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Journal of Electrical Systems and Inf Technol (2025) 12:9
https://doi.org/10.1186/s43067-025-00195-z

Journal of Electrical Systems
and Information Technology

REVIEW **Open Access**

An in-depth survey of latest progress in smart grids: paving the way for a sustainable future through renewable energy resources

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Abstract

The smart grid presents an unparalleled opportunity to revolutionize the present scenario energy industry, ushering in a contemporary era of an upgraded network. In this advanced system, electric energy generation, electric energy transmission, and electric energy distribution are intelligently and collaboratively controlled via a two-way automation system, promoting responsiveness and efficiency. The applications and technologies of smart grids may vary in their functions and forms, but they all share common potential benefits. These include intelligent energy curtailment, seamless integration of demand response, distributed renewable generation, and energy storage solutions. This paper provides a comprehensive review covering the past two decades, encompassing recent advancements and prior research developments in the smart grid paradigm. The primary aim of this study is to conduct an application-focused survey, comprehensively examining each category and subcategory independently. The paper's introduction provides insights into the concept and structure of smart grids. It delves deeply into reviewing recent advances in energy data management within smart grids, pricing models in modernized power grids, and the key components of smart grid systems. Furthermore, the paper thoroughly explores recent advancements in network reliability. Conversely, the growing dependence on urban areas utilizing sophisticated communication technologies and their infrastructure raises concerns about data integrity. Hence, a dedicated subsection is devoted to highlighting the existing challenges and the latest state-of-the-art advancements in cybersecurity. Lastly, the review concludes by emphasizing the unfolding advancements in pricing mechanisms.

Introduction

Smart grids (SGs) represent a modernized energy infrastructure designed to integrate renewable energy sources (RES) and promote sustainability through automation and digitization. They enhance grid flexibility, reliability, and adaptability while addressing the growing demand for decentralized energy systems. Key challenges in SG implementation include renewable integration, consumer acceptance, operational flexibility, regulatory issues, and the need for standardization and interoperability [1].

In remote communities where connecting to utility networks is technically and economically impractical, autonomous grids in the form of microgrids are prevalent.

During the early stages of integrating renewable energy sources, their contribution to the power network was relatively small compared to conventional generators, and their impact on the overall power system was initially inconspicuous. In light of recent advancements and growing commitments toward renewable and sustainable power generation, various RES (renewable energy sources), such as solar photovoltaics, wind, hydropower, and hydrogen technologies, have become highly popular and prioritized for integration into electrical power networks. Microgrids play a vital role in providing the flexibility required to consolidate appropriate control schemes and power management algorithms, ensuring the consistent quality of power supplied by transient RES through power electronic interventions [2].

Power electronic devices serve as essential tools for integrating an extensive variety of distinct RES, energy storage devices, and diverse loads. Various envisioned configurations of power converter have been proposed [3–5] to define a PCC (point of common coupling), a key component in forming microgrids of AC, DC and hybrid grids across various voltage and frequency levels. As a result, several power electronic interfacing configurations and structures have been suggested to create a diversified power generation framework and enable microgrids to efficiently manage power and energy flow [6, 7].

Upon integrating the RES (renewable energy sources) on a large scale and deregulation become prominent trends, close monitoring of overall operations and implementation of power management frameworks become crucial to support controllable power sharing and load sharing [8]. Accordingly, the adoption of microgrids in this context enables a structured and intensive solution for various challenges posed by deregulated power networks. This approach significantly reduces the reliance on sophisticated central coordination and paves the way for the creation and implementation of smart grids. The term "Smart Grid" (SG) lacks a singular, precise definition to fully capture its complexity [9]. However, it can be succinctly described as an intelligent network that operates with automation, storage, communication, and decision-making capabilities.

The drive for sustainable modernization in the energy sector has necessitated the implementation of deregulation in the present power industry. Among various innovative proposals, the concept of microgrids has emerged as the most promising solution [10]. Microgrids (MG) are small-scale electrical distribution networks composed of distributed generators (renewable and/or nonrenewable), diverse loads, and energy storage devices. They can operate in either isolated or grid-connected modes, facilitated by appropriate interfacial power electronic devices [11].

The US Energy Independence and Security Act 2007 [12] align with a similar definition, defining the smart grid as a modernized electrical network that monitors, enhances grid resiliency against disruptions, and optimizes the operation of interconnected components, ranging from central generating units to distributed generation, transmission networks, and load centers.

Moreover, the US-NIST [13] characterizes the smart grid as a modern grid that enables bidirectional energy flows, employing two-way communication and control capabilities to introduce a wide array of new applications and functionalities. Unlike the traditional one-way energy flow from generation centers to demand centers, smart grids allow for a seamless exchange of energy and data. Multiple entities and researchers have stated the delineation of the smart grid, as referenced in [14–22]. Although varied in their expressions, these definitions are conceptually aligned with the general framework of the term.

Additionally, the EPRI based in the USA defines the smart grid as "the transformation from the current grid, where power flows one-way from central generation to load locations, into a network enabling end-to-end consumer engagements, control centers and distributed generations" [17]. In the UK, DECC underscores that a smarter grid enables operators to be more aware of supply–demand balance information, leading to intelligent system management and the ability to shift demand from peak to off-peak periods for improved efficiency [18].

Australia has launched an initiative called "SmartGrid SmartCity," in collaboration with Energy Australia, Ausgrid, and the Australian government. Echoing EPRI's definition, they describe the smart grid as a novel and highly intelligent approach to electricity supply. It involves advanced communication infrastructure, cutting-edge sensing and metering (measuring) technologies integrated into the electrical network, creating a bidirectional participatory grid. Smart sensing technologies contribute to smaller grid interruptions and downtime, while smart metering empowers consumers to efficiently control their energy usage, leading to reduced billing costs. References [23–35] have highlighted the development and rising patterns in smart grids.

Researchers highlighted that the smart grid represents a transformation of the traditional grid into a new modernized and cooperative system, intelligently integrating consumers, generators, and users to ensure efficient, secure, and economically feasible power supplies [19]. Through distributed intelligence and bidirectional communication infrastructure, the smart grid enhances system efficiency, reliability, and sustainability. It integrates intensively automated services and digital information processing capabilities into the present power infrastructure, empowering the grid with improved robustness and self-healing capabilities [21]. Table 1 provides a concise comparison between the conventional power grid and smart grid.

To successfully implement the concept of smart grids, effective deployment of information and communication technology is essential. One of the primary challenges is enhancing the traditional power grid to enable bidirectional communication capabilities, which is vital for the active network in smart grids (SGs). To adapt to the diversification of the power grid, a seamless transition has been accomplished

Table 1 Basic difference between conventional/traditional grid and smart grid

	Conventional grid	Smart grid
1	Controlled manually	Automated control
2	Operated mechanically	Digitalized
3	Slow responsive actions	Faster response
4	Unilateral	Bidirectional
5	Fewer security issues	Vulnerable to security issues
6	Less number of sensors	More sensors
7	Less monitoring capabilities	Highly monitored
8	Centralized power generation	Distributed generation

by implementing suitable categorical standardization to incorporate smart grid (SG) technologies [36–45].

The rest of this paper is structured as follows:

- In Sect. "Structure," we provide details of the structure and key characteristics of smart grids. Additionally, we highlight essential technologies that facilitate the transition toward a highly functional infrastructure.
- Sect. "Smart grid predominant components" focuses on the power system perspective, comprehensively studying the main components of smart grids as independent entities. Furthermore, recent advances in reliability and resiliency indices in smart grids are presented in this section.
- In Sect. "Data management systems in smart grids," we delve into the review of energy data management and cybersecurity in smart grids.
- Sect. "Cost model scenario in smart grids" is dedicated to a thorough investigation of pricing mechanisms in smart grids.
- Fig. 1 gives an idea about a graphic depiction of the organization of the paper.

Structure

Definitions

According to the NIST [13], smart grids can be classified into seven categories, each with their respective subcategories, comprising various actors and applications. These actors encompass devices, like renewable energy generators and smart meters, control systems, programs, decision-makers (stakeholders), and telecom stations for data exchange. The applications are the specific tasks that these actors can perform within their respective categories, like energy management, site automation, and energy storage. Additionally, interactions between actors can occur within the same category or between different categories. It is worth noting that a particular category might contain components from other categories. For instance, a distribution utility category may include actors from operation categories like distribution management systems and customer categories such as electric meters. For a more detailed classification, please refer to Table 2.

