions that underpin integrated PSDF building energy systems. The 2026 values include records indexed up to 31 July 2026 and therefore represent a partial year.

Table 3. Preliminary search queries for the four PSDF technology domains.

Name	Searching Query
Photovoltaic	Topic = (“building*” OR “office building” OR “public building” OR “residential building” OR “commercial building” OR “home” OR “house*” OR “industrial building” OR “apartment” OR “school” OR “hospital” OR “library” OR “museum” OR “hotel” OR “factory” OR “power station” OR “airport”) AND (“energy”) AND (“solar power” OR “photovoltaic*” OR “PV”)
Energy Storage	Topic = (“building*” OR “office building” OR “public building” OR “residential building” OR “commercial building” OR “home” OR “house*” OR “industrial building” OR “apartment” OR “school” OR “hospital” OR “library” OR “museum” OR “hotel” OR “factory” OR “power station” OR “airport”) AND (“energy”) AND (“energy storage” OR “battery” OR “batteries”)
DC Power Distribution	Topic = (“building*” OR “office building” OR “public building” OR “residential building” OR “commercial building” OR “home” OR “house*” OR “industrial building” OR “apartment” OR “school” OR “hospital” OR “library” OR “museum” OR “hotel” OR “factory” OR “power station” OR “airport”) AND (“energy”) AND (“direct current” OR “DC/DC”)
Flexible Load	Topic = (“building*” OR “office building” OR “public building” OR “residential building” OR “commercial building” OR “home” OR “house*” OR “industrial building” OR “apartment” OR “school” OR “hospital” OR “library” OR “museum” OR “hotel” OR “factory” OR “power station” OR “airport”) AND (“energy”) AND (“flexibility” OR “demand response” OR “resilience”)

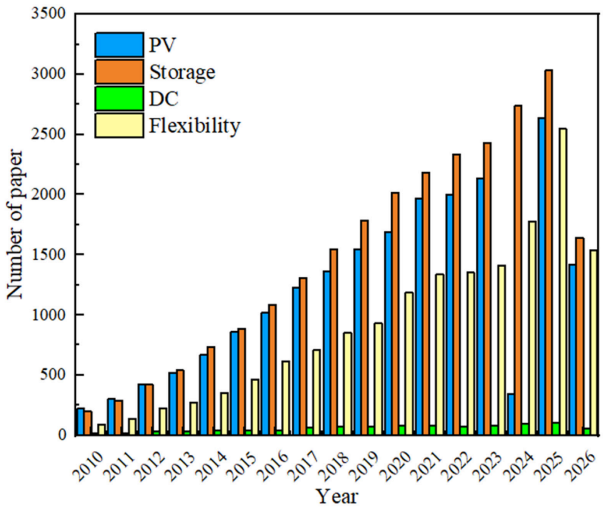


Figure 1. Research trends of the four key topics.

The literature identification and selection process was reported in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [36]. Web of Science was used as the principal database, supplemented by searches in ScienceDirect, Google Scholar, CNKI, and Wanfang to capture additional relevant studies. The preliminary queries in Table 3 were used only to characterize publication trends in Figure 1; the formal literature selection search used the search-term groups summarized in Table 4. In Web of Science, the core search used Query 1 AND (Query 2 OR Query 3 OR Query 4), while the additional DC search used Query 1 AND Query 5. Equivalent concept combinations were adapted to the interfaces of the supplementary sources. As of 31 July 2026, the core Web of Science search returned 1393 records. Because direct current distribution was less well represented in the core results, a dedicated DC search identified an additional 1016 records. Supplementary searches contributed 486 additional potentially

relevant records after preliminary relevance checking, yielding 2895 records for screening. Studies were eligible if they addressed at least one PSDF functional domain or closely related DSM/DR/EMS coordination in buildings or building-related community energy systems and provided sufficient methodological, operational, or application-level information. Studies focused solely on materials or device performance without system-level relevance, or on utility-scale and industrial systems without transferable implications for buildings, were excluded. Duplicate records were removed using EndNote (n = 229), and conference papers (n = 753) and review articles (n = 137) were excluded before title and abstract screening, leaving 1776 records. Review articles were excluded from the final primary study evidence set so that the bibliometric and thematic synthesis reflected original research findings; representative reviews were retained separately for background, terminology, and comparison with previous review literature in the Introduction. Title and abstract screening excluded studies outside the review scope and retained 490 papers for full-text assessment. The full-text assessment further excluded studies with insufficient relevance to the PSDF functional framework, limited building or coordinated operation relevance, substantial overlap with already retained evidence, or insufficient methodological or application detail. A final set of 184 publications was included in the review, as illustrated in the PRISMA flow diagram in Figure 2.

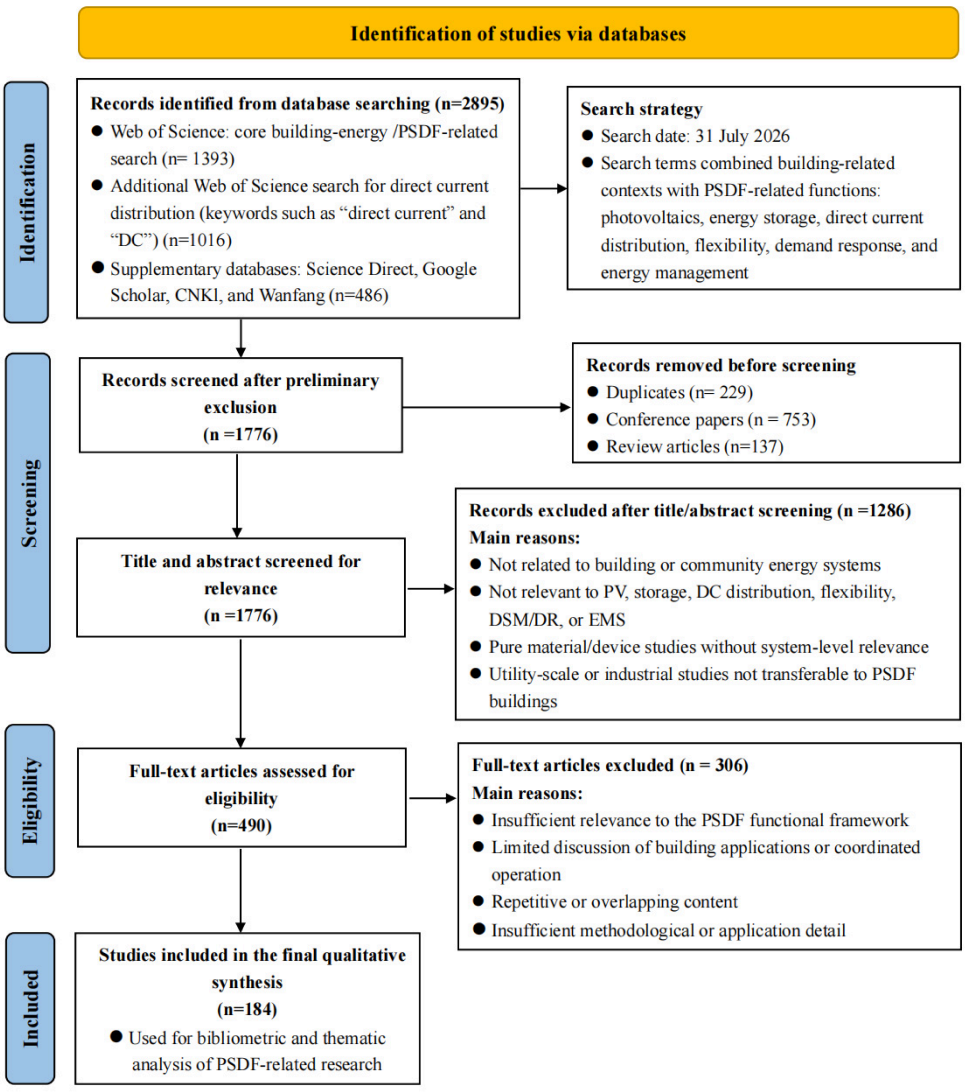


Figure 2. PRISMA flow diagram.

Table 4. Search-term groups used in the formal literature selection search.

No.	Searching Query
1	Topic = (“building*” OR “office building” OR “public building” OR “residential building” OR “commercial building” OR “home” OR “house*” OR “industrial building” OR “apartment” OR “school” OR “hospital” OR “library” OR “museum” OR “hotel” OR “factory” OR “power station” OR “airport”) AND (“energy”)
2	Topic = (“solar power” OR “photovoltaic*” OR “PV”)
3	Topic = (“energy storage” OR “battery” OR “batteries”)
4	Topic = (“flexibility” OR “demand response” OR “resilience”)
5	Topic = (“direct current” OR “DC/DC”)

2.2. Bibliometric Analysis and Thematic Synthesis

This review employs bibliometric analysis to identify the knowledge structure and major research themes of the selected literature based on keyword co-occurrences and clustering [37]. Using the publications included in the review, CiteSpace software [38] was used to generate a bibliometric network that maps the relationships among major research topics related to PSDF technology. Keywords from the selected literature are used to identify clusters representing recurrent research themes, technologies, and methodological concerns. Figure 3 presents the resulting keyword-clustering network and illustrates the interconnections among these research topics.

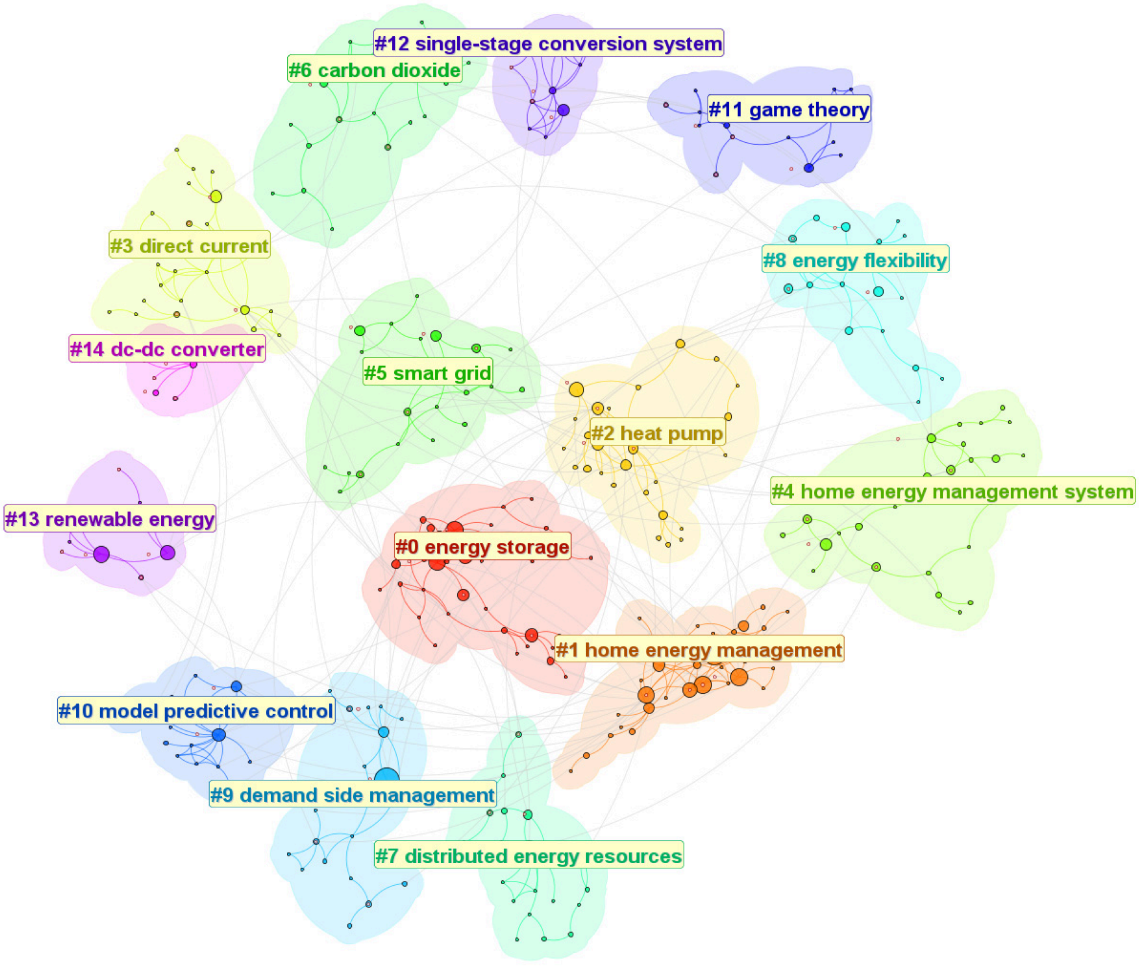


Figure 3. Keyword clustering map.