Smart grid technologies

The implementation of various technologies is essential to achieve effective control and automation in smart grids [22, 46]. These technologies play a very important role in facilitating the transition toward a well-functioning infrastructure, benefiting both grid designers and consumers alike. Some of the key technologies include AVR (automatic voltage regulation), EMS (energy management system), AGC (automatic generation control), AMI (advanced metering infrastructure), MDM (meter data management), DMS (distribution management system), GIS (geographical information system), OMS (outage management system), WAMS (wide area management system), and DSM (demand-side management). Table 3 highlights some of these important technologies. AVR (automatic voltage regulation) plays an important role in stabilizing voltage profiles within acceptable limits, while EMS ensures reliability and secures operating points for supervisory control and data acquisition (SCADA), acting as a comprehensive optimizer

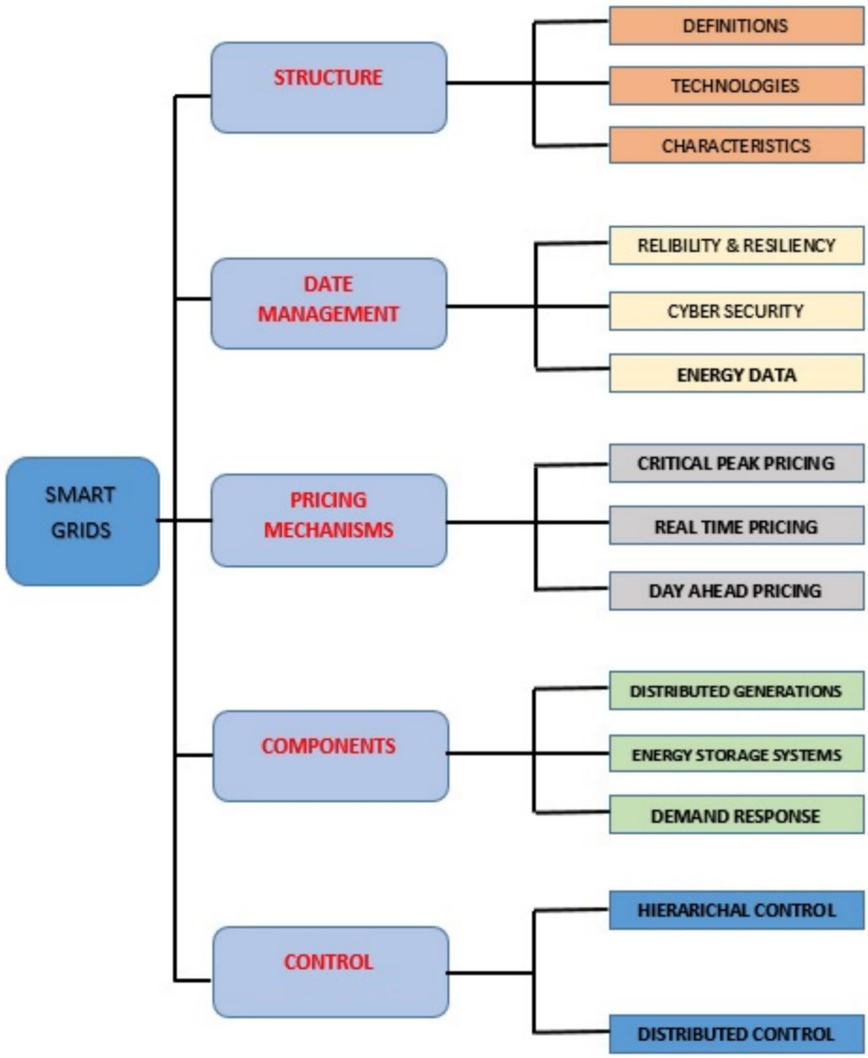

Fig. 1 Organization of the review paper

for the entire smart grid. AGC significantly contributes to grid stability by optimizing load distribution among generating units to restore stability margins.

Smart meters (smart measuring devices) facilitate bidirectional communication between end users and service providers [16], empowering consumers to control their energy usage and ensuring more accurate billing. Additionally, smart meters can offer notifications for power outages and monitor power quality. They are often used to enable controllable demand, allowing grid aggregators or grid operators to effectively manage loads [54, 55]. For example, Reference [54] investigated the use of smart or intelligent meters for domestic demand control to regulate frequency. Meanwhile, Reference [26] proposed a controlled load-blocking scheme for domestic loads based on smart meters to support initial frequency control, taking into account end users lifestyles and safety.

The AMI (advanced metering infrastructure) represents a fundamental step toward grid modernization. It is an integration of various technologies that enable intelligent communication between consumers and system operators. AMI empowers consumers

Table 2 Classifications of smart grids

Category	Descriptions
Customer	The consumption of electricity occurs primarily among end users, which can be further divided into two subcategories: domestic consumers and large consumers, such as those in commercial and industrial sectors. These end users can both generate and manage electricity while also having the option to store it for later use
Market	Electricity markets serve as the platform for asset exchange. In these markets, the key actors involved are the operators and participants
Service provider	A company that offers services related to the development and reliable functioning of smart grids, tailored to meet the specific needs of consumers and utilities
Operations	The power system's efficient operation is closely monitored by individuals responsible for managing the flow of electricity
Bulk generation	The process of delivering substantial amounts of electricity to consumers commences with the involvement of bulk electricity generators, who play a vital role as actors in this context. Additionally, there is an option to store energy for subsequent distribution
Transmission	In the transition of bulk power from generation centers to distribution points, the key actors are the electricity carriers, who not only facilitate the transfer but also can generate and store electricity themselves
Distribution	In this interconnected system involving distributed generation, distributed storage, transmission, and consumer interconnect, the actors are the entities responsible for distributing electricity to and from customers. They play a crucial role in ensuring a seamless flow of power within the network

Table 3 Advancement and application of smart grids

Technique	Objectives	Authors	Years
AVR	AVR control based on sensitivity and voltage regulation	Morris et al. [47]	2010
	Power control using FLC and hybrid protocol	Ting Chia et al. [48]	2014
AGC	Controller for high-frequency fluctuations and smart grid mitigation	Ali et al. [49]	2012
	Data investigation and attack detection	Siddaharth et al. [47]	2014
OMS	Restoration of power with automated problem-solving	Eduardo et al. [46]	2011
	Smart grid control and advanced analysis by OMS assistance, with emergencies and normal operation modes	John Dirkman [50]	2013
GIS	Component tracking and network modeling	Esri inc [51]	2009
	Reduction in time and accuracy in data leads to efficient smart grids	Schneider electric [52]	2012
EMS	Efficient operation of EMS along with efficient battery backups	Rahman et al. [53]	2012
AMI	Cost reduction in gathering data, connection, and disconnection of end-user data	Eduardo et al. [46]	2011

providing crucial information for making informed decisions and execute actions that lead to significant benefits they did not have before. Furthermore, distribution automation and AMI facilitate a grid with modernized features by monitoring transformers and feeders, managing outages, and integrating electric vehicles. The decision-making process and data flow management were done with the support of MDM.

DMS serves several essential functions, including efficient control and monitoring of the distribution network. It functions as a system for supporting decisions, aiding personnel in responding to outages and maintaining voltage and frequency within their nominal values. DMS also enables consumers to control their appliances when necessary.

GIS provides the necessary infrastructure to integrate data onto geographical maps, playing a crucial role in visualization within smart grids. OMS plays an important role in restoring system functionality after outages. WAMS aids in grid synchronization within high voltage networks and can be utilized for analysis of disturbance and verification of FACTS [56]. Additionally, WAMS can provide time measurements through PMUs (phasor measurement units) [57–59]. DSM offers intelligent energy curtailment and will be thoroughly investigated in the subsequent sections of this paper.

Characteristics of smart grids

The key characteristics of smart grids, as reported in the literature [60–62], can be summarized as follows:

- Integration of distributed resources (DER), including sustainable energy sources.
- Continuous dynamic optimization of grid operation.
- Utilization of digitized information and control technologies to enhance electric network reliability and efficiency.
- Incorporation of demand-side response (DSR) programs and demand-side resources.
- Integration of smart appliances.
- Robustness against cyber threats.
- Adoption of advanced storage devices and peak-shaving technologies, such as hybrid and plug-in electric vehicles.

Advantages of smart grid transformation

The transformation of utilities to efficiently generate and distribute electricity with minimal environmental impact is not only driven by corporate responsibility but also influenced by various regulations and incentives imposed by countries to control the emissions of carbon. For instance, the "Cap and Trade" principle in Europe and certain other countries set limits on greenhouse gas production from power plants and factories, allowing utilities to operate as long as their carbon emission allowance remains below the specified cap level. Additionally, utilities can trade spare allowances with companies exceeding their assigned caps [63].

In the USA, 40% of greenhouse gas emissions are attributed to electricity consumption. By 2030, the implementation of smart grid-supported applications, ranging from voltage control to the addition of resources of renewable energy, is estimated to reduce the nation's annual emissions level of carbon dioxide from 210 to 60 million metric tons [12, 17].

Though the migration to smart grids may occur over an extended period, the incremental progress in this area offers significant advantages, as highlighted in References [64–70]. A modernized network can:

- Improve the quality and reliability of the conventional power grid.
- Optimize the operation of existing assets, reducing the need for future expansion of backup plants.
- Enhance overall system efficiency.

- Improve system resiliency.
- Facilitate the integration of distributed resources.
- Enable predictive maintenance and self-healing capabilities.
- Lower greenhouse gas emissions.
- Provide consumers with more diverse options.
- Increase opportunities to enhance system security.

Smart grid predominant components

Distributed generation

The conventional centralized energy or power grid is transforming due to the increasing penetration of DG (distributed generation). This emergence of DG has disrupted traditional methods of power generation and supply to the electrical grid. Factors, such as the depletion of fossil fuels, rising greenhouse gas emissions, and advancements in informatics and technology, have contributed to the resurgence of DG. Researchers recognize DG as a key player in structuring the future of the electrical grid, alongside storage technologies and demand response [71–74]. However, the extent of change in the future energy or power grid remains uncertain and largely depends on the widespread deployment of DGs. Additionally, the precise role of DGs is a subject of ongoing debate and requires comprehensive exploration to envision how the power grid might evolve in the future. For example, the authors [71] have dedicated their research to investigating the contribution of distributed generators in shaping the future power grid.

The meaning of distributed generators as discussed in the literature is somewhat unclear [70], as there is no exact description that fully encompasses the term. Some resources [75, 76] define DGs as small-scale renewable-based units located near load centers. However, DGs can also include large-scale parameters that are not renewable-based resources. In another reference [77], DGs are described as electricity generation sources physically linked to a distribution network or located at the consumer's meter side.

Reference [78] classifies cogeneration, DGs, storage capabilities, backup generation, and microgrids are classified as DER (distributed energy resources). Those DERs are smaller capacity sources that may be deployed to meet routine loads, and their integration may aid the shift toward smart grids.

The substitution of fossil fuel generators and meeting the increasing energy demands can be achieved through the deployment of RESs (renewable energy sources). However, effectively harnessing and managing these aggregated sources require sophisticated control capabilities due to the tremendous amount of data involved.

The expansion of DGs has been predominantly motivated by the imperative to reduce greenhouse emissions [79–81]. Additionally, factors, such as increasing electrical demands [82, 83], governmental regulations [84, 85], market liberalization [86], and lower capital costs [87–89], have contributed to the widespread deployment of DGs. When properly optimized in terms of size, location, and operation, DGs offer a broad spectrum of technical benefits [71]. They can help reduce network losses when installed close to load centers [79–83], improve voltage profiles [90–94], enhance system reliability [89, 95, 96], and give computational flexibility [97–99] for effective system controllability, particularly in generation [100–102] and Load-side management [103–105].

With technological advancements and the increasing use of sustainable resources, DER plays a crucial role in influencing the future grid infrastructure. According to Reference [106], by the later part of 2026 the DER capability is projected to be approximately 530GW which was 134GW in 2017, fueled through the integration of dispersed solar photovoltaic systems, small- or medium-sized wind turbines, fuel cells, microturbines, and electric vehicles (EVs), distributed energy storage (DES), and demand response (DR). For instance, in the USA DER (distributed energy resources) comprised 2% of the total installed capacity, with distributed PV accounting for 12% of the total in 2016. California, for instance, seeks to incorporate 12 gigawatts by 2020 by utilizing DER. Further insights into the progress of DER in the USA can be found in Reference [107]. Similarly, in China, by later part of June 2017, the overall installed size of dispersed PVs reached 16.15 GW, representing 17% of the total PV installed capacity [108].

Reliability assessment of DGs in modern grids

The electrical energy or power grid is a highly complex integrated system, where any failure can have severe consequences. In reliability studies, various terms, like resiliency, vulnerability, robustness, and security, are used to assess different aspects of the system. Generally, reliability is employed as a comprehensive term encompassing these metrics [70, 109–120]. Researchers have conducted extensive investigations on reliability assessment for applications connected to the smart grid.

Reliability is evaluated differently at various levels of the power system, including transmission, generation, and distribution. At the level of distribution, parameters, such as SAIFI and SAIDI, are commonly used. SAIFI quantifies the average occurrence rate of outages for each consumer, while SAIDI measures the average time period of outages [121–123].

At the level of larger generation, the term LOLE (loss of load expectation) is utilized to describe the amount of energy demand that goes unmet during a specific duration. In recent literature, the term "resiliency" has gained prominence. According to EPRI [124], resiliency refers to the grid's ability to rapidly recover from low and high-frequency events, such as cyberattacks, physical attacks, natural disasters, and severe geomagnetic disturbances, which can severely disrupt the entire electrical grid.

An in-depth analysis of resilience metrics (RMs) for power systems, focusing on the high-impact, low-frequency (HILF) events that significantly affect electric power infrastructure. It highlights the necessity of incorporating resilience into power systems to withstand, adapt, and recover from disasters. The authors effectively identify the shortcomings in existing RM frameworks and propose a conceptual framework to address these gaps. [125, 126]

A comprehensive review of resilience in electrical energy systems, emphasizing the challenges posed by high-impact, low-probability (HILP) events. The authors present a resilience evaluation framework encompassing key concepts, definitions, assessment indices, enhancement strategies, and optimization approaches. Their effort to address resilience from both short-term and long-term perspectives is commendable.

The researchers identified critical gaps in current research, such as the absence of a universally accepted resilience definition and standard indicators to assess resilience comprehensively. The discussion highlights the need for better predictive, adaptive, and restorative metrics, improved modeling techniques for system failures, and enhanced weather forecasting and cyberattack simulations. Furthermore, the authors point out the lack of emphasis on preventive strategies, cost-related considerations, and integration of dependent systems like water, gas, and communications. The challenges outlined are insightful and reflect real-world complexities in resilience enhancement. However, the paper could have benefitted from more detailed examples of successful implementations or case studies to contextualize its findings. Overall, it provides a valuable foundation for academic and industrial researchers, guiding future studies to address the outlined gaps and improve system resilience [125, 127].

The authors provides a thorough review of power system resilience, addressing the critical need to enhance grid resilience against extreme natural events and man-made attacks. It highlights the increasing frequency and severity of such disruptions and underscores the necessity of developing standardized resilience definitions, metrics, and evaluation methods to improve planning and operational strategies. Also authors critically analyze existing resilience metrics, identifying key research gaps and challenges, such as the lack of universally accepted definitions and multi-objective optimization methods for resilience enhancement. The paper emphasizes the importance of comprehensive modeling of system components and interactions to develop effective resilience strategies. Recommendations for future directions, including potential solutions to existing limitations, add substantial value to the work. Overall, as a significant contribution to advancing power system resilience research. While it effectively outlines the current state of the field and provides actionable insights, including more specific case studies or practical examples could further enhance its utility for practitioners [127, 128].

To assess the impact of installing DGs on reliability indices, it is essential to determine the available capacity of the DG unit for restoring disrupted supply in reliability analysis [129]. Several attributes must be considered during reliability assessment studies:

1. Availability of DGs: Distributed generation units may encounter failures that may impact their functionality. Hence, models of reliability should take into account the presence of DGs across various contingency scenarios. Probabilistic approaches are required to handle this stochastic nature.
2. Operating State of DGs (Grid-Connected and Islanded): In islanded mode, the absence of communication infrastructure, protection capabilities, and suitable control might constrain this operational state [129]. However, various studies have addressed the reliability assessment of distribution networks to facilitate the transition to an intelligently managed grid. In grid-connected mode, they deployed near load centers to enhance system reliability by partially relieving centralized units during peak or maximum loading situations. It is crucial to measure the power exchange between feeders in the presence of DGs. A summary of prevailing techniques within microgrid layouts is presented in Tables 4 and 5.

Table 4 Distributed generation assessment techniques in islanded mode

Technique	Type of DG	Load model	Generation model
Analytical [131, 132]	Dispatchable DG	NIL	NIL
Monte Carlo simulation [133–135]	Both dispatchable and non-dispatchable DGs	Averaging	Markov models −3
Monte Carlo simulation [136]	Both dispatchable and non-dispatchable DGs	Probabilistic approach	Probabilistic approach
Monte Carlo simulation [136–138]	Both dispatchable and non-dispatchable DGs	Hourly profile	Hourly profile
Analytical [139]	Both dispatchable and non-dispatchable DGs	Levels of a typical day	Levels of a typical day
Analytical [135, 140, 141]	Both dispatchable and non-dispatchable DGs	Probabilistic approach	Probabilistic approach
Analytical [142–145]	Both dispatchable and non-dispatchable DGs	Part of the year	Part of the year

Table 5 Distributed generation assessment techniques in grid-connected mode

Technique	Power flow	System constraints	Capacity transferred
Analytical [146, 147]	Yes	Voltage and load	Computed
Monte Carlo simulation [148]	No	Loading	Computed
Analytical with Monte Carlo simulation [149]	No	Loading	Computed

3. Power Source (Dispatchable and Non-Dispatchable): Dispatchable DGs have a fixed and known generated power, modeled using Markov state models [129, 130]. On the other hand, non-dispatchable units, such as wind and solar, generate power based on the availability of intermittent sources.

Demand response (DR) is specified by the Federal Energy Regulatory Commission as "the deviations in consumers' electric consumption from their regular usage behavior in response to new pricing schemes, a heightened sense of responsibility, and incentive prices that are primarily crafted to encourage reduced electricity consumption during high price periods or when the reliability of the system is at risk" [150]. DR enables users to actively engage in grid operations by allowing them to modify their power usage during peak hours, providing financial incentives as a reward. This approach not only benefits consumers but also contributes to system stability, as DR can offer sufficient capacity during contingencies without resorting to traditional measures like shedding loads to restore system functionality [129].

In addition to the relevant references cited earlier and later in this paper, the essential function of demand response in smart grids has been thoroughly reviewed in References [150–157]. The categorization of DR (demand response) program can be found in Fig. 2.

Demand response holds significant importance in influencing the future power grid, alongside storage technologies, distributed generation, and communication infrastructure [74, 156, 158]. In conventional/traditional power grids, users are typically passive with limited control over their adjustable devices. However, in smart grids, consumers

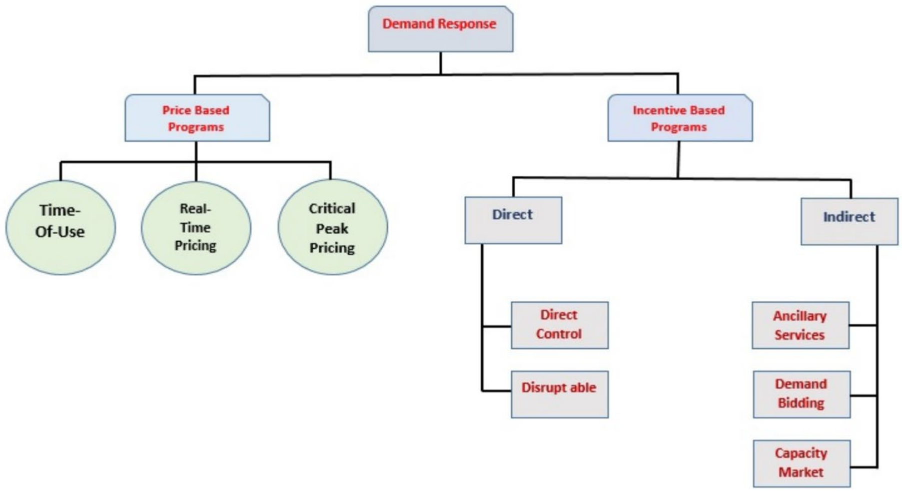

Fig. 2 Demand response

are more actively involved in various aspects of the restructured power grid. Demand response programs can fall under incentive-based programs and price-based programs. In price-based programs, end users are offered various pricing mechanisms, while incentive-based programs provide rewards for specific tasks performed by end users [74, 129, 158, 159].