As shown in Figure 3, the keyword clusters indicate that PSDF-related research spans several interconnected technological and methodological domains rather than forming a single homogeneous research field. To facilitate interpretation, the identified clusters were further consolidated according to their dominant functional roles within building energy systems. Clusters associated with home energy management, demand-side management, model predictive control, distributed energy resources, and energy flexibility were grouped under Energy Management and Coordination. Clusters related to renewable energy, energy storage, heat pumps, and carbon-related performance were grouped under Energy Resources and Flexible Loads. Clusters concerning smart grids, direct current, DC–DC converters, single-stage conversion systems, and related system-level coordination were grouped under Grid Architecture and Power Conversion. The resulting three knowledge groups, together with their representative cluster labels and functional interpretations, are summarized in Table 5.

Table 5. Functional interpretation of the major keyword clusters in PSDF-related research.

No.	Knowledge Group	Major Cluster Labels	Functional Interpretation	Role in This Review
1	Energy management and coordination	#4 home energy management system, #1 home energy management, #10 model predictive control, #9 demand-side management, #7 distributed energy resources, #8 energy flexibility	Scheduling, optimization, demand response, and coordination of distributed building energy resources.	DSM, EMS, DR, and control strategies (Section 4).
2	Energy resources and flexible loads	#13 renewable energy, #0 energy storage, #2 heat pump, #6 carbon dioxide	Renewable generation, energy storage, flexible loads, and energy/carbon performance.	PV, ESS, and flexible building loads (Section 3).
3	Grid architecture and power conversion	#5 smart grid, #14 dc-dc converter, #3 direct current, #11 game theory, #12 single-stage conversion system	DC distribution, power-conversion, grid connection, and distributed coordination.	DC-distribution (Section 3) and the building–grid interaction (Section 5).

Table 5 shows that the bibliometric knowledge structure of PSDF-related research can be broadly interpreted through three complementary dimensions: energy resources, energy management and coordination, and electrical/grid infrastructure. These knowledge groups are not intended to reproduce the manuscript sections on a one-to-one basis. Instead, they provide an empirical basis for the functional review framework adopted in this study. Cross-cutting methodological terms, such as game theory, were assigned according to the dominant context of their associated clusters rather than treated as exclusive technological categories. Specifically, the energy resource and grid architecture groups mainly inform the component-level analysis of photovoltaics, energy storage, DC distribution, and flexible loads in Section 3; the energy management group supports the coordination-level discussion of DSM, DR, EMS, and optimization strategies in Section 4; and cross-cutting topics such as smart grids, energy flexibility, distributed coordination, and game-theoretic approaches further motivate the building–grid interaction and application analysis in Section 5. Accordingly, the bibliometric analysis serves as a basis for organizing the subsequent review into the component, coordination, and interaction/application layers.

3. Component Technologies of Integrated PSDF Building Energy Systems

This section reviews the component layer of the PSDF framework, including photovoltaic (PV) generation, energy storage, direct current (DC) distribution, and flexible loads. As illustrated in Figure 4, these technologies form a coupled building energy system rather than four independent subsystems. PV provides local renewable generation; storage

shifts energy across time; DC distribution provides an electrical integration pathway for DC-native sources, storage devices, and loads; and flexible loads provide controllable demand. Their coordinated operation through DSM/DR and EMS is discussed in Section 4, while their interaction with communities and external grids is addressed in Section 5.

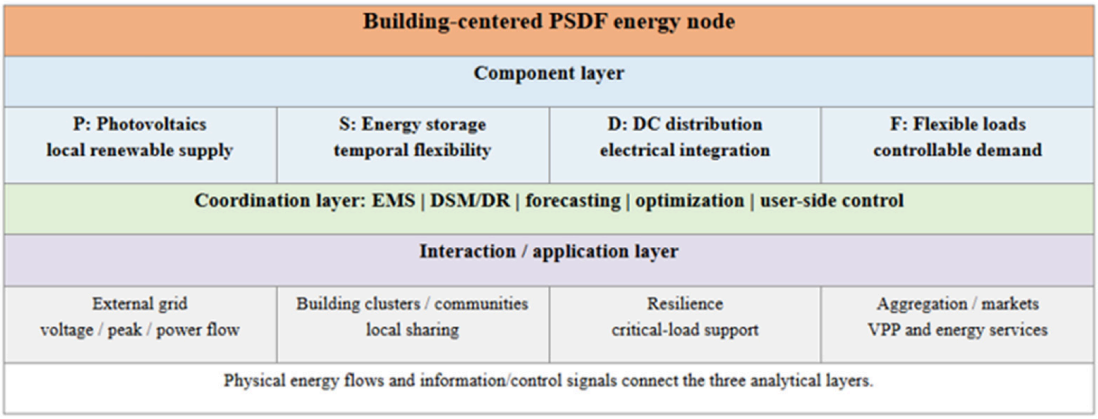


Figure 4. Multi-layer architecture of a building-centered PSDF system.

3.1. Photovoltaic (PV) Systems

A complete PV system typically consists of a photovoltaic module array, inverter, grid-connection switch cabinet, and cables. Buildings can improve their energy performance through the use of photovoltaics. Building-mounted photovoltaic (BMPV) technology is a promising approach for reducing operational carbon emissions because it converts building surfaces into local renewable-energy generation areas [39]. However, PV output is strongly affected by weather conditions and may not coincide with building demand, so system design must consider both generation performance and the temporal match between supply and load. Building-integrated PV studies further show that energy performance and load matching depend on building configuration and climatic conditions, reinforcing the need for building-specific PV design [40,41].

To mitigate power system fluctuations caused by photovoltaic grid integration, Budin et al. [42] employed a two-stage stochastic optimization model combined with unsupervised clustering to address the variability of load and photovoltaic generation. This approach reduced 365 days of load data to eight typical daily scenarios and reduced the total system investment cost by 18% in the investigated case. Jeksen et al. [43] showed that uncertainties in building operation can have a substantial effect on PV capacity planning: compared with the planned scenario, annual electricity demand increased by 60% and the required installed PV capacity increased by 42%. To improve renewable-energy accommodation, a dynamic PV–heat pump–storage system was investigated in [44], while [45] evaluated heat pump integration with thermal storage for coordinated PV utilization.

Dynamic control provides another pathway for improving the real-time match between PV generation and building demand. Zou et al. [46] proposed a dual-resolution scheduling framework combining minute-scale thermostatically controlled loads with second-scale battery power tracking, reporting substantial improvements in the real-time matching rate (RTMR) and self-consumption rate (SCR). Zou et al. [47] compared dynamic-programming and rule-based strategies under flexible tariffs, while Liu et al. [48] combined day-ahead optimization with real-time adaptive control to improve PV self-consumption and reduce user electricity expenditure. Other studies have linked PV operation with power quality, demand response, and building–grid co-ordination [49–51].

Overall, PV technology is comparatively mature at the building scale, but the main research challenge has shifted from electricity generation alone to system integration.

When PV generation and building demand are poorly matched, high local penetration can increase midday export, ramping requirements, reverse power flow, and voltage regulation pressure. The reviewed studies therefore indicate that the value of building PV in PSDF systems depends increasingly on coordinated storage, flexible demand, and grid-aware control rather than on PV capacity alone [46–51].

3.2. Energy Storage Systems (ESS)

3.2.1. Building Energy Storage Technology

In recent years, photovoltaic technology has become increasingly mature and its cost has declined, leading to higher penetration of distributed PV generation. Energy storage is therefore widely used to mitigate mismatches between renewable generation and building demand. Battery energy storage systems (BESS) can shift surplus electricity across time, reduce power fluctuations, and support energy management in PV-dominated building systems [35]. Their practical value, however, depends on the service being provided, the operating strategy, battery degradation, and the interaction with other building resources.

The high cost of energy storage technology remains a major barrier to wider deployment. Battery degradation-aware operation can reduce life cycle cost and improve economic performance [52,53]. Al Muala et al. [54] incorporated degradation and depth-of-discharge effects into long-term scheduling, reporting an extension of winter battery life from 9.2 to 17.7 years and a 28.9% reduction in the LCOS in the investigated case. Other studies have examined battery-balancing methods [55], PV-direct-driven air conditioning [56], and stochastic techno-economic optimization [57] to improve the coordination of storage with building loads.

3.2.2. Photovoltaic-Energy Storage Systems (PV-ESS)

Photovoltaic-energy storage systems (PV-ESS) aim to improve system efficiency, economics, and operational stability through coordinated capacity configuration, dispatch, and technology integration. Existing work has considered electrical and thermal storage, heat pumps, phase-change materials, EV batteries, and water heating in combination with PV [58,59]. Economic performance is particularly sensitive to tariff structures, storage sizing, degradation, and the selected control strategy.

Li et al. [60] proposed a two-stage optimization model integrating time-of-use electricity prices and battery-aging costs for an office building PV-storage system. Bagalini et al. [61] showed that system profitability depends strongly on electricity prices, technology costs, policy conditions, and capacity configuration. Other studies have examined heat pump thermal storage [62], domestic hot water storage [63,64], distributed storage economics [65], and resilience-oriented planning for building microgrids [66–68]. Table 6 summarizes representative studies on PV and energy storage systems.

Table 6. Representative research topics and findings on photovoltaic and energy storage systems.