Incentive-based programs are additionally divided into ICL (indirect control load) and DCL (direct control load). DCL enables utilities to adjust the energy consumption of controllable devices with prior notification, while ICL is designed for appliances that can be temporarily disrupted to reduce peak loads during heavy demand periods. The following flow outlines the reliability and applications of demand response [DR].

Reliability considerations for demand response

When assessing reliability within the framework of demand response, it is crucial to differentiate between DR actions and natural interruptions, such as partial or complete component failures, which are typically evaluated in traditional reliability assessments [160]. Demand response actions are preplanned and coordinated, while natural interruptions are unforeseen and occur without consumer intervention.

Furthermore, DR is usually applied to less sensitive loads, such as thermostatically controlled devices, allowing certain devices to remain energized even during load curtailment. The effect of DR (demand response) on reliability necessitates additional metrics compared to conventional reliability assessments [129, 160]. For more in-depth information, few researchers [160] have thoroughly discussed various reliability techniques applicable to demand response. Table 6 provides a summary of different reliability techniques that can be utilized in DR programs.

The precise allocation of available capacity resulting from load curtailment is essential to consider when conducting reliability studies. Additionally, load profiles over various time horizons must be modeled to assess demand in reliability evaluations. SMCS which

Table 6 Different ideas and methods for evaluating DG reliability

Technique	DR program	DR criteria	ICT impact	Operating mode
Analytical [161]	Incentivized	Interruption cost minimization	No	Grid connected
SMCS [112]	Incentivized	Shifting less amount of critical loads	No	Grid connected
SMCS [162]	TOU	Conflictive maximization of profit from suppliers and payment minimization from consumers	Yes	Off-grid
SMCS [163]	Incentivized	Interruption cost minimization	Yes	Off-grid
Analytical SMCS [164, 165]	Incentivized	Minimization of payback incentives and also the cost of interruption	Yes	Grid connected

is sequential Monte Carlo simulation is frequently utilized for reliability assessment, as seen in References [112, 162–164].

Demand response programs can be classified into three classes based on the party in charge:

1. Reliability-based Programs: Here, a group of demand reduction signals is conveyed to participants through either voluntary requests or obligatory commands.
2. Rate-based Programs: Prices are predetermined over a specific period, with consumers obligated to pay higher rates during peak periods and lower prices during non-peak periods. This program follows a TOC (time-of-use) structure.
3. Demand Reduction Bids: Here, engaged consumers present their offers to the ISO (independent system operator) or a demand aggregator, proposing the capacity they are willing to reduce.

Applications of demand response

Aggregated DR (demand response) or controllable demands can serve as VESS (virtual energy storage systems). By intelligently managing energy and power consumption through DR, functions similar to energy storage devices can be achieved. This approach allows for the smart utilization of existing assets, providing ancillary services at a much lower cost. For example, aggregating 1.5 million refrigerators with a total capacity of 20 MW could cost around £3 million, while a VESS may cost approximately £20-£25 million [166–168]. DR also can reduce the market share of ESS (energy storage systems) by 50% by the year 2030 [168].

Frequency regulation services may be effectively provided through appropriate modifications to the power utilization of manageable devices.[169–177]. For instance, a control topology or algorithm for refrigerators with dynamic control was suggested in Reference [169] and offers primary frequency regulation services in Great Britain. Researchers in Reference [170] investigated the ability of loads under dynamic control to uphold grid frequency within a defined range following an abrupt generation loss. The study revealed a notable delay in frequency decline and reduced dependence on instantly deployable backup power generators. In another study [171], the researchers utilized controlled aggregate bitumen tanks to frequency oriented application with ample reserve capacity. The model demonstrated higher reliability and faster response compared to frequency-responsive generating units.

The potential of electric water heaters to offer average power for power-balancing applications was investigated by the authors [172]. A control strategy involving adjustments to the setpoint temperature and drawn hot water was implemented. Reference [173] presented an approach to aid voltage profile and grid frequency by employing an adjustable load consisting of electric water heaters and electric vehicles. A distributed controllable protocol was created to alleviate active power and reactive power deviations from renewable sources.

The researchers examined the suitability of domestic refrigerator-type loads and industrial bitumen tank loads for frequency response services. They recommended employing a decentralized controller to modulate load power consumption based on grid frequency [174]. In another study [175], the researchers introduced a dual-layer control topology for thermostatically adjustable loads to actively engage in rapid frequency regulation services within a microgrid highly penetrated by renewable energy sources (RESs).

On a different note, Reference [176] proposed a collaborative control scheme to enhance the stability of islanded microgrids. Unlike other control schemes, this study involved all agents in the microgrid to support the reserves necessary for achieving system stability. An algorithm utilizing MPPT (maximum power point tracking) was used to limit the power output of solar panels during frequency rise events. Furthermore, Reference [177] presented a comprehensive central demand response strategy for frequency regulation support with minimal load adjustments. The study was validated through simulations on the 13-bus IEEE benchmark. Aggregated electric vehicles were proposed to offer centralized additional frequency regulation by acting as an intermediary between demands and power system control center while considering charging requirements [178].

Energy storage systems in smart grids

The ESSs (energy storage systems) play a pivotal role in smart grids that incorporate renewable energy resources. ESSs effectively mitigate the variability of these resources by enabling efficient energy management. These systems accumulate surplus power during the low demand and supply it during peak hours, ensuring a stable and reliable power supply. While applications of energy storage system are not new, continuous developments are required to optimize their operational efficiency and reduce capital costs, especially in light of the advancements in electric vehicle (EV) technologies. Figure 3 illustrates the various applications of energy storage technologies that are used in power systems [178, 179]. Despite their significant contributions, the inherent inefficiencies and capital costs of conventional energy storage technologies remain a topic of discussion. Therefore, careful optimization of their operation and size is essential. Extensive research, as highlighted in References [180–186], has focused on the role of storage systems in modern smart grids. These studies cover a broad range of topics, including applications, costs, characteristics, optimal operation, sizing, and hybridization of storage topologies [187].

The applications of energy storage technologies in smart grids are diverse and include energy arbitrage[188–193], frequency regulation [194–197], spinning

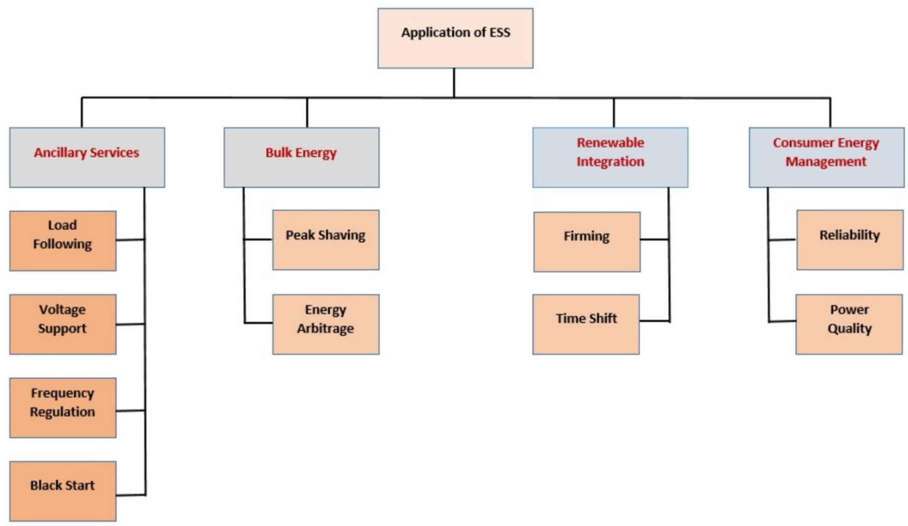

Fig. 3 Various usage of energy storage systems in smart grids

reserves [198, 199], peak shaving [200–202], voltage support [203–205], black start capabilities [206], intermittency smoothing [207], congestion mitigation [208], system expansion deferrals [209], multi-agent grid services [210–213], and load-following applications[214]. Recent characteristics of storage technologies are presented in Tables 7 and 8, providing insights into their capabilities and potential uses in smart grid environments. In the realm of ancillary services, electric vehicles (EVs) can serve as an independent energy source, enabling a concept known as V2G (vehicle-to-grid) [215–218]. When parked, the energy stored in the batteries of EV can be returned to the grid, contributing to grid stability and reliability. Additionally, fixed or movable energy storage systems can be strategically deployed to provide reserve capacity for ancillary services [218–222].

Researchers have proposed various control strategies to harness the potential of EVs for ancillary services. For example, in Reference [216], a strategy for real-time control of a group of EVs was developed, considering bidirectional charging and discharging efficiency within an extended MPC (model predictive control) framework. The simulation results demonstrated substantial enhancements in battery lifetime extension, tracking error, and regulation capacity.

Another study in Reference [217] presented a planning framework for a virtual investor seeking to provide additional services to a wholesale market. Two approaches were considered: one using a dedicated battery and the other utilizing aggregated EVs. The optimization model aimed to maximize long-term payoffs for the investor by devising an optimized daily bidding strategy. An economic measure, such as present worth, was employed to compare the two alternatives. A sensitivity analysis was conducted to assess the impact of planning and operational variables on the feasibility of each approach.