System Type	Year	Research Objective	Methodology	Key Findings	Ref.
PV System	2025	Capacity planning of PV systems	Two-stage stochastic optimization model	Overall system investment was reduced by 18%	[42]
	2024	Quantifying system uncertainties	Framework quantifying uncertainties in building operation and electricity demand	Building electricity demand increased by 60%	[43]
	2025	Enhancing system stability	Bi-level framework integrating day-ahead optimization and real-time adaptive control	PV self-consumption increased by 3%; user electricity bills were reduced by 8.01%	[48]

Table 6. *Cont.*

System Type	Year	Research Objective	Methodology	Key Findings	Ref.
PV-BESS	2025	Matching PV generation with load profiles	Dual-resolution scheduling architecture (minute–second scale)	RTMR increased by 482%; SCR improved by 40.8%	[46]
	2022	Adapting to grid fluctuations and flexible tariffs	DP and rule-based strategies	Improved flexibility, economic performance, and reduced grid burden	[47]
	2024/2024	Extending battery lifetime	Nonlinear degradation model	Optimized battery lifetime via nonlinear degradation modeling	[52,53]
	2024	Battery-life optimization	Particle Swarm Optimization (PSO)	Winter battery lifetime extended from 9.2 to 17.7 years; LCOS reduced by 28.9%	[54]
	2025	Battery economic assessment	Active battery-balancing algorithm	Achieved 40% cost reduction via optimized drive circuitry and parallel expansion	[55]
	2025	Techno-economic assessment of grid integration	Stochastic optimization framework	Adjusted electrical/physical parameters to enhance demand flexibility	[57]
	2025	Mitigating PV intermittency	Two-stage optimization using DP	Improved charge/discharge scheduling and reduced operational cost	[60]
	2019	System capacity optimization	/	Optimized sizing significantly improved PV self-consumption	[61]
	2024	Assessing distributed storage economics	SDSE and wind-turbine-driven model	LCOE of 0.13–0.16 $/kWh; up to 30,000 kg CO_2 reduction per year	[65]
	2021	Ensuring outage resilience	Mixed-integer linear programming (MILP)	PV integration significantly reduced electricity bills	[66]
	2019	Enhancing power resilience	MILP	Reduced electricity costs for office buildings and improved outage resilience	[67]
	2018	Improving system resilience	CVaR model	Significantly enhanced resilience of commercial-building microgrids	[68]
Hybrid System	2025	Heat pump storage optimization	Multi-objective optimization	Annual performance factor improved by 10.45%; carbon emissions reduced by 94.01%	[44]
	2021	Heat pump integrated thermal storage	Open-source sector-coupled scheduling model	Heat pumps boosted local PV self-consumption and increased feasible PV capacity	[45]
	2024	Heating, ventilation, and air conditioning (HVAC)	Photovoltaic direct-drive air conditioning (PVAC) model	Peak power was reduced by 45.2%; system self-sufficiency ratio (SSR) increased to 0.91	[56]
	2024	PCM thermal storage	Hybrid electric-heating model with PCM	PV self-consumption increased by 10.93 kWh; payback period shortened to 1.31 years	[58]
	2024	Heat-pump thermal storage	Rule-based PV-heat pump operational strategy	PV self-consumption decreased by 2.39%; annual total cost reduced by 6.61%	[62]
	2026	Stationary lithium iron phosphate (LFP) and nickel–manganese–cobalt (NMC)	Enhanced D3QNPER Algorithm	43.39% reduction in system operating costs, with EV battery SoH degradation limited to 0.04%	[59]
	2024	ACWH thermal storage	Residential microgrid optimization framework	PV-ACWH integration shortened payback period by 46.99%	[63]
	2026	Grid-connected microgrid with diesel generation	REopt-based MILP optimization model	PV–ACWH integration shortened the payback period by 46.99%; 100% critical load supply was achieved with a 1.4–3.4% cost premium.	[64]

Note: Quantitative outcomes are reported under different building types, climates, system boundaries, tariffs, baselines, and control horizons, and therefore should not be interpreted as directly comparable benchmarks.

The reviewed evidence shows that storage serves several distinct functions in PSDF buildings. Self-consumption-oriented storage shifts surplus PV to periods of local demand; grid-support storage can reduce peak exchange, ramping, and feeder stress; resilience-oriented storage supports critical loads during outages; and DSM-oriented storage provides temporal flexibility in response to tariffs, control signals, and coordinated building operations. These functions should not be evaluated using a single metric because higher cycling for grid or DSM services can conflict with battery life and life cycle cost, while resilience-oriented designs may require additional capacity that is underutilized during normal operation [54,60–68].

3.3. Direct Current (DC) Distribution Systems

Compared with conventional AC distribution, DC distribution can offer advantages in buildings that integrate PV, storage, power-electronic interfaces, and DC-native loads [33]. Because PV modules and batteries operate internally in DC and many modern end-use devices ultimately require DC power, a DC architecture can reduce repeated AC/DC conversion stages. The achievable benefit, however, depends on system topology, voltage level, converter efficiency, and the proportion of loads that can be supplied directly from the DC bus [69,70]. Figure 5 illustrates the energy management system for DC microgrids.

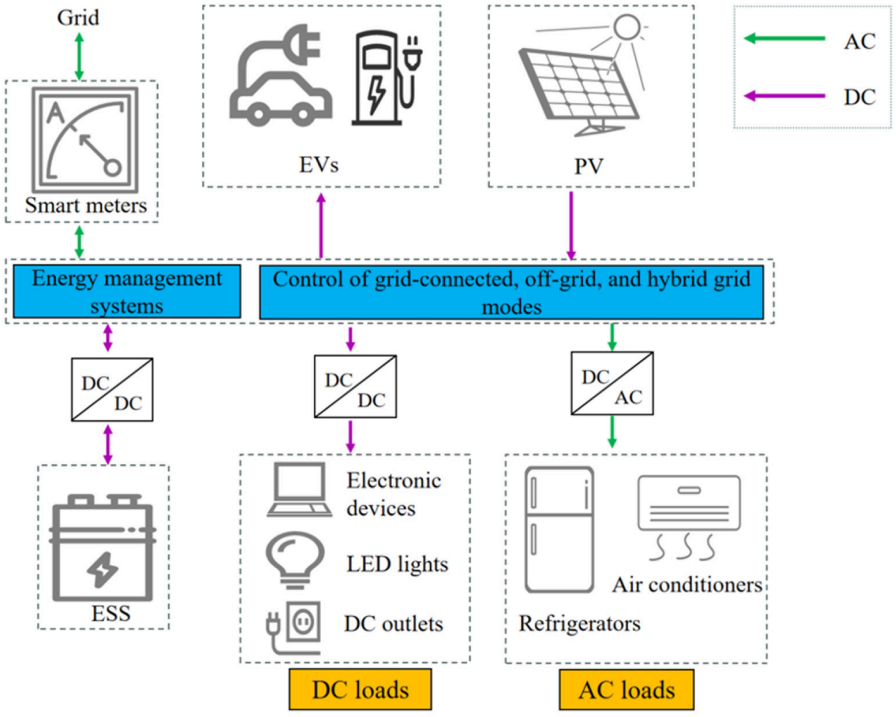


Figure 5. Energy management system for DC microgrids.

3.3.1. Comparison with Traditional AC Systems

By reducing energy conversion stages, direct current distribution systems can improve efficiency in building energy applications that combine PV, storage, and DC-native loads. Time series and converter-level studies have reported lower conversion losses and improved integration under specific configurations [71–77]. Alilou et al. [78] further proposed a life cycle planning framework for an off-grid AC/DC hybrid microgrid that jointly optimizes sizing and energy management, while other building-scale studies have compared AC, DC, and hybrid architectures under different equipment and load assumptions [79–82].

These studies indicate that the efficiency advantage of DC is conditional rather than universal. It is most pronounced when a large share of generation, storage, and end uses is

DC-coupled and unnecessary conversion stages can be removed. Additional converters, mixed AC/DC loads, unsuitable voltage levels, or inefficient interfaces can reduce this advantage. Consequently, AC/DC comparisons should be interpreted in relation to the actual building topology and equipment configuration rather than as an inherent superiority of one distribution architecture.

3.3.2. DC Loads and Device-Level Integration

Direct current loads in buildings, including LED lighting, electronic devices, selected motor-driven equipment, and other DC-compatible appliances, can reduce the repeated AC-to-DC conversions associated with conventional distribution [83]. Existing studies have examined capacitor requirements, household DC appliances, converter control, and distributed coordination [84–87]. Nevertheless, device-level integration remains constrained by non-unified interfaces, voltage compatibility, equipment availability, and the need for reliable bidirectional power-electronic converters.

3.3.3. Operating Modes and Engineering Barriers

A DC microgrid can operate in grid-connected, islanded, or hybrid modes. In grid-connected operation, coordinated DC/AC conversion and control are required to maintain DC-bus voltage and manage bidirectional power exchange [88]. During grid faults or outages, islanded operation requires rapid power-flow reconfiguration and priority supply to critical loads [89]. Consensus-based control and optimization have also been investigated to reduce losses and coordinate off-grid DC nanogrids [90], while resilience-oriented microgrid studies have considered multi-energy resources and extreme weather operation [91–94].

Table 7 summarizes representative research on DC distribution, DC microgrids, and DC-connected resources. Several entries involving EVs and flexible loads are cross-cutting and are also discussed in Section 3.4.

Table 7. Representative research on DC distribution, DC microgrids, and DC-connected resources.

Year	Algorithm/Method	Key Findings	Ref.
2023	Time series simulation; battery charge–discharge control logic	DC distribution demonstrates lower conversion losses compared with AC systems, yielding significant efficiency gains	[71]
2021	Improved Perturb-and-Observe (P&O) algorithm	Bidirectional converters stabilize the system and enhance system-level integration with the DC bus	[73]
2023	Incremental Conductance (INC) algorithm for MPPT	Enables efficient integration of PV, storage, and loads in bipolar DC households	[74]
2023	MPPT algorithm	Mitigates mismatch and intermittency-induced losses, improving overall reliability of standalone PV systems.	[75]
2021	PI control; modular current control	Provides flexibility for integrating DERs	[76]
2021	MPPT algorithm	Achieves a 10% efficiency improvement over traditional architectures; however, the lack of standardized interfaces limits scalability	[77]
2022	Life cycle assessment (LCA)	DC microgrid-based distribution reduces environmental impacts associated with power-electronic components	[82]
2018	Comparative AC/DC load and conversion-loss analysis	Reduces multiple AC–DC conversion losses	[83]
2019	Nonlinear battery degradation model	Demonstrates that DC input significantly reduces capacitor capacity requirements	[84]
2023	MPPT system	DC microgrid maintains accurate voltage supply for small household DC appliances	[85]

Table 7. *Cont.*

Year	Algorithm/Method	Key Findings	Ref.
2024	Nash equilibrium strategy; non-cooperative game; PPBSD-ADMM	Reduces costs for prosumers, consumers, and microgrids by 54.55%, 33.28%, and 34.65%, respectively	[86]
2020	MPPT algorithm	PV systems can reduce annual greenhouse gas emissions by 35.05 tons, shortening payback period to 7 years	[87]
2023	Multi-attribute decision-making; evidence reasoning; symmetric averaging	Develops an intelligent control framework for DC building microgrids, validated experimentally for performance and practicality	[95]
2024	Minimum Fuzzy Carbon Emission Method (MFCEM)	Balances economic performance and carbon emissions; bidirectional EV charging substantially enhances economic efficiency	[96]
2019	IGDT under risk-averse and risk-seeking modes	IGDT effectively manages uncertainty in plug-in hybrid electric vehicles (PHEVs) electricity demand	[97]
2020	Rule-based optimization algorithm	HEMS automatically switches to V2H mode during outages, ensuring supply to critical loads	[98]
2023	Control algorithm for smart EV chargers	Distributed charging strategy coordinates PV generation and EV demand, raising annual solar self-consumption to 67.9%	[99]
2021	Direct quadrature (DQ) control; incremental-conductance MPPT	Improves DC–AC converter coordination and significantly enhances DC-bus voltage stability	[88]
2023	Incremental-conductance MPPT	Rapidly reconfigures power flow during grid faults to maintain supply to critical loads	[89]
2022	Incremental Loss Consensus Algorithm (ILCA); Voltage Consensus Algorithm (VCA)	Joint optimization reduces power losses in off-grid solar DC nano-grids	[90]
2023	MILP	Demonstrates benefits of integrating PV, batteries, combined heat and power (CHP), TES tanks, and absorption chillers for improved energy resilience	[91]
2020	Three load-shifting mechanisms	Ensures microgrid survivability under extreme weather scenarios	[92]
2026	Surrogate model (logistic regression) and Monte Carlo simulation	80% PV oversizing and 20% ESS undersizing for optimal resilience	[93]
2024	MILP; Model Predictive Control (MPC)	Dynamic energy management balances PV, storage, and loads, supporting net-zero energy goals	[94]

Note: The reported results are specific to the topology, equipment, operating mode, and baseline adopted in each study and should not be interpreted as directly comparable performance rankings.