Within the framework of power system ancillary services, innovative approaches using VESS (virtual energy storage systems) have been proposed. For instance, in

Table 7 Specific traits of energy storage technologies

Energy technology	Power density W/Kg	Energy density Wh/Kg	Discharge density	Life time in years	Capital cost		Technology maturity
					Rate/Kw	Rate/Kwh	
Electrical energy storage							
Super capacitor	500 to 1300	2.5 to 15	Millisec to 60 Min	More than 20	7000–21,000	21,000–700,000	Developed
SMES	500 to 2000	0.5 to 5	Millisec–sec	More than 20	14,000–21,000	70,000–700,000	Demonstration
Electrochemical energy storage							
Lead acid battery	75 to 300	30 to 50	Sec to Hrs	5 to 15	14,000–21,000	8400–10,500	Commercial
Nicd battery	150 to 300	50 to 75	Sec to Hrs	10 to 20	35,000–105,000	56,000–105,000	Commercial
NaS battery	150 to 230	150 to 240	Sec to Hrs	10 to 15	70,000–210,000	21,000–35,000	Commercial
Li-ion battery	150 to 315	75 to 250	Mins to Hrs	5 to 15	84,000–280,000	21,000–91,000	Demonstration
VRFB	NA	10 to 30	Sec to 10 Hrs	5 to 10	42,000–105,000	3500–70,000	Demonstration
Mechanical energy storage							
PHES	NA	0.5 to 1.5	1–24 + Hrs	40–60	42,000–140,000	350–7000	Matured
CAES	0.5 to 2.0	30 to 60	1–24 + Hrs	20–40	28,000–56,000	140–3500	Developed
Flywheel	400 to 1500	10 to 30	Millisec–15 min	15	3500–21,000	35,000–70,000	Commercial
Thermal energy storage							
CSP	NA	−43.05	Mins–Hrs	30	NA	3500–7000	Developing

Table 8 Interrelated traits of energy storage technologies

Energy & technology	Power in MW	Charging time	Self-discharge\ day in %	Life cycle	Efficiency	Time for response	Class
Electrical energy storage systems							
Double-layer super capacitor	0 to 0.3	Sec-Hrs	20–40	100,000	90–95	Milliseconds	Short term
SMES	0.1–10	Sec-Hrs	10–15	100,000	95–98	Milliseconds	Short term
Mechanical energy storage							
PHES	0.1 to 5000	Hrs-Mons	Very small	–	65–87	1–2 Min	Long term
CAES	0.005–300	Hrs-Mons	Small	–	50–89	1–2 Min	Long term
Flywheel	0 to 0.250	Sec-Mins	100%	–	85–95	1–2 Min	Short term
Chemical energy storage systems							
Hydrogen fuel	0 to 50	Hrs-Mons	Nearly 0	100+	20–50	Sec–Mins	Long term
Electrochemical energy storage							
Lead acid battery	0 to 20	Mins-Days	0,1–0.3	500–1000	75–80	Seconds	Long term
NiCd battery	0 to 40	Mins-Days	0.2–0.6	200–2500	85–90	Seconds	Long term
NaS battery	0.05 to 8	Sec-Hrs	20	2500	85–90	Seconds	Short term
Li-ion battery	0 to 0.1	Mins-Days	0.1 to 0.3	10,000+	85–90	Seconds	Long term
VRFB	0.03 to 3	Hrs-Mons	Small	12,000+	85–90	Seconds	Long term
Thermal energy storage systems							
CSP	0.01 to 20	–	1	–	Below 55	10 Min	Long term

Reference [218], a VESS comprising FSS (flywheel storage systems) and controllable demands was introduced to offer supplementary services to the power grid. Feasibility studies were conducted to demonstrate the advantages of such protocols compared to conventional measures.

Another study in Reference [219] presented a hybrid ultra-capacitor and battery storage system for large-scale regulation services. This scheme aimed to alleviate battery overuse and enhance the profitability of regulation services. In Reference [220], a vanadium-redox flow battery-based energy device model was proposed to offer multiple ancillary services, with a focus on peak-shaving applications and frequency support. Below table shows the different traits related to energy storage technologies [179, 223, 224]

Energy storage technologies are categorized into mechanical, electrochemical, electrical, chemical, and thermal systems. Mechanical systems (e.g., PHES) are mature with long discharge times, while electrochemical systems (e.g., lithium-ion batteries) have high energy densities and varying costs. Electrical systems, like supercapacitors, provide high power density and quick responses. Chemical and thermal systems (e.g., hydrogen fuel cells, CSP) are still developing with unique applications.

Associative characteristics highlight storage duration, self-discharge rates, cycle life, and efficiency. Mechanical storage supports long-term use with moderate efficiency, while electrochemical systems are versatile. Electrical systems, like supercapacitors, excel in short-term, rapid-response scenarios. Chemical and thermal systems have limitations in efficiency but are suitable for specific long-term needs.

Moreover, Reference [221] investigated a collaborative dynamic strategy for balancing energy levels through consensus control within distributed energy storage devices in droop-controlled microgrid. This approach facilitated frequency regulation capabilities. In the realm of market-based frequency regulation services, the financial effectiveness of a BESS (battery energy storage system) was assessed in Reference [225]. The potential impact on profitability was also evaluated, providing valuable insights into the economic aspects of employing BESS for ancillary services.

Additionally, the replacement of conventional generators with renewables may lead to a reduction in inertial mass, posing challenges to grid stability. To state this issue, Reference [194] proposed a coordinated control scheme that effectively operated a hybrid system comprising ultra-capacitors and batteries to fulfill ancillary services requirements in the electricity market.

Data management systems in smart grids

Energy data management system in smart grids

The transition toward a fully functional smart grid presents significant challenges, particularly due to resource scarcity [226]. In the framework of a smart city, that incorporates advanced engineering solutions and informatics capabilities, the smart grid plays a pivotal role as the foundation for integrating various intelligent services such as smart transportation, smart education, smart waste management, and smart communication. To ensure the successful integration of these services, smart grids require sophisticated data management systems. Handling and processing the vast amount of information generated in such grids demands careful attention. Generally in smart grids, efficiently managing big energy data is crucial, and numerous studies have been devoted to exploring different aspects of data management. These studies encompass data preprocessing, data collection, data integration, data analytics, data storage, data visualization, and decision-making [227–238]. Researchers have been dedicated to examining advancements in the realm of large-scale energy data management to facilitate the seamless functioning of smart grids.

In contrast to the traditional grid that relies on limited data collected from a few points within the network, the smart grid operates on a much larger scale, capturing real-time data from numerous data points throughout the grid. This abundance of data is often referred to as "big energy data" and includes information from various sources, such as smart meters, distributed sensors, weather forecasts, and load profiles. These data facilitate various power system applications, allowing utilities to make well-defined choices and consumers to modify their power usage during peak load periods. Additionally, the data can be utilized to identify and address faulty networks, restoring the grid to its regular operation.

However, with the expansion of advanced infrastructure, new challenges arise in the context of data management. Issues, such as data security, data privacy, the cost of data storage, and data retrieval, become critical considerations for ensuring the effective and secure functioning of the smart grid. These challenges must be carefully addressed to fully realize the potential benefits of big energy data in the smart grid.

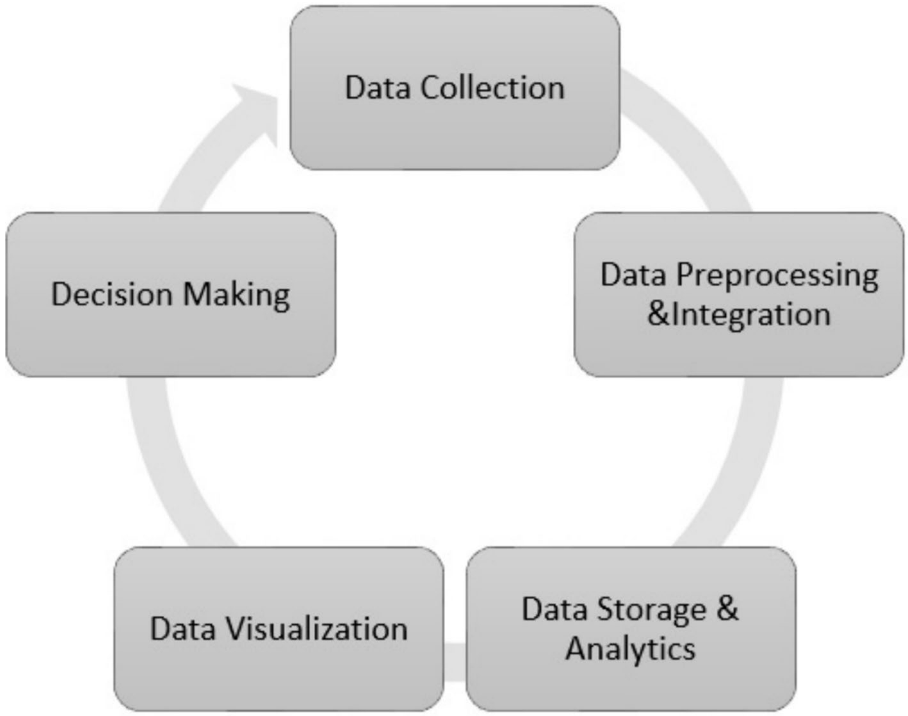

Fig. 4 Data flow in the smart grids

Data collection in the smart grids

The data management process in smart grids follows a sequential organization, as illustrated in Fig. 4. The initial step in this process is data collection, where information is gathered from data centers [239]. The primary source of data is the AMI (advanced metering infrastructure), which retrieves information from end users' premises. The AMI collects data at regular intervals, typically every 10–15 min. The size of the data generated can vary depending on the population of a given area. For instance, in a city like Sydney, Australia, with a population of approximately 4,000,000, there are around 1,850 dwellings in Greater Sydney alone [240]. This large number of dwellings results in approximately 267,228,432 messages being sent to the control center every day.