3.4. Flexible Loads and Demand-Side Flexibility

Flexible loads form the demand-side component of the PSDF framework. Their flexibility arises from the ability to shift, curtail, or modulate electricity use while maintaining the required building services. Thermostatically controlled loads and thermal storage systems are important examples because building thermal inertia allows short-term changes in electrical demand without immediately violating comfort constraints. The studies reviewed in Section 3 include heat pumps [45], PV-direct-driven air conditioning [56], phase-change thermal storage [58], PV–heat pump coordination [62], and dual-resolution control of thermostatically controlled loads [46].

EVs and other schedulable electrical loads provide another source of flexibility. Existing studies have examined uncertainty in EV demand, bidirectional charging, V2H/V2G operation, robust scheduling, and coordinated PV-EV charging [95–100]. These resources can contribute to peak management, renewable-energy utilization, and outage support, but their availability is constrained by mobility requirements, the state of charge, user schedules, and charging infrastructure.

The flexibility of building loads is therefore heterogeneous and time-dependent. HVAC systems and heat pumps are constrained by comfort and thermal dynamics; appliances by task-completion windows; and EVs by mobility and battery requirements. Physical flexibility should therefore be distinguished from usable flexibility. Converting this potential into reliable building and grid services requires forecasting, user participation, control strategies, and economic incentives, which are examined in Section 4.

3.5. Component-Level Synthesis

The component technologies reviewed above have reached different levels of maturity. PV and conventional battery storage are comparatively mature and widely studied at the building scale, although uncertainty, degradation, sizing, and coordinated operation remain important issues. DC distribution can reduce conversion stages and facilitate the coupling of DC-native resources, but its large-scale adoption is more dependent on standards, protection, interoperable converters, and compatible end-use equipment. Flexible loads provide substantial regulation potential, but their practical availability depends on building services constraints and user behavior.

Accordingly, the value of PSDF does not arise from installing P, S, D, and F independently. It arises from using storage and flexible demand to mitigate PV variability, applying DC distribution where it can meaningfully reduce conversion and integration losses, and coordinating the resulting building energy node with the distribution network. At the grid interface, relevant outcomes extend beyond building energy savings to peak shaving, ramp-rate control, voltage regulation, reverse power flow management, hosting capacity, and resilience [49–51,88–94]. These interactions provide the transition from the component layer reviewed here to the coordination strategies discussed in Section 4 and the interaction/application layer discussed in Section 5.

4. Demand-Side Management Strategies in PSDF Systems

In conventional building operations, electricity demand is largely treated as passive and supplied by the grid. In contrast, buildings integrated with PSDF systems actively regulate electrical loads through flexible demand control. In this context, effectively balancing power system supply and demand, fully utilizing the capacity of various flexible resources, and maintaining stable grid operations have become pressing issues that need to be addressed [101]. To address this challenge, two primary strategies for increasing self-consumption in residential buildings are DSM and battery-based energy storage [22]. Within the multi-layer framework adopted in this review, DSM, DR, and EMS form the coordination layer that translates the physical flexibility of PV, energy storage, DC infrastructure, and controllable loads into operational actions. Accordingly, this section examines DSM from three complementary perspectives: techno-economic design, control-based coordination, and user-centered participation. Figure 6 summarizes these three dimensions and their principal mechanisms.

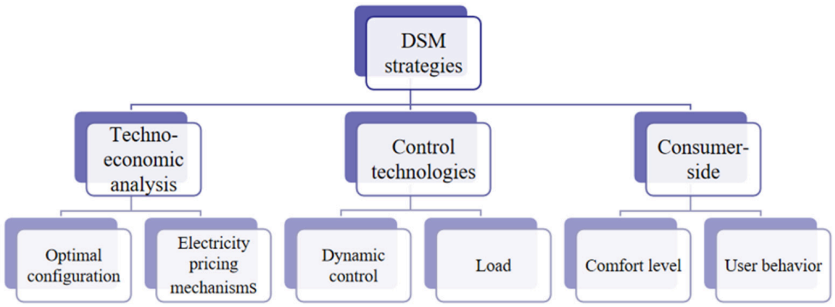


Figure 6. Classification of demand-side management strategies in PSDF systems.

4.1. Techno-Economic DSM Strategies

DSM strategies significantly influence the techno-economic design of PSDF systems. Techno-economic analysis, in turn, quantifies the value of the system and highlights its advantages over conventional approaches. By leveraging the load regulation capabilities of DSM strategies, system configuration can be optimized to avoid unnecessary equipment investment and shorten payback periods. For instance, Chen [102] proposed an integrated capacity planning model for residential distributed photovoltaics (RDPV) incorporating EV charging, vehicle-to-home (V2H), and flexible load demand response (DR). The study demonstrated that DR and V2H technologies can reduce the optimal installed PV capacity and lower total electricity costs. Similarly, Jiao et al. [103] introduced a bi-level optimization framework that simplifies load time series through global K-means clustering to optimize the capacity allocation and scheduling of thermal power, hydropower, pumped storage, energy storage, and DR. This approach reduces wind curtailment rates while decreasing both investment and operational costs. Han et al. [104] employed a demand-side management (DSM) strategy to optimize the charging and discharging schedule of a thermal storage tank, shifting the electricity consumption of heat pumps from daytime peak periods to nighttime off-peak periods. Compared with conventional operations, the proposed strategy reduced net operating costs by 66.8% and electricity costs by 43.5%, while improving the daily peak-to-valley load ratio from 2.8:1 to 1.6:1. Zhou [105] proposed a dynamic self-learning grid response strategy that dynamically adjusts grid charging power during off-peak hours, significantly enhancing techno-economic performance, energy flexibility, and battery relative capacity (RC). Researchers not only compare initial investment costs but also focus on long-term operational benefits. For example, Xiang et al. [106] introduced a MILP model based on life cycle costs, integrating a hydrogen–photovoltaic–storage microgrid solution for airport electrification. Similarly, Al Muala et al. [54] further optimized household energy scheduling by applying life cycle cost principles.

A key driver of cost-effective power systems is the electricity pricing mechanism, as different pricing schemes directly affect the magnitude and risk of economic returns. Yang et al. [107] proposed a bilevel Stackelberg game framework based on distribution locational marginal pricing (DLMP), aiming to minimize electricity costs. Karimianfard [100] developed a two-stage robust optimization model that considers electricity costs under different pricing schemes, such as TOU and real-time pricing (RTP). In a hospital setting, Nebey et al. [108] introduced a fuzzy logic controller integrated with TOU pricing and a PV-storage system, achieving a 20.8% reduction in total energy consumption and an 18.64% decrease in electricity costs. Kafaei et al. [109] employed a two-stage stochastic optimization model and incorporated DR mechanisms such as TOU pricing to enhance system flexibility. Alilou et al. [110] proposed a clustered electricity pricing strategy that divides tariffs into multiple tiers, coordinating residential PVs, sodium-sulfur batteries, and EVs to reduce electricity costs by 23–43% and linearize load consumption patterns. In P2P electricity trading, pricing is assigned individually to each trading pair, or node, rather than using a uniform rate. This approach more accurately reflects local costs and the time- and location-dependent value of electricity [111]. Clift et al. [112] developed a P2P energy trading framework based on advanced multi-zone electric water storage heaters featuring autonomous and aggregated control, which generates economic benefits by participating in electricity market ancillary services, demand management, and P2P transactions. Thus, compared with traditional markets, P2P trading can better reflect the spatiotemporal value of electricity through more granular and dynamic individual pricing, thereby guiding the system toward more economical operations.

Taken together, these studies show that the techno-economic value of DSM is determined not only by short-term electricity cost reduction but also by its influence on

capacity sizing, asset utilization, life cycle cost, and exposure to tariff or market signals. Capacity planning studies [102,103], storage and life cycle analyses [54,104–106], and pricing or trading studies [100,107–112] therefore address different but complementary dimensions of economic performance. Their reported savings should be interpreted as study-specific outcomes rather than directly comparable benchmarks because the building types, system boundaries, tariff structures, baseline cases, and optimization objectives differ across studies.

4.2. Control-Based DSM Strategies

Advanced control algorithms enhance the demand response (DR) capabilities of building energy systems. For instance, Ferahtia et al. [113] proposed an EMS for microgrids operating in both grid-connected and islanded modes, applying the Bald Eagle Search (BES) algorithm to achieve the lowest operating cost (0.1577 €¢/kWh) and a system efficiency of 87.395%. Ebeed et al. [114] introduced a novel modified Mean of Vectors algorithm (MINFO), which reduces the peak-to-average ratio (PAR) by up to 53.19%. In [115], a HEMS integrated with smart thermostats combines MILP and fuzzy logic for DR in smart grids. In addition, dynamic control strategies provide flexibility to power systems, enabling them to respond to sudden load variations or faults, and thereby ensuring stable, secure, and economical grid operations. Sridhar et al. [116] designed a dynamic load control mechanism that optimizes the operation of individual appliances such as heat pumps, electric boilers, battery storage, solar photovoltaics, and EVs. Their results indicate that users with variable electricity contracts achieve the highest cost savings. Horrillo-Quintero et al. [117] proposed a novel dynamic control strategy integrating fuzzy logic, model predictive control, and nonlinear optimization, aiming to minimize operational costs, natural gas consumption, and grid dependency while maximizing system flexibility.

Under smart control technologies, loads are no longer merely consumers of electricity but can also be actively managed. Based on their demand response (DR) flexibility, household loads can be categorized into thermostatically controlled loads (TCLs), such as air conditioners (ACs) and electric water heaters (EWHs); shiftable loads, such as washing machines and dishwashers; and non-flexible or rigid loads, such as plug-in appliances and security devices. Zou et al. [46] demonstrated that, by dispatching TCLs such as ACs and EWHs, the PV generation profile can be matched at a minute-level resolution, increasing the real-time matching rate (RTMR) by up to 482%. Saber et al. [118] proposed an energy management model for office buildings based on a transactive market framework. By integrating the flexibility of EVs, with owners submitting response curves and target state of charge, batteries, and rooftop PV systems, and by employing distributionally robust chance-constrained programming to address uncertainties, the study showed reductions in both the total operational cost of the EMS and the aging rate of the transformer. As a key flexible load, the optimization of air conditioning systems significantly enhances energy matching efficiency. Implementing DSM strategies to optimize solar-assisted air conditioning systems can effectively improve building energy flexibility [119]. In [120], a PVAC system uses the indoor thermal comfort temperature range (TCTR) and a machine learning model to dynamically adjust temperature at a minute-level resolution, thereby maximizing the photovoltaic self-consumption rate. Wang et al. [121] introduced a novel PVAC system and experimentally demonstrated a control strategy in which compressor speed directly responds to real-time photovoltaic generation, thereby optimizing energy matching between PV output and air conditioning demand. Esmaeel Nezhad et al. [122] employed inverter air conditioning coordinated with energy storage to optimize scheduling under TOU electricity tariffs, effectively reducing peak grid dependence. These findings indicate that load-side optimization can provide operational flexibility when the control-

lable characteristics of different loads are explicitly represented. Coordinated dispatch of thermostatically controlled loads, EVs, batteries, and other flexible resources can improve PV–load matching, reduce peak grid dependence, and support building–grid operation.

The control-oriented literature also shows that DSM performance is inherently multi-objective. Depending on the application, studies evaluate operating costs [113,117,118], the peak-to-average ratio [114], PV self-consumption or real-time matching [46,120,121], transformer aging [118], grid dependence [117,122], and indoor thermal comfort [120]. Consequently, no single control metric is sufficient to characterize DSM performance. Higher temporal resolution and more sophisticated optimization can improve coordination, but they also increase dependence on accurate forecasts, device-level controllability, and reliable operational data. Uncertainty-aware EMS studies have also coordinated PV generation and stochastic EV mobility in grid-connected smart buildings, highlighting the importance of joint scheduling when multiple flexible resources interact [123].