Various data loggers are employed in smart grids for transmitting different types of data, including sensor data, power metrics data, mobile terminal data, metadata, control device data, historical data, and reliability data [241]. GIS (Geographical information systems) also play a very important role in smart grids, providing valuable information that aids in specific tasks such as identifying suitable locations for PV farms, visualizing generation and distribution facilities, and facilitating grid planning [242–244].

There has been continuous advancement in the field of energy data management to tackle various challenges, including standards, security, privacy, reliability, and scalability [226]. For example, researchers in References [245, 246] focused on data collection concerning security and privacy aspects. Additionally, studies conducted in References [247, 248] explored data collection within a nonhierarchical network, proposing lightweight message authentication frameworks for secure data communication while ensuring privacy [249]. Other investigations aimed to reduce storage requirements when establishing multiple sessions with source devices or sensors [250]. In Reference [251], a strategy for reporting smart meter data was suggested, integrating three innovative data collection methodology to enhance the efficiency of communication networks, and TCP-based communication in IEEE 802.11 s mesh AMI networks. These research efforts contribute to enhancing the efficiency and security of data management in smart grids.

Data preprocessing

In this phase, the collected data undergo several processing steps before any analysis can take place. The acquired data may suffer from incompleteness or inaccuracies, requiring a process known as data cleansing to filter out errors [252]. Data cleansing involves five steps, which include defining, identifying, correcting, documenting, and modifying erroneous data to prevent future faults [253]. Sometimes in smart grids, precise forecasting relies on the essential process of data cleansing of PV system generation to determine appropriate dynamic tariff rates [254, 255].

Additionally, the acquired data may contain redundant and repetitive information, leading to increased storage costs. Identifying and eliminating redundant data becomes necessary to optimize storage capacity [256–258]. Researchers in Reference [259] likened the data received from smart grid facilities to data created from media space. Therefore, data preprocessing may include data cleaning, aggregation, redundancy elimination, and repetition removal [260–263]. Notably, privacy preservation is an essential consideration when aggregating data to keep them anonymous [264].

Data integration

Data collected from various scattered sources may not be uniform and requires proper integration before conducting analysis [226, 265]. For example, integrating load profile data and weather condition data allows utilities to optimize and schedule power production according to demand while considering uncertainties [265–267]. This data integration process ensures that the information obtained from diverse sources is combined in a coherent and compatible manner for more effective analysis and decision-making in smart grids.

Data storage

In the data storage phase, the collected information is stored, organized, and made accessible at any given time [227]. Traditional grids typically store load data patterns for load forecasting applications, requiring relatively limited data storage capabilities. Yet, in smart grids, a diverse set of data must be assigned and stored. The speed of processing input/output information from the data storage is crucial due to the real-time operations that must be performed [268]. Smart grids collect diverse and enormous numbers of data from various sources, necessitating fast access to the stored data for real-time applications. Several approaches have been reported in the literature to establish effective data storage mechanisms. For example, Reference [269] proposed a framework founded on SMACK (simplified mandatory access control kernel) that combines Kappa and Lambda for data storage in microgrids, while Reference [270] utilized a graph storage approach to effectively store collected data/information in smart grids. The authors proposed automating the migration of a database from the RDF (resource description framework) to a graph storage engine. The overall data flow is schematically represented in Fig. 4.

Data mining and data analytics

In smart grids, a substantial volume of data is consistently collected, followed by the execution of numerous applications on the acquired data, including end-user behavior analysis, state analysis, and fault analysis. These analyses are classified based on the required response time for processing the data. The first category comprises nonurgent operations that do not require high response time, such as long-term load forecasting [271] and customer analysis. Conversely, fault analysis and smart metering data fall under applications that require quick analysis. For instance, Reference [227] proposed the use of a machine-learning algorithm to process local data, saving network bandwidth and reducing time delays. The study also deployed a central processor as a mediator between local processors, contributing to overall cost reduction.

Data visualization

Data visualization holds a pivotal role in providing decision-makers with a clear and insightful representation of the data [272, 273]. Visualizing data through graphs and charts makes it easier to understand complex numerical information. It helps identify both areas of concern and opportunities within the data. Various visualization tools, including 2D and 3D visualization tools, are available in the market, allowing both consumers and utilities to visualize power consumption, renewable energy generation, and power quality data. Additionally, GIS software, such as ArcGIS, QGIS, MapInfo, and Maptitude, offers valuable alternatives for mapping smart grid data [273].

Online decision-making

One of the key advantages of smart grids is the ability to make real-time and automated decisions, a feature not commonly seen in traditional grids [274]. Real-time decision-making facilitates important actions such as implementing real-time pricing mechanisms, managing on-demand renewable generation, and estimating capacity constraints [274, 275]. This capability enhances the reliability of smart grids and boosts the confidence of end users in the technology. By analyzing data in real-time, defective segments in the smart grid may be displayed, isolated, and addressed promptly to resolve issues [276]

Data management challenges in smart grids

While the data gathered from diverse origins supports the functionality of smart grids and enables intelligent decision-making, it also presents substantial challenges in relation to volume, reliability, scalability, as well as privacy and data security. The massive amount of data generated requires substantial storage capacity. However, the current infrastructure may lack the necessary workforce skilled in managing such vast quantities of data. Therefore, active participation from end users in dealing with smart metering data becomes crucial to ensure its optimal utilization. Ensuring data reliability and scalability is vital to instill confidence in the data and to facilitate trustworthy decision-making processes.

Cybersecurity of smart grids

Addressing the critical importance of data security, this subsection highlights the complexity of the widespread cybersecurity challenges. The sophisticated automation and communication features within smart grids render the entire system vulnerable to potential cyberattacks. As smart grids are incorporated, they empower both electric utilities and end users, thereby improving the reliability and availability of services, with continuous monitoring and management of demands, it also introduces various security constraints and vulnerabilities [277, 278]. Malicious actors can exploit these vulnerabilities to illegally disrupt the system dynamics or cause secondary perturbations if proper security measures are not in place [279].

The literature extensively investigates cybersecurity threats, issues, vulnerabilities, and countermeasures, particularly over the past decade, as automation rapidly advances [280–292]. Within the analysis framework, finding suitable mathematical models to describe cyberattacks becomes crucial. Cyberattacks can be classified into various types, including DoS (denial of service) attacks, reply attacks, and deception attacks, and their models are summarized in Table 9. Safeguarding protecting smart grids from cyber threats requires robust and adaptive security strategies to ensure the integrity, availability, and confidentiality of the data and services within the system.

DoS attacks involve adversaries attempting to disrupt system resources and render them unavailable. Various models have been suggested to quantify the performance degradation caused by such attacks, including Queuing models, Bernoulli models, and Markov models [293, 294]. In Queuing models, attacks are transformed into a delayed system, allowing traditional analysis to investigate stability. For instance, Reference [295] proposed a round-trip-based predictive control protocol to mitigate the impact of weak DoS attacks.

Replay attacks involve adversaries contaminating valid data, making them difficult to detect as they can pass cryptographic key examinations. Attackers may also create channels between two terminals to relay repetitive messages. In deception attacks, adversaries manipulate the integrity of transmitted data. The objective of these cyberattacks is to disrupt system performance and temporarily or permanently immobilize the network, potentially impacting the economy as well [296–302].

In cyber–physical systems, especially in power system applications, detecting cyberattacks is crucial. Bad data detectors are utilized to detect deviated estimates and provide alerts based on predefined tolerance levels. There are two defense approaches

Table 9 Mathematical representations of cyberattacks

Attacks	Model
Deception attacks	$yk = yak + yk$, where yak indicates the erroneous data injected by intruders
DoS attacks	ykr∊∅: refers to ykr and yk are the received data &and measured data
Reply attacks	$ykr = Y$: refers to the previous information

against cyberattacks: proactive protection of essential components before the attack occurs and reactive identification and removal of contaminated data injected by adversaries. For example, sensitive information can be embedded within normal readings using wavelet-based steganography techniques [303–312]

Regarding detection schemes, four techniques are commonly used in cyber systems: Bayesian detection, weighted least square (WLS), Kalman filters-based $\chi 2$-detector, and quasi-FDI (fault detection and isolation) techniques. These methods play a crucial role in safeguarding cyber–physical systems against potential threats and ensuring the integrity and reliability of the power system [313–320].

Understanding the interaction involving cyber systems and physical systems is of utmost importance in the framework of smart grids [321, 322]. The SCADA which is a supervisory control and data acquisition system, responsible for controlling the electrical grid, is a primary target for potential attackers. For instance, vulnerabilities in data exchanged through the wide area network (WANs) between various entities have been identified [323].

SCADA systems incorporate sophisticated units like AMI (advanced metering infrastructure), DER (distributed energy resources), and DA (distribution automation) in the distribution system, increasing the potential damages that can result from cyberattacks. Other systems that are susceptible to attacks include PLC—programmable logic controllers and nuclear facilities [324, 325]. To assess potential vulnerabilities in the SCADA system, a layout for evaluating these vulnerabilities was proposed, utilizing the "mean-time-to-compromise" index as a quantifying measure [326].