4.3. User-Centered and Behavioral DSM Strategies

With technological advancements, an increasing number of users are becoming active participants in the energy market. User-side DSM strategies promote the implementation and sustainable development of PSDF systems by enabling users to exercise demand response (DR) based on their comfort preferences, dynamic willingness to participate, and actual needs. Abu Gunmi et al. [124] employed fuzzy logic decision-making combined with a support vector machine–particle swarm optimization (SVM-PSO) model to co-optimize energy storage configuration and DR strategies, thereby balancing economic benefits and user comfort under uncertain conditions. Giuzio et al. [125] balanced economic costs, namely energy expenses, and non-economic costs, namely thermal comfort, through thermostat adjustments and load shifting, thereby increasing RES utilization by 8–25%. A DRL-based HEMS has been used to coordinate PV generation, energy storage, and EV operations while reducing overall energy costs and accounting for user satisfaction [126]. Deng et al. [127] proposed a distributed direct current energy system combined with DRL, which significantly enhances energy efficiency. While maintaining user satisfaction, the approach achieves a 38% energy saving rate, increases PV self-consumption by 38%, and reduces battery dependence by 33%. Vidya et al. [128] employed binary particle swarm optimization (BPSO) to schedule household loads, reducing the peak-to-average ratio (PAR) by 22% without compromising user comfort. Sumayli and Anubi [129] proposed a distributed energy management framework based on federated reinforcement learning (FRL). Compared with the non-optimized baseline, the proposed approach reduced the average electricity cost by 42%, while reducing peak-period demand and minimizing energy costs without compromising user comfort.

By incorporating user behavioral patterns, consumer participation can be enhanced to provide flexibility services. Reference [130] examines differences in residential electricity demand and explores the impacts of uncertainties related to tariff mechanisms, battery energy storage, and residential flexible load demand response (DR). Vashistha et al. [131] incorporated incentive mechanisms directly into the utility function to characterize prosumers' price responsiveness to differentiated electricity tariffs. Sensitivity analysis showed that, as the incentive level increased from 0% to 100%, the total system operating cost increased from 14.23 to 17.41. Hussain et al. [86] employed a non-cooperative game with distributed optimization to select DR participants and optimize appliance scheduling. This approach protects user privacy while reducing prosumer costs by 54.55% and microgrid costs by 34.65%. Kement et al. [132] proposed a privacy-aware stochastic optimization method that balances user privacy, comfort, and grid requirements, demonstrating that near-optimal privacy performance can be achieved with minor compromises. In [133],

the Teaching-Learning-Based Optimization (TLBO) algorithm is employed to optimize day-ahead electricity scheduling by accounting for temperature forecasts, energy prices, solar irradiance, system constraints, and user preferences, aiming to address multi-objective power management optimization. Hou et al. [134] proposed a novel framework based on transactive energy (TE), in which aggregators negotiate with distribution system operators to ensure grid security and convey additional price signals, representing the cost of security, to prosumers, who submit schedules via HEMS, in order to incentivize responsive behavior.

These studies demonstrate that technically available flexibility does not automatically translate into usable DSM flexibility. Its realization depends on occupant comfort constraints, willingness to participate, responsiveness to price or incentive signals, and the treatment of privacy and fairness. Accordingly, user-centered DSM should be evaluated jointly with technical and economic objectives rather than as a separate behavioral issue. The results reported in [124–134] also illustrate recurring trade-offs among electricity cost, renewable-energy utilization, comfort, privacy, and grid-support requirements. Table 8 lists a summary of the relevant literature.

Table 8. Representative studies on demand-side management strategies.

Category	Year	Model/Algorithm	Key Findings	Ref.
Techno-Economic Analysis	2024	Capacity-planning model	Reduces optimal PV installed capacity and total electricity costs	[102]
	2024	Global K-means load-clustering model	Achieves optimal capacity configuration	[103]
	2026	Hooke–Jeeves pattern search method	Optimal thermal storage temperature of 50 °C, reducing net operating costs by 66.8% and electricity costs by 43.5% compared with conventional operations	[104]
	2023	Dynamic self-learning grid-response strategy	Adjusts off-peak grid-charging power dynamically, improving techno-economic performance, energy flexibility, and relative battery capacity	[105]
	2021	MILP	Minimizes total economic cost and carbon emissions of an airport microgrid	[106]
	2023	Bilevel Stackelberg game model	Reduces electricity costs	[107]
	2025	Smart-home optimized energy management framework	PV–battery-integrated robust model saves up to 53.8% in time-of-use electricity expenditure	[100]
	2024	Energy management model with fuzzy-logic controller	Enables more intelligent control, reducing total energy use and electricity costs	[108]
	2021	Stochastic day-ahead optimization	Reduces total cost of the energy hub	[109]
	2024	Clustered electricity-price strategy	Lowers household electricity cost and induces more linear consumption patterns	[110]
	2023	Market-driven P2P energy trading framework	P2P trading under TOU tariffs yields greater economic efficiency	[111]
	2023	Market-driven P2P framework	Increases PV aggregation; 17% surplus supports the grid during shortages, reducing energy trading cost	[112]
Control Strategy Analysis	2021	EMS	Achieves economic operations	[113]
	2025	MINFO	Enhances performance of smart-building/HEMS	[114]
	2021	MILP	Minimizes cost while enabling optimal DR and PV self-consumption	[115]
	2024	Dynamic load control mechanism	Users on variable-price contracts achieve highest cost savings and deliver maximum grid flexibility	[116]
	2025	Dynamic control strategy	Reduces costs significantly—by 33.86% and 18.38%	[117]
	2024	Multi-time-resolution scheduling strategy	Improves real-time energy-matching performance in PV home energy systems (HES)	[46]

Table 8. *Cont.*

Category	Year	Model/Algorithm	Key Findings	Ref.
Control Strategy Analysis	2022	Energy management model	Achieves optimal scheduling while reducing operational cost and transformer aging	[118]
	2021	DSM strategy	Improves building energy flexibility	[119]
	2021	Evaluation framework with TCTR	PVAC maximizes PV utilization and load flexibility under TCTR	[120]
	2024	PVAC	Enhances power matching between PV output and air conditioning demand	[121]
	2021	MILP	Optimizes air conditioning and home appliance operations, reducing energy consumption	[122]
User-Side Analysis	2024	Smart-home EMS	Minimizes costs in zero-emission power systems while balancing cost-effectiveness, technical feasibility, and occupant comfort	[124]
	2024	Framework for clustered energy flexibility strategies	Increases renewable utilization by up to 25%; load adjustments raise renewable consumption by 8%	[125]
	2023	Deep reinforcement learning (DRL)–based HEMS	Optimizes energy use across appliances, storage, PV, and EVs	[126]
	2024	Novel operational approaches based on DRL	Increases user satisfaction by 9% and reduces battery dependence by 33%	[127]
	2024	Binary Particle Swarm Optimization (BPSO)	Balances user comfort and peak-to-average ratio (PAR)	[128]
	2026	Federated Reinforcement Learning (FRL)	42% reduction in average household electricity costs compared with the non-HEMS baseline	[129]
	2024	Techno-economic evaluation of rooftop PV	More cost-effective under time-of-use tariffs than under flat tariffs	[130]
	2026	Two-stage MSNN-GBO optimization method	19.4% reduction in daily operating costs; system efficiency of 98%	[131]
	2024	Non-cooperative game with Nash equilibrium	Privacy-preserving multi-objective scheduling for smart appliances	[86]
	2021	Stochastic multi-objective optimization framework	Balances privacy, comfort, and grid requirements with near-optimal privacy performance and limited performance trade-offs	[132]
	2024	Smart-home EMS	Ensures optimal energy utilization and cost efficiency	[133]
	2022	Novel transactive energy (TE) framework	Ensures economic operations for aggregators and prosumers while maintaining grid security	[134]

Note: The category labels in Table 8 have been aligned with Sections 4.1–4.3. Quantitative outcomes are reported as study-specific results and should not be compared directly across studies because baseline conditions, building/system boundaries, tariffs, control horizons, and performance definitions differ.

Across the three DSM categories, the literature employs several groups of performance indicators. Economic indicators include operating costs, electricity expenditures, and life cycle cost; load-shape and grid indicators include the peak-to-average ratio, peak-to-valley ratio, peak grid dependence, and grid-support capability; renewable-energy indicators include PV self-consumption and real-time matching; asset-related indicators include battery capacity and transformer aging; and user-oriented indicators include comfort, satisfaction, privacy, and participation. These indicators describe different dimensions of flexibility and should not be treated as interchangeable measures. For PSDF systems, a more complete DSM assessment therefore requires simultaneous consideration of building economics, device operation, user constraints, and the services provided to the external grid.

5. Interaction and Application of PSDF Systems

Building on the component technologies reviewed in Section 3 and the DSM/EMS coordination strategies discussed in Section 4, this section examines the interaction and application layer of PSDF systems. At this level, buildings operate not only as local energy

consumers and producers, but also as flexible nodes that exchange energy, flexibility, and information with neighboring buildings, communities, aggregators, and distribution networks. The following subsections therefore focus on community-scale coordination and building-grid interaction, resilience and emergency operations, intelligent and digital technologies, and policy or deployment frameworks.

5.1. Smart Communities and Building-Grid Interaction

Internationally, as exemplified by European energy communities, research on distributed energy systems explores new approaches to user empowerment, local consumption, and system flexibility that are functionally related to the PSDF framework. Innovative economic incentive mechanisms in energy communities are essential for increasing user participation and unlocking demand-side flexibility [135]. Chen et al. [136] compared individual battery storage with community-shared energy storage and found that the community-based configuration resulted in lower annual power exports and a more balanced distribution of exports across different time periods. These findings are relevant to the community-scale deployment of integrated PSDF systems. Figure 7 illustrates the interactions among consumers, distributed resources, DSM strategies, policy drivers, and market mechanisms, while Table 9 summarizes representative studies from different regions.

For user-involved smart communities, Anbarasu et al. [137] proposed a framework based on the Modelica language and quasi-Monte Carlo sensitivity analysis, finding that resident behavior has the greatest impact on the energy system, with a variation of 23.3%. Izadi et al. [29] introduced a three-stage iterative framework to study the trading behaviors of prosumers in P2P energy markets within smart energy communities, aiming to maximize community welfare and user engagement. Silva et al. [138] employed a hybrid HACO-GA combining ant colony optimization (ACO) and a genetic algorithm (GA) to optimize grid electricity costs, peak load, and user comfort. To enhance the economic performance, security, and environmental sustainability of DR and shared ESS, Hou et al. [139] employed a two-stage scheduling optimization model involving multiple stakeholders to explore optimal scheduling within smart communities. Mukundufite et al. [140] investigated an EMS for smart microgrids in rural Rwandan communities based on optimal operational costs, reducing electricity costs to 0.186 $/kWh when subsidies are considered. Angizeh et al. [141] studied an integrated scheduling model based on the branch flow-based AC power flow model and mixed-integer nonlinear programming (MINLP), which reduces community operational costs and improves grid stability by optimally scheduling flexible loads such as EVs and smart appliances. Huang et al. [142] examined the impact of smart charging for EVs on grid regulation performance and battery degradation in Swedish solar building communities. The results show that smart charging significantly reduces grid peak exchange by 9.3–13% without substantially increasing battery degradation.

Smart communities, as carriers of DERs, integrate photovoltaics, energy storage, direct current distribution, and flexible loads across multiple smart buildings to achieve energy self-sufficiency and grid interaction. Zhang et al. [143] applied a prototype-based modeling approach to a case study of 54 buildings. Compared with normal operations, the clustered buildings demonstrated an average peak demand reduction of 22–27%, highlighting the operational energy flexibility value of building clusters. Gerber et al. [84] verified through a U.S. residential case study that direct current distribution reduces conversion losses compared with alternating current systems, saving 5% of the total household electricity load in homes without storage and 14% in homes with storage. EVs, as key flexible resources, are often used as adjustable loads for flexible electricity consumption. In [144], a German residential case study employed model predictive control (MPC) to coordinate PVs, energy storage, EVs, and heat pumps, achieving a 69–100% peak reduction during DR.

Huang et al. [145] optimized the capacity and siting of photovoltaics at the cluster level through a Swedish residential case study using a coupled photovoltaic–heat pump–thermal storage–EV system, significantly enhancing system flexibility. In [146], an electric scooter battery-swapping system in Taiwan optimized charging and discharging through vehicle-to-grid (V2G) strategies; the study reported substantial peak-demand mitigation and an 18.9% reduction in operating costs. In [147], a community used shared energy storage and an EV fleet to establish an energy credit mechanism (ECM), lowering community energy costs through V2G technology. At the aggregation level, VPP-based studies have coordinated PV, storage, demand response, and other distributed energy resources under uncertainty and across multiple timescales [148–150], while smart demand-supply EMS has been used to coordinate distributed resources [151]. Market-oriented VPP dispatch has also been extended to carbon and green certificate trading [152].

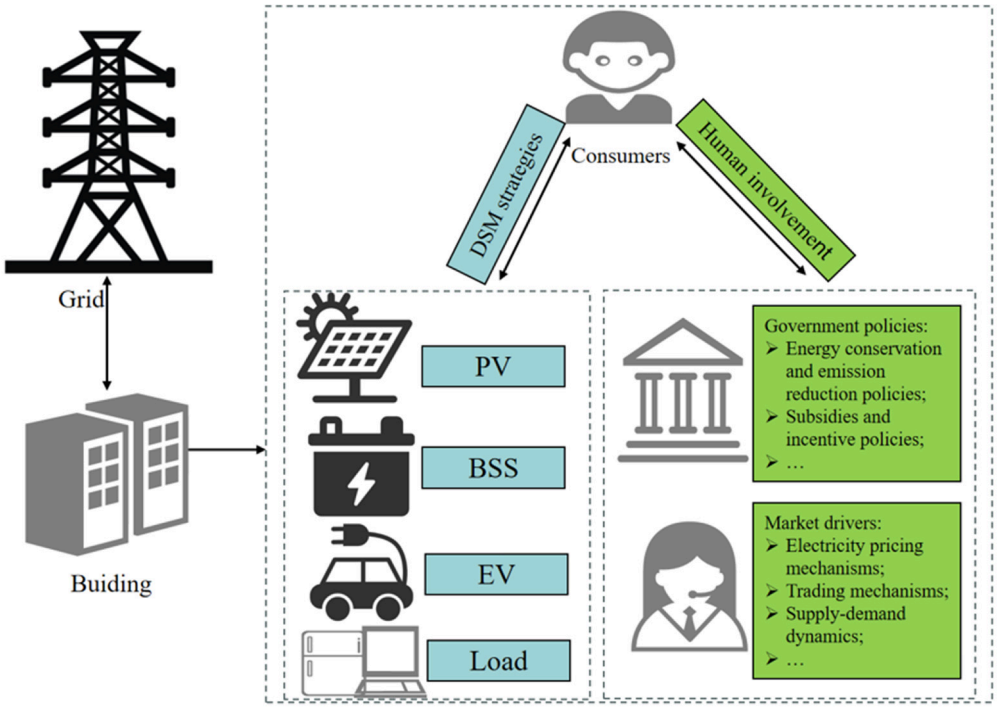


Figure 7. Conceptual system model of a smart community with distributed resources, DSM, policy, and market interactions.

Table 9. Representative smart community and building-grid studies across different regions.

Year	Country	Methodology	Research Focus	Key Findings	Ref.
2022	Germany	Blockchain-based tokenization system	Incentivizing PV self-consumption and enabling gradual asset ownership in energy communities	Economically feasible over a 15-year simulation period (payback < 5 years); self-consumption reached 69%; household electricity bills decreased by 24%	[135]
2026	Japan	K-means clustering and Monte Carlo simulation	Comparison of individual and community-shared energy storage in Fukuoka, Japan	7.8% reduction in total storage capacity compared with individual storage	[136]
2024	United States	Quasi-Monte Carlo sensitivity analysis	Quantifying nonlinear interdependencies across energy, transportation, communication, and water infrastructure in smart communities	Resident behavioral patterns exert the strongest influence on energy systems, followed by road-traffic delays	[137]
2024	Iran	Three-stage iterative framework	Prosumers' behavior in P2P energy markets within smart communities	Achieved 69.51% cost reduction	[29]

Table 9. *Cont.*

Year	Country	Methodology	Research Focus	Key Findings	Ref.
2024	Sri Lanka	HACO–GA	Demand-side management based on metaheuristic optimization	Achieved 35.4% peak-load reduction and 33.67% cumulative cost savings	[138]
2024	China	Two-stage scheduling optimization	Optimal dispatch in smart communities considering unit productivity and energy trading	Reduced operational cost by 40.22% and increased PV absorption by 22.57%	[139]
2024	Rwanda	HOMER simulation + GA optimization	Energy-system management for smart microgrids	Electricity cost reduced to 0.186 $/kWh under subsidy scenarios	[140]
2024	United States	AC power-flow model + MINLP integrated scheduling	Demand-flexibility management in smart communities	Reduced operational cost by ~10% without compromising user comfort	[141]
2022	Sweden	Particle Swarm Optimization (PSO) + rainflow counting algorithm	Impact of EV smart charging on grid regulation and battery degradation in solar communities	Smart charging reduced peak grid exchange by 9.3–13% with no major increase in battery degradation	[142]
2024	Canada	Prototype-based bottom-up modeling	Case study of 54 buildings	Peak demand for building clusters reduced by 22–27% compared with baseline	[143]
2019	United States	Optimization model for DC load design	Retrofit and performance assessment of five typical household loads	DC distribution reduced conversion losses, lowering total electricity load by 5% (no storage) and 14% (with storage)	[84]
2024	Germany	Model Predictive Control (MPC)	Coordinated control of PV, storage, EVs, and heat pumps	Achieved 69–100% peak-load reduction through DR	[144]
2019	Sweden	GA-based optimization	PV–heat pump–thermal storage–EV-coupled residential cluster	Achieved 77% PV self-consumption at district scale	[145]
2025	China	Multi-objective optimization	Optimizing Vehicle-to-Grid (V2G) charging/discharging strategy	Substantial peak-demand mitigation; operating costs were reduced by 18.9%	[146]
2022	Turkey	Battery degradation cost model	Shared storage and EV fleet energy credit mechanism (ECM) with V2G	Lowered community-level energy cost through V2G-enabled flexibility	[147]

Note: Quantitative outcomes in Table 9 are study-specific and are not directly comparable across studies because system boundaries, climates, tariffs, baseline definitions, and control horizons differ.

Collectively, these studies show that extending PSDF functions from a single building to a building cluster or community enables coordination across heterogeneous DERs, flexible loads, and market mechanisms. The benefits extend beyond local self-consumption and operating cost reduction: coordinated flexible resources can also reduce peak grid exchange [142–144], mitigate conversion losses through DC distribution [84], and support voltage regulation, ramp-rate control, and more balanced building–grid operation [25,51]. These grid-oriented functions are especially important under high distributed PV penetration, where unmanaged exports can aggravate reverse power flow and voltage rise problems [51]. Thus, community-scale PSDF should be evaluated through both building-side objectives (cost, comfort, self-consumption, and asset use) and distribution network objectives (peak management, voltage quality, power-flow coordination, and the ability to accommodate additional distributed resources). Quantitative results reported in Table 9 remain study-specific because the system boundaries, climates, tariffs, baseline definitions, and control horizons differ substantially.

5.2. Resilience and Emergency Operation

Extreme weather events pose significant challenges to conventional power systems, and prolonged grid outages expose the limitations of relying solely on centralized supply or single-purpose backup resources. Maintaining a reliable energy supply to critical building loads is therefore an important application of distributed PV, storage, and demand flexibility.

Sun et al. [153] developed a reliability valuation model for PV-storage systems based on grid interruption probability. By quantifying the coupling relationship between outage risks and economic benefits, they derived an optimal capacity planning strategy for household PV and energy storage. A case study involving 600 households across eight regions in the United States from 2006 to 2015 demonstrated that this strategy improves system economics and reduces outage-loss risks. Hwang et al. [154] quantitatively evaluated the resilience value of diesel generators and PV-storage microgrids under three outage durations based on historical load data, showing the potential of PV-plus-storage systems to replace or supplement conventional backup generation under defined critical-load requirements.

To enhance hospital energy resilience during grid failures through optimized design and scheduling strategies, Masrur et al. [155] proposed an optimization model for a grid-connected electric–thermal microgrid integrated with DR. Using MILP, the model coordinates the scheduling of PVs, batteries, and combined heat and power generation. Empirical results demonstrate its ability to maintain a continuous energy supply and reduce costs under outage scenarios. The techno-economic advantages were validated through testing at a hospital in California, USA. Nazari-Heris et al. [156] developed a reliable energy management model for residential buildings. This model integrates the DR participation rate as a variable to optimize the coordinated scheduling of PVs, fuel cells, and the grid, with the aim of addressing emergency scenarios in hybrid residential energy systems. The results indicate that engaging 30% DR participation during off-peak periods reduces daily energy replenishment costs by approximately one-third, while DR participation during peak periods can lower these costs by more than 76%. Hervás-Zaragoza et al. [157] employed MILP to study a hospital microgrid comprising PV systems, ESS, and diesel generators. Their findings demonstrate that the microgrid can maintain a 72 h power supply under the most adverse conditions while reducing electricity costs by $147,000. Candan et al. [158] addressed the time-varying power constraints caused by dynamic microgrid boundaries after disasters. By using a predictive assessment of the remaining energy in EV batteries, the proposed approach dynamically selects appliance groups with different priority levels to extend the power supply duration of critical loads and improve post-disaster occupant well-being. Masrur et al. [159] incorporated EVs into a microgrid system and proposed a multi-energy microgrid integrating electrical, thermal, and EV systems. Using a MILP optimization approach, the model was tested through several case studies at a hospital in Okinawa, Japan, equipped with an EV charging station. The results demonstrate that this method effectively reduces annual total costs and enhances system survivability during grid failures.

The evidence in [153–159] is largely derived from PV-storage systems and building or community microgrids rather than from systems explicitly labeled as PSDF. Accordingly, the resilience contribution of PSDF should not be interpreted as inherently superior to that of conventional PV-storage microgrids. Its distinctive potential lies in combining several resilience mechanisms within one building-centered architecture: local PV and storage provide autonomous supply, DC distribution can reduce conversion stages for native DC resources and loads [84], flexible load management enables prioritization or shedding of non-critical demand [155,156,158], and EVs can provide mobile or bidirectional storage [158,159]. This combination allows resilience to be addressed not only through backup capacity, but also through load prioritization, multi-energy coordination, and adaptive operations during and after grid disturbances.