Moreover, the extensive adoption of AMI in smart grids introduces additional challenges concerning data security. Potential issue of cyberattacks targeting AMI units includes the leakage of customer information, false data injection, and energy theft [326–330]. Various detection techniques can be employed to safeguard smart grids against cyber threats. Table 10 provides a summary of common detection techniques that can be adopted in these advanced energy systems. Enforcing resilient security measures and efficient detection techniques is crucial to ensure the resilience and integrity of smart grids against potential cyberattacks.

The vulnerability of medium control layers in smart grids allows intruders to inject false signals or malware, potentially leading to a complete network failure. To prevent future threats, data encryption becomes crucial. An illustrative example of the

Table 10 Methods for identifying issues in smart grids

Protection	Domains	Detections
AMI	Host	[331–334]
SCADA	Networked	[330, 335, 336]
GPS [PMU]	Host	[337]
Wide area monitoring [WAM]	Host	[277, 338]
Distribution systems	Host	[339]
Substations	Host	[340]
	Networked	[341]
	Integrated	[342–344]

devastating consequences of cyberattacks on power systems occurred in June 2017, at the time when Ukrainian power system experienced an unprecedented cyberattack, resulting in a six-hour blackout affecting around 80,000 people [345, 346]. This incident marked a significant milestone in cybersecurity as it marked as the initial significant attack to cause such a substantial collapse, exposing the critical nature of cybersecurity in power systems. The attack involved the cultivation of two types of malicious software in the facilities, and the attackers further hindered resolution efforts by flooding the company's call center with calls, preventing consumers from reporting their outages. The severity of this incident highlights the urgent need for robust countermeasures to safeguard smart grids against potential cyberattacks and mitigate their severe consequences.

Cost model scenario in smart grids

In contrast to the early unidirectional power flow in conventional power grids, smart grids introduce more dynamic pricing mechanisms to enhance efficiency and consumer control. Unlike the vertically integrated structure of conventional grids, where a single entity governs all aspects of generation, distribution, and transmission, smart grids embrace more decentralized and market-driven approaches. These market-oriented pricing mechanisms aim to promote competition, cost optimization, and consumer empowerment [347].

In traditional power grids, regulated monopolistic utilities set fixed pricing rates based on the operating costs and anticipated profits. However, critics argue that such a model lacks flexibility and can lead to inefficiencies, monopolies, and political interference. The lack of real-time control over pricing and the inability to adapt to changing demand patterns can hinder the grid's overall efficiency and responsiveness to consumers' needs.

Smart grids, alternatively, introduce innovative pricing mechanisms that enable consumers to actively manage their energy usage based on real-time market conditions. TOU (Time-of-use) pricing, for instance, allows consumers to modify their electricity intake during peak and nonpeak periods, encouraging load shifting to times with lower prices [348, 349]. This approach encourages consumers to utilize electricity when it is less costly, alleviating stress on the grid during peak periods. Additionally, demand response programs provide monetary incentives for consumers to minimize their electricity usage during peak periods, effectively providing grid support as an alternative to building expensive new power plants. This encourages a more dynamic interaction between consumers and the grid, fostering a balance between supply and demand while ensuring a stable and reliable power system. By embracing these modern pricing mechanisms, smart grids aim to provide fair, efficient, and sustainable energy pricing while empowering consumers to play an active role in managing their energy consumption. This shift toward market-driven pricing fosters innovation and competition, ultimately contributing to a more resilient and responsive power grid [350, 351]

However, the increasing demands for electricity, coupled with mounting criticism of the traditional power grid's inefficiencies, prompted a restructuring of the electricity market. The outcome was the establishment of a restructured and deregulated market, which introduced various entities into the system. These entities include GENCOs (generating utilities), TRANSCOs (transmission utilities), DISCOs (distribution utilities), RESCOs (retailers), and ISOs (independent system operators) [352, 353]. The

IEA (International Energy Agency) emphasizes that restructuring electricity markets is designed to break monopolistic practices and promote healthy competition among market participants.

The restructured market underwent several reforms to reduce entry barriers, rely more on market-based pricing, and offer consumers the freedom to choose their power suppliers [352, 354]. These reforms shift the traditional vertically integrated structure toward an open and competitive market environment, altering the regulatory regime that once shielded utilities from the impacts of cost and demand fluctuations [354, 355]. From the government's perspective, deregulation attracts investments and encourages competitors to diversify their resources. By allowing companies to compete freely for electricity provision, the efficiency gains resulting from these reforms ultimately benefit consumers.

In an ideally competitive market, all participants act as "price takers," meaning that no single company has the power to influence prices. In such a scenario, the most efficient electricity generators are the ones that earn higher profits [356]. When the selling or equilibrium price is determined, these efficient generators become inframarginal producers. In a deregulated market, renewable-based generators can bid with a zero marginal cost since their operating costs are negligible [357]. This setup illustrates why perfect competition fosters more efficient electricity production and incentivizes the adoption of renewable energy sources.

Dynamic pricing mechanisms

Unlike conventional grids where demand is typically passive, smart grids enable active and engaged participation of consumers in various applications. In 1980s demand-side management (DSM), implemented by the EPRI (Electric Power Research Institute), encompasses a range of activities aimed at managing load consumption and improving energy efficiency [357, 358]. DSM can be implemented through energy efficiency measures or demand response (DR) programs. The dynamic pricing framework is designed to provide economic incentives for consumers to participate in demand management, fostering a collaborative relationship between consumers and utilities to achieve these objectives within the smart grid infrastructure.

Several dynamic pricing mechanisms have been introduced for demand response, including TOU (time-of-use), CPP (critical peak pricing), RTP (real-time pricing), and DAP (day-ahead pricing) [359]. For example, some articles have adopted TOU as a pricing model [360–365], while others have explored RTP schemes [366–376]. CPP modality has also proven to be effective in certain scenarios [377–383], and DAP has been proposed as a pricing modality in competitive electricity markets [347, 384–387].

However, despite the potential benefits of dynamic pricing mechanisms, there are challenges to their widespread adoption. The complexity and cost involved in implementing different pricing frameworks can be significant barriers to their day-to-day use in the existing grid [388–390]. As the smart grid continues to evolve, addressing these barriers will be crucial in realizing the full potential of dynamic pricing systems for demand response and efficient energy management.

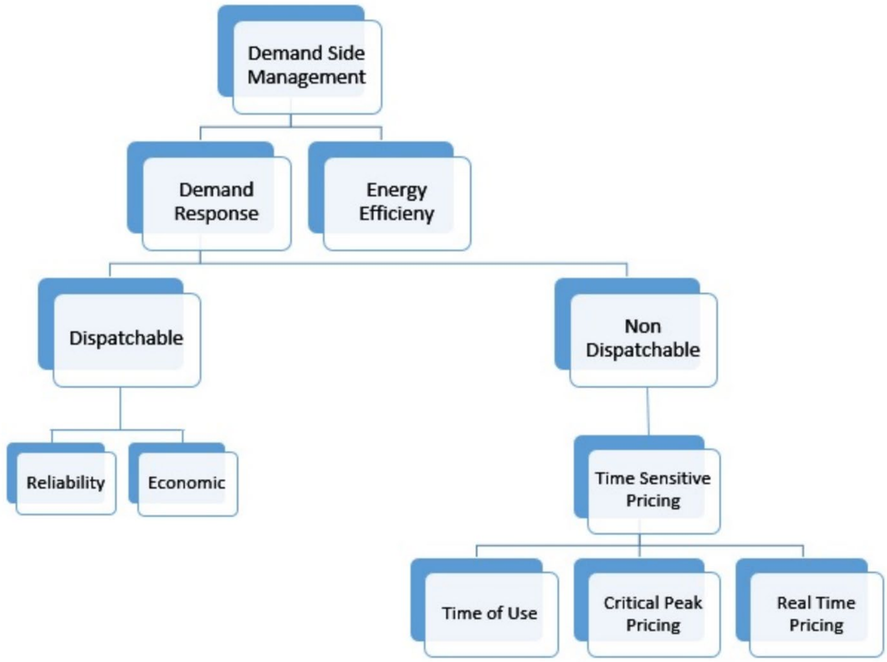

Fig. 5 Categorization of demand-side management approaches

The main goal of demand response programs is to modify the load pattern, achieved either by reducing consumption during peak hours or by shifting loads to off-peak periods. These programs can be categorized into two categories: non-dispatchable and dispatchable programs based on pricing, as illustrated in Fig. 5. A dispatchable program allows the utility to directly control the load during peak hours. On the other hand, non-dispatchable programs based on pricing, also known as price-sensitive programs, offer different pricing options through dynamic pricing schemes to influence and manage demand [391–393].

Time-of-use (TOU)

The time-of-use (TOU) pricing approach involves predefining different tariff rates for various periods throughout the day or seasonally within a given billing cycle. This strategy is employed by utilities to manage the surge in demand during peak hours by implementing a tariff structure that charges higher rates for energy consumption during those peak periods [384, 385].

TOU tariffs are often introduced in areas where consumers were previously subject to a flat rate. The main objective of this pricing scheme is to incentivize consumers to move their energy consumption from peak hours to off-peak periods. Despite facing some challenges, TOU pricing remains a popular choice for utilities due to its simplicity. Consumers also tend to prefer this approach over others because they are accustomed to fixed tariffs and might feel uncertain about adhering to frequently changing rates, as well as being uncomfortable with the variability of real-time pricing [347].