5.3. Integration with Intelligent and Digital Technologies

Intelligent and digital technologies provide an additional coordination mechanism for PSDF systems by improving forecasting, real-time decision-making, and distributed re-

source management. To address the intermittency and volatility of PV generation, reinforcement learning methods have been applied to building energy management, with reported reductions in energy cost while maintaining user comfort [160,161]. Aghdam et al. [162] developed a real-time home energy management architecture integrating digital twin (DT) technology with edge computing. The framework creates a virtual representation of the physical components of a smart home and employs an LSTM network to forecast PV power generation, EV arrival times, and load demand, enabling real-time coordinated scheduling of energy storage systems and flexible loads. For behind-the-meter PV, Rafy and Srivastava [163] proposed an adaptive estimation architecture that combines deterministic, transformer-based, and hybrid estimation according to data observability, thereby improving distributed PV estimation under heterogeneous measurement conditions. Building on reinforcement-learning algorithms, Binyamin et al. [30] introduced a Markov decision process (MDP) for uncertainty modeling and an intelligent bidding strategy, reducing electricity costs, improving RES utilization, and supporting equitable energy allocation within communities. Robles-Enciso et al. [164] proposed an adaptive energy coordinator based on multi-agent reinforcement learning (MARL) to optimize RES use in smart homes and reduce reliance on non-renewable sources. Eltamaly et al. [165] introduced a DR strategy based on dynamic electricity pricing and battery state of charge to optimize the configuration of off-grid hybrid energy systems (HES), while Nicoletti et al. [166] used artificial neural networks to optimize the operation of hybrid heat pump–boiler systems integrated with PV and battery storage.

The integration of deep learning algorithms has emerged as an important research direction for achieving higher computational accuracy and more intelligent energy allocation. Alabi et al. [167] developed a modular energy management platform that integrates multivariate time series forecasting and autonomous scheduling for energy infrastructure. They proposed a DRL approach using the soft actor critic (SAC) algorithm, and the model was trained and tested on real-world datasets from Arizona, USA. Faghri et al. [168] introduced a real-time energy scheduling framework based on DRL to optimize energy flexibility in grid-connected smart building communities (SBCs) with electric vehicle parking lots (EVPLs), while incorporating mathematical optimization methods to ensure the secure operation of the distribution grid. Toolabi Moghadam et al. [169] proposed a bi-level optimization-based scheduling method for integrated energy systems. This approach combines machine learning for forecasting uncertain parameters with a price-based DR program, enabling coordinated operations in both electricity and heating markets. The results indicate that the DR program increased system profits by 40%. Li et al. [170] introduced a grid-edge controller based on multi-agent deep deterministic policy gradient (MADDPG) to optimize DR management for distributed BESS within a low-voltage transformer-powered area (LVTPA). By integrating price-based and incentive-based DR strategies, the method significantly improved user benefits and reduced three-phase imbalance. Table 10 summarizes the algorithms, target systems, and principal outcomes reported across these studies.

The studies summarized in Table 10 indicate three main roles for intelligent technologies in PSDF-related applications: forecasting uncertain PV, load, and mobility variables; optimizing multi-device scheduling and demand response; and coordinating distributed resources through agent-based or grid-edge decision-making. These methods can improve renewable-energy utilization, operating cost, carbon performance, and grid flexibility, but the reported gains are highly dependent on the selected baseline, data set, model assumptions, and control horizon. Moreover, much of the reviewed work emphasizes algorithmic performance, while practical deployment issues such as data quality, model generalization across buildings, communication reliability, interoperability, cybersecurity, and explainability receive less consistent treatment. In this direction, Ren et al. [171] integrated digital

twins with explainable and privacy-preserving federated learning for voltage-stability assessment, illustrating the potential of decentralized intelligent monitoring for secure building–grid and smart grid applications. These issues become increasingly important as PSDF systems move from isolated demonstrations toward continuously connected building–community–grid operation.

Table 10. Representative intelligent and digital approaches for PSDF-related energy management.

Year	Target System/Strategy	Algorithm	Key Findings	Ref.
2024	Building Energy Management System	Two-stage deep reinforcement learning (DRL) algorithm	Reduced PV forecasting error by 12%; decreased user energy cost by 10%; increased PV utilization by 15%; improved user satisfaction by 20%	[160]
2025	Home Energy Management System	Proximal Policy Optimization (PPO)–based DRL	Achieved significant reductions in household energy cost while maintaining user comfort	[161]
2026	Digital twin-assisted home energy management system (DT-HEMS)	LSTM-based forecasting	~10% lower operating costs at a 15 min resolution and a further ~7% reduction at a 1 min resolution compared with conventional HEMS	[162]
2024	AI-based Energy Management System	DRL	Reduced electricity costs, enhanced renewable-energy utilization, and achieved fair energy allocation within communities via intelligent bidding	[30]
2024	Smart-Home Energy Management System	Multi-agent reinforcement learning (MARL)	Demonstrated superior performance in reducing carbon emissions and improving energy management efficiency	[164]
2021	Off-grid hybrid energy system/novel DR strategy	Bat algorithm	Lowered system cost by 20.66%; significantly enhanced economic performance and reliability	[165]
2025	Hybrid heat pump–boiler operational optimization	Artificial neural network (ANN) algorithm	Achieved 19% cost savings and 12% CO_2 reduction in cold climates	[166]
2024	Multivariate time-series forecasting and autonomous energy-infrastructure scheduling	DRL	Outperformed existing methods in prediction accuracy, energy-cost reduction, and carbon-emission mitigation	[167]
2025	Real-time energy-dispatch framework	DRL	Provided superior operational-cost reduction and enhanced grid flexibility compared with classical optimization strategies	[168]
2022	Bi-level optimization for integrated energy systems	Machine learning algorithm	DR programs increased system profit by 40%	[169]
2021	DR management system	Deep reinforcement learning	Increased total energy revenue by 40% and reduced three-phase imbalance by 10.3%	[170]

Note: The quantitative outcomes in Table 10 are reported under different data sets, baselines, objectives, and control horizons; they should therefore be interpreted as study-specific evidence rather than as directly comparable algorithm rankings.

5.4. Policy and Deployment Framework

To advance the transformation of energy systems, efficient and flexible buildings are increasingly serving as key platforms for accommodating distributed energy resources, including photovoltaics, energy storage, and responsive loads [172]. The International Energy Agency has noted that energy efficiency policies are evolving from a singular focus on conservation toward broader frameworks that also address electrification, demand-side flexibility, and system coordination [173]. In this context, different countries and regions are developing policy and regulatory instruments that support building decarbonization and flexible-resource deployment. The European Union has promoted building efficiency, photovoltaic readiness, and intelligent retrofitting [174], while Singapore's Future Grid Capabilities Roadmap advances future grid development and pilots involving V2G, storage, digitalization, and community-scale flexibility [175]. Figure 8 summarizes representative policy directions related to distributed photovoltaics, energy storage, demand response, home energy management, EV charging, and smart community development.

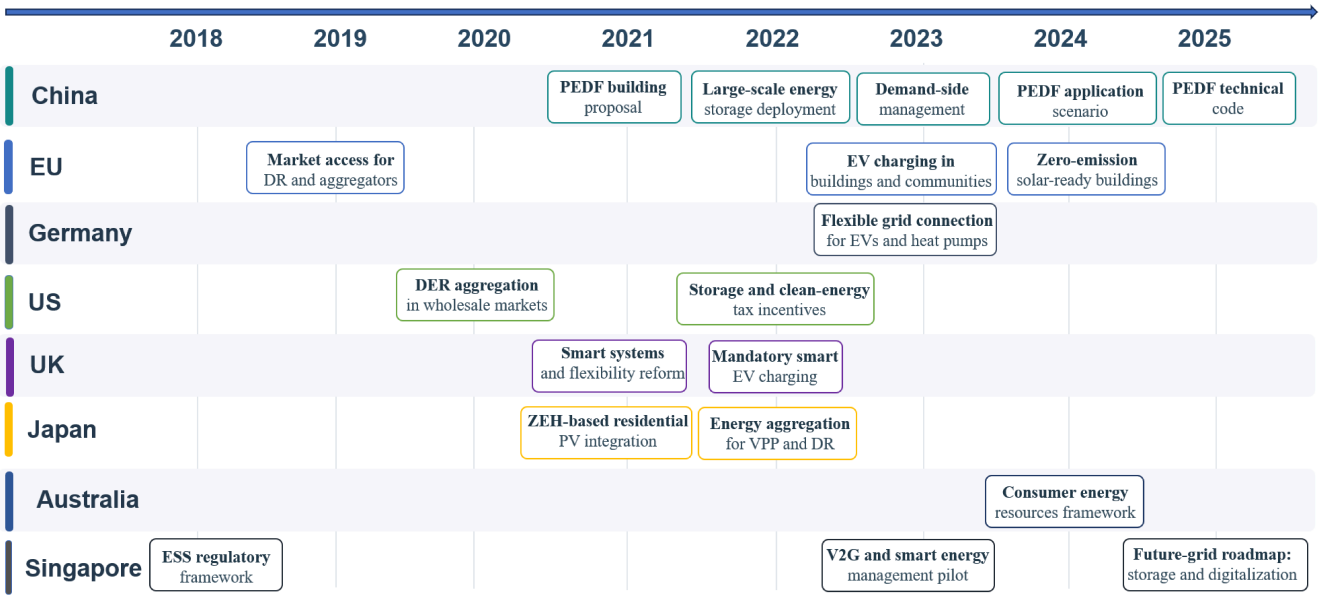


Figure 8. Representative policy and regulatory developments relevant to flexible and grid-interactive building energy systems.

From a PSDF perspective, policy support is most effective when it addresses the interfaces among the four component technologies rather than promoting them independently. Building and PV requirements influence local generation deployment; storage and EV rules determine access to mobile and stationary flexibility; demand-response and aggregation mechanisms affect whether flexible loads can participate in grid services; and technical standards influence interoperability among DC equipment, converters, EMS platforms, and the external grid. Policy development is therefore closely linked to the engineering and market barriers discussed in Section 6. The examples in Figure 8 should be interpreted as representative policy directions rather than as an exhaustive international comparison.

Taken together, Section 5 shows how the PSDF concept extends beyond internal building energy management. At the interaction and application level, the same component and coordination capabilities reviewed in Sections 3 and 4 can support community energy sharing, distribution network services, outage resilience, data-driven operation, and participation in emerging policy and market frameworks. At the same time, scaling from individual buildings to connected communities introduces additional requirements for interoperability, communication, cybersecurity, consistent performance metrics, and coordinated governance. These unresolved issues provide the basis for the challenges and future research priorities discussed in Section 6.

6. Challenges and Future Research Priorities

6.1. Challenges

The preceding sections show that the value of PSDF systems depends on the coordinated operation of component technologies, DSM/EMS strategies, and building–grid interaction. Their wider deployment is therefore constrained not by a single technology, but by coupled technical, methodological, economic, and implementation challenges. The principal challenges identified across the reviewed literature are summarized below:

(1) Renewable generation uncertainty and grid interactions remain fundamental challenges. Zubi et al. [176] noted that, with PV penetration at 30%, the start–stop cycles of gas-fired units increased by 109%, from 3721 to 7793 cycles per year, efficiency decreased by 1.1%, and 3.45 GWh of energy storage was required to balance variability. Baik et al. [177], using the Power Reliability Event Simulation Tool (PRESTO), found

that residential PV systems with storage could meet only part of the heating and cooling loads during outages, illustrating that installed PV-storage capacity does not automatically guarantee resilience under extreme conditions. At the building scale, Jeksen et al. [43] further showed that uncertainties in operational patterns and load profiles can cause large deviations in optimal PV sizing. These findings indicate that high PV penetration must be evaluated together with building load uncertainty, storage availability, reverse power flow, voltage regulation, and resilience requirements rather than as a generation-only problem.

(2) DC distribution can reduce repeated conversion stages, but its large-scale building deployment still depends on engineering standardization and interoperable equipment. PV intermittency and partial shading can cause nonlinear variations in array output [178], while DC bus voltage is sensitive to source–load imbalance [179]. Seasonal mismatches among PV generation, heating demand, storage, and heat pump operation can further lead to curtailment or supply deficits when scheduling is inadequate [180,181], and high distributed PV penetration may contribute to voltage violations and network losses [182]. In addition, the reviewed DC literature identifies non-unified interfaces and device compatibility limitations [77,83–85]. Protection coordination, fault isolation, grounding, converter interoperability, and converter reliability therefore require more systematic building-scale validation, particularly for systems that combine multiple DC voltage levels and grid-connected/islanded operating modes.

(3) Multi-resource coordination becomes increasingly complex as PSDF systems integrate storage, HVAC, EVs, flexible loads, and building–grid services across different time scales. Kafaei et al. [109] demonstrated the value of stochastic day-ahead optimization for coordinated energy-hub operation, while Zhang et al. [145] showed that EV penetration, thermal storage capacity, and energy-sharing behavior affect PV sizing and system performance. Wang et al. [183] further used a bilevel stochastic model to coordinate smart buildings and energy storage in a highly renewable microgrid. These studies illustrate the need for uncertainty-aware and multi-timescale scheduling; however, greater digital connectivity also increases dependence on data quality, forecasting accuracy, communication reliability, and computational tractability. As intelligent control and distributed coordination become more widely used, cybersecurity, privacy, and fail-safe operation also need to be treated as explicit design constraints rather than as secondary implementation issues. Rafy et al. [184] further demonstrated that IoT-based BESS control introduces cyber-physical vulnerabilities and developed resilience metrics, anomaly detection methods, and mitigation strategies validated through a real-time cyber-physical co-simulation platform.

(4) Economic performance, asset degradation, user requirements, and grid services can impose conflicting objectives. EVs provide mobile storage and can enhance PV integration, but their planning and dispatch must balance operating costs, battery degradation, mobility needs, and grid reliability [185]. Integrated expansion planning is also challenged by renewable and load uncertainty as well as the computational burden of high-dimensional decision variables [186]. Large-scale EV charging adds further spatiotemporal uncertainty; although V2G can increase flexibility, additional cycling may accelerate battery degradation [187]. For battery health monitoring, Wang and Dong [188] proposed a peer-to-peer personalized federated transfer-learning method for EV battery SOH estimation, enabling model sharing across different operating conditions while retaining battery data locally. Similar trade-offs arise in building DSM, where cost reduction, renewable-energy utilization, occupant comfort, privacy, and participation cannot always be optimized simultaneously [124–134].

Consequently, the practical value of PSDF should be assessed through multi-objective and life cycle criteria rather than by a single energy- or cost-saving indicator.

(5) Scaling from individual buildings to communities and distribution networks introduces additional interoperability, governance, and evaluation challenges. The studies reviewed in Section 5 show that building clusters, shared storage, EV fleets, and community energy mechanisms can provide peak management and energy-sharing benefits [136,142–147], but their performance depends strongly on local tariffs, market rules, network constraints, and user participation. At the same time, policy frameworks are evolving at different rates across regions [172–175]. The lack of consistent system boundaries, benchmark datasets, and common flexibility or resilience metrics makes it difficult to compare results or transfer control strategies across buildings, climates, and regulatory environments.

6.2. Future Research Priorities

The future research agenda should follow directly from the above limitations. Rather than treating the four PSDF technologies as independent research topics, future work should focus on the interfaces among components, coordination strategies, users, and the external grid. Five priorities are particularly important.

(1) Establish interoperable and safety-oriented DC building architectures. Future studies should develop and experimentally validate common voltage levels, equipment interfaces, converter requirements, protection coordination, fault isolation strategies, and grounding schemes. The objective is not only to reduce conversion losses but also to ensure that PV, stationary storage, EV interfaces, flexible DC loads, and grid converters can operate safely and interchangeably across building types [77,83–85].

(2) Develop uncertainty-aware, multi-timescale, and cyber-resilient coordination. Scheduling methods should jointly represent short-term PV and load fluctuations, thermal dynamics, EV mobility, storage state, electricity price signals, and longer-term capacity decisions [43,109,145,183,185–187]. Forecasting, MPC, stochastic/robust optimization, and data-driven control should be evaluated not only for numerical performance but also for communication requirements, computational burden, fault tolerance, privacy, and cybersecurity. Hybrid approaches that combine physical models with data-driven adaptation are especially relevant for moving from simulation studies toward dependable real-time operation.

(3) Integrate degradation, life cycle cost, carbon, comfort, and resilience into common multi-objective assessment frameworks. Battery and EV degradation, converter replacement, thermal storage performance, user comfort, and outage support should be represented explicitly so that energy savings are not obtained at the expense of asset life or service quality [54,59,142,185,187]. Future studies should also report system boundaries, baseline definitions, climate conditions, tariff structures, and evaluation horizons consistently to improve cross-study comparability.

(4) Strengthen occupant-centered and market-compatible flexibility. User participation should be modeled as a dynamic constraint rather than as an assumed source of flexibility. Research should connect comfort preferences, willingness to participate, incentive design, privacy, and fairness with building control and market participation [124–134]. This is particularly important for EV charging, thermostat control, appliance scheduling, and community energy sharing, where technically available flexibility may not be continuously accessible in practice.

(5) Move from isolated demonstrations toward scalable building–community–grid validation. Future work should test PSDF coordination across multiple buildings, feeders, climates, and regulatory settings, with explicit consideration of voltage regulation,

reverse power flow, hosting capacity, peak management, resilience, and local energy sharing [143–147]. Shared benchmark data sets, reproducible simulation cases, hardware-in-the-loop tests, and long-term demonstration projects would help determine whether benefits observed in individual case studies remain robust at larger scales. Policy and market designs should evolve in parallel so that flexibility services can be valued without compromising building performance or user requirements [172–175].

Table 11 lists the gaps and research priorities for PSDF building energy systems.

Table 11. Gap-driven research priorities for PSDF building energy systems.

Identified Gap	Main Limitation	Priority Research Direction	Ref.
DC engineering and interoperability	Non-unified interfaces; device compatibility; protection/grounding validation needs; converter-integration issues	Standardized voltage/interface schemes; experimental protection and grounding validation; interoperable converters and DC appliances	[77,83–85]
Uncertainty and multi-timescale coordination	PV/load variability; EV mobility; thermal dynamics; high-dimensional scheduling and planning	Stochastic/robust/MPC/data-driven coordination across operational and planning time scales; explicit communication and cybersecurity constraints	[43,109,145,183,185–187]
Life cycle and multi-objective trade-offs	Cost, carbon, comfort, resilience, and degradation objectives may conflict	Degradation-aware and life cycle optimization; consistent system boundaries, baselines, and reporting metrics	[54,59,142,185,187]
User participation and market integration	Comfort, privacy, participation willingness, and incentive response limit usable flexibility	Occupant-in-the-loop control; incentive/fairness models; privacy-aware market participation	[124–134]
Scalability and building–grid validation	Results are often case-specific; limited comparability across climates, networks, and policies	Multi-building/feeder demonstrations; benchmark data sets; HIL and long-term validation; coordinated policy and market design	[143–147,172–175]

Overall, future PSDF research should shift from demonstrating the isolated performance of individual technologies toward validating coordinated, interoperable, and scalable building energy systems. Progress will depend on combining engineering standardization with uncertainty-aware control, life cycle and multi-objective evaluation, user participation, digital security, and building–grid validation. These priorities provide a more direct pathway from the limitations identified in the current literature to the large-scale and reliable deployment of PSDF systems.

7. Conclusions

This review examined PSDF-related building energy systems through a building-centered, multi-layer framework linking component technologies, DSM/EMS coordination, and building–grid interaction. The main conclusions are summarized as follows.

(1) Scientific and theoretical findings. The reviewed literature indicates that the value of PSDF does not arise from photovoltaics, energy storage, DC distribution, and flexible loads as isolated technologies, but from the functional coupling among these elements and their coordinated interaction with the external grid. The component–coordination–interaction/application framework provides a common basis for comparing studies conducted under different terminologies and clarifies the distinction between physical building energy architecture, coordination mechanisms, and community/grid applications. The evidence also shows that different PSDF functions have reached different levels of maturity: PV and conventional battery storage are comparatively

well established, whereas DC system standardization, interoperable control, and the scalable integration of flexible loads remain less mature.

(2) Technical and engineering implications. For building applications, PV and storage can improve local renewable-energy utilization and resilience, while DC distribution can reduce conversion stages when a sufficiently large share of generation, storage, and end uses is DC-coupled. However, these benefits are conditional on converter efficiency, voltage level, protection, equipment compatibility, and system configuration. Flexible loads such as HVAC systems, heat pumps, appliances, and EVs provide additional regulation capabilities, but their usable flexibility is constrained by comfort, mobility, task completion requirements, and user participation. DSM, DR, and EMS therefore serve as the coordination layer that converts physical flexibility into economic, operational, and grid-support services, with trade-offs among cost, renewable self-consumption, asset degradation, comfort, privacy, and resilience.

(3) Building–grid and application implications. At larger scales, coordinated buildings can act as grid-interactive energy nodes rather than passive consumers. Community energy sharing, shared storage, EV/V2G resources, and coordinated flexible loads can contribute to peak management, voltage regulation, reverse power flow mitigation, local energy balancing, and emergency operations. The reviewed evidence nevertheless remains strongly case-dependent, and the reported quantitative benefits should not be interpreted as directly comparable benchmarks across studies with different climates, tariffs, system boundaries, baselines, and control horizons. Wider deployment will also depend on supportive market mechanisms, technical standards, and policy frameworks that enable building flexibility to participate in external grid services.

(4) Future research priorities. The principal research needs identified in this review are: interoperable and safety-oriented DC building architectures; uncertainty-aware, multi-timescale, and cyber-resilient coordination; life cycle and multi-objective assessment that includes degradation, carbon, comfort, and resilience; occupant-centered and market-compatible flexibility; and validation from single-building demonstrations to building–community–grid applications. Addressing these gaps will require stronger integration of building science, power electronics, control, data-driven methods, user behavior, and distribution network operations, together with reproducible benchmarks and long-term engineering demonstrations.

Overall, PSDF is best regarded as an integrative framework for developing flexible and grid-interactive building energy systems rather than as a fixed combination of four technologies. Its practical contribution will depend on whether the four functional elements can be coordinated safely, economically, and scalably while meeting both building services requirements and power system needs.

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Abbreviations

The following abbreviations are used in this manuscript:

B2G	Battery-to-grid
BESS	Battery energy storage systems
BMPV	Building-mounted photovoltaic
CVaR	Conditional value-at-risk
DC	Direct current
DER	Distributed energy resources
DR	Demand response
DRL	Deep reinforcement learning
DSM	Demand-side management
DSFR	Demand-side flexible resources
EMS	Energy management systems
ESS	Energy storage systems
EV	Electric vehicle
G2B	Grid-to-battery
HEMS	Home energy management systems
HVAC	Heating, ventilation, and air conditioning
LCOE	Levelized cost of energy
LCOS	Levelized cost of storage
LFP	Lithium iron phosphate
LVDC	Low-voltage direct current
MILP	Mixed-integer linear programming
MSC	Maximum self-consumption
OES	Open energy system
PCM	Phase change materials
P2P	Peer-to-peer
PSDF	Photovoltaic, storage, direct current, and flexibility
PSO	Particle swarm optimization
PVs	Photovoltaics
RES	Renewable energy sources
RTMR	Real-time matching rate
SCR	Self-consumption rate
SDSE	Solar/dish-Stirling engine
SoH	State of health
TOU	Time-of-use
V2B	Vehicle-to-building
VPP	Virtual power plant

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