TOU pricing remains a prominent and essential element of demand response (DR) programs. It is a static time-dependent pricing system, and while its implementation cost is relatively low, practical challenges arise when integrating it into the existing distribution system. The lack of real-time consumer behavior data in the current infrastructure necessitates the adoption of smart meters to facilitate the expansion of this pricing policy. Additionally, uncertainties arise in designing the TOU policy due to the dynamic nature of generation and demand [360, 361]. Moreover, different jurisdictions have diverse market structures, leading to the need for tailor-made TOU policies based on their specific requirements. For instance, the addition of space heaters might be required in specific regions due to climatic conditions, while it might not be relevant in other places.

The presence of DERs (distributed energy resources) also needs to be taken into account when devising an effective TOU scheme. To address these challenges, numerous efforts have been made and documented in the literature. Table 11 provides an overview of the challenges faced and recent developments related to the TOU approach.

Real-time pricing method

The RTP (real-time pricing) method was first introduced in early 1982 [365, 366] and has since gained widespread recognition as a promising approach for optimizing the welfare of both consumers and service providers. RTP represents a dynamic pricing approach that aligns with the spot price of the wholesale market [64]. Electricity is treated as a tradable commodity, subject to bidding and offering in the market. The transactions are settled and cleared by the system or market operator through the market clearing process. After establishing the price, a cost signal is transmitted to market participants based on the market timeframe, which can be a day ahead or an hour ahead. Unlike the static TOU pricing scheme that follows predefined blocks over a cycle, RTP is agile and constantly changes in response to the spot market conditions. In a distribution network, a retailer may disclose the price a day ahead or on an hourly basis, enabling end users to adjust their energy consumption accordingly [367–372, 396].

However, it is essential to carefully address the potential challenges that might occur during the execution of this plan. Ensuring a win–win situation for both consumers and electricity providers should be a priority when designing the framework. Additionally,

Table 11 Latest developments in time-of-use [TOU] systems

Years	References	Objective
August 2012	[362]	The researchers suggested using variation inequality models to create an ideal TOU (time-of-use) pricing strategy tailored to various market structures. Their study examined how social welfare varied across different market schemes
May 2013, January 2019	[361, 394]	There's a suggestion to use game theory in crafting the best time-of-use (TOU) pricing. This involves developing utility functions to achieve a Nash equilibrium
May 2013, May 2018	[363, 364]	The researchers have explored how the presence of DER (distributed energy resources) affects time-of-use (TOU) tariffs
December 2013	[395]	The authors utilized stochastic optimization and quadratic programming techniques to develop an optimal time-of-use (TOU) pricing structure, accommodating uncertainties in both demand and generation

Table 12 Recent progress in real-time pricing [RTP] policies

Years	References	Importance
December 2010	[373]	The authors utilized a least-square support vector machine to calculate short-term tariffs by implementing a model predictive control approach
June 2012	[374]	This study presented an effective strategy for managing household loads, utilizing the communication capabilities of a typical smart grid. Its key focus was establishing an optimal relationship between spot prices and users' electrical appliances, including electric vehicles within a standard smart building
May 2018	[375]	An algorithm for decision-making across multiple stages, influenced by Markov, has been proposed to enhance social welfare in the real-time pricing (RTP) scheme. This optimization is split into two segments: one focusing on consumer perspectives and the other specifically designed for energy suppliers, employing dual-subgradient convex optimization
January 2019	[397]	The researchers proposed an EMS (energy management system) tailored for real-time application, specifically suited for rooftop PV systems with integrated battery storage. This grid-connected EMS controls power flow within the system, responding to price signals. The main aim of the study is to maximize revenue over a specific cycle, utilizing a Lagrange multiplier-based optimization algorithm
January 2019	[372]	The authors introduced a decentralized online pricing strategy tailored for demand-side programs, accommodating uncertainties and constrained communication links. This approach aims to minimize operational costs for utilities while factoring in time-variable demand responses (DRs). Their research effectively bridged the divide between online algorithms and traditional offline optimization processes

the individual load profiles and comfort of consumers need to be taken into consideration. Some consumers are not readily available or responsive to take corrective actions once the price signal is received, potentially leading to higher charges during their absence. Nonetheless, automated load management capabilities can mitigate some of these adverse impacts.

Moreover, the successful application of such a policy for pricing necessitates new intelligent metering and also advanced infrastructure technologies, which increase the exposure to potential cyber threats. Therefore, cybersecurity measures should be thoroughly implemented to safeguard the system. The following Table 12 highlights recent developments in the RTP structure, shedding light on potential advancements and improvements.

Critical peak pricing

Despite the benefits of TOU and RTP pricing schemes, there are still obstacles to their widespread adoption. TOU lacks the necessary incentives to significantly reduce peak demand during heavily loaded periods, while RTP can be complex to implement. However, the limitations observed in TOU and RTP, coupled with the rapidly evolving infrastructure, have spurred increased interest in peak demand reduction through dynamic rates.

Critical peak pricing (CPP) has emerged as a solution to address these challenges. In CPP, a penalty is imposed during predetermined peaking periods, encouraging consumers to lower their electricity usage during these peak hours. CPP enhances the traditional TOU pricing framework by incorporating a dispatchable price (penalized rate) when the system experiences high demand [398]. Although CPP may be less dynamic compared to RTP, it has proven successful in reducing demand peaks.

CPP pricing follows the structure of a typical TOU policy, with the addition of critical events that are adjusted by utilities based on system constraints. These critical events are usually announced a day ahead, providing consumers with prior knowledge of the peaking periods. However, it is important for utilities to carefully optimize the new tariffs to ensure profitability while still incentivizing consumers to curtail their energy consumption. Establishing prices at excessively high levels could deter consumers from shifting their demands; however, fixing prices too low may lead to a limited or inadequate response from consumers to the new price signals aimed at reducing peak demand. Striking the right balance is essential for the effectiveness of CPP pricing.

Designing a successful CPP mechanism requires careful consideration due to its inherent constraints compared to RTP. Researchers have focused on developing CPP frameworks that maximize utility profits while encouraging consumers to respond to dynamic pricing signals, taking into account factors such as the number of critical events, duration cycles, and peak rates [377, 378]. For instance, in one study, a profit index was utilized to assess the impact of these metrics on utility profits, leading to a significant reduction in average consumer energy consumption [378].

Comparative studies between TOU and CPP pricing structures have also been conducted to understand consumer behavior under different pricing schemes. The findings showed that CPP outperforms TOU in reducing overall energy consumption [379]. However, it is essential to recognize that dynamic pricing approaches may face challenges in the distribution network, as some consumers are not interested in closely monitoring and responding to frequent price signals [388]. This issue was further studied, keeping that in consideration the preferences and mobility restrictions of different age groups, with the conclusion that dynamic pricing mechanisms might negatively affect elderly consumers [388, 390].

Table 13 Advancements in critical peak pricing [CPP]

Years	References	Objective
May 2018	[375]	The authors introduced a multistage optimization algorithm based on Markov decision-making to maximize social welfare within the RTP pricing scheme. This optimization approach is segmented into subproblems: the initial phase focuses on consumer perspectives, while the subsequent phase targets the energy supplier, utilizing dual-subgradient convex optimization
June 2018	[382]	A method focusing on security in managing supply and demand using a refined pricing strategy has been proposed. The aim is to pinpoint the best pricing models for different demand-side programs (e.g., TOU, CPP, and RTP) to boost effectiveness while meeting environmental regulations. Employing a approach for optimizing multiple objectives, the study targets reducing ISO operational costs and curbing greenhouse gas emissions from generating units
June 2018	[379]	The authors merged pricing frameworks (RTP and CPP) to determine the most efficient operating cycle for a smart home appliance according to a priority list. This study utilized an improved differential evolution (EDE) and teacher learning-based optimization (TLBO) to achieve the highest consumer satisfaction
December 2018	[381]	This paper presented a model using mixed-integer linear programming to determine the best size and planning scheme for an onsite generation system (OGS) within a critical pricing structure. Their findings showcased a substantial decrease in electricity costs when the OGS is sized and operated correctly
January 2019	[380]	An outlined bi-level framework has been suggested to optimize the profits of a smart distribution company managing electric vehicle parking lots. The goal is to reduce the cost of purchasing energy from the wholesale market for the leading entity (like the distribution company) and to maximize the profits of the parking lot owners (as followers), all under the critical pricing policy

Advancements in optimizing CPP frameworks have been made to overcome these challenges. Table 13 gives a brief note of the recent developments achieved in this area. The ongoing research aims to fine-tune CPP mechanisms to strike a balance between utility profitability, consumer response, and the efficient reduction of peak demand.

Day-ahead pricing

The advancement of smart metering technologies and the increasing need for price-responsive demand have prompted utilities to explore different pricing approaches to incentivize consumers to lower their energy utilization during peak periods [383, 384]. Recent research indicates that hourly real-time pricing mechanisms successfully drive consumers to adopt wiser and more efficient energy usage practices [399–401]. Real-time pricing enables consumers to adapt their energy consumption in response to varying prices during both low and high periods, it faces challenges such as regulatory concerns, lack of consumer interest, and implementation issues.

In response to these barriers and to offer benefits to both utilities and consumers, the day-ahead pricing (DAP) policy has emerged as an attractive alternative. Under the DAP scheme, prices are set a day in advance, allowing consumers to plan and schedule their energy usage accordingly. This provides consumers with the chance to benefit from reduced rates during off-peak periods, thereby optimizing their energy costs [100]. Table 14 gives a summary of various strategies and progress made in optimizing the day-ahead pricing mechanism. The DAP policy holds promise in encouraging demand response and promoting more efficient energy consumption among consumers.

The day-ahead pricing modality shows potential for both energy providers and consumers. However, its successful application requires addressing certain challenges. Designing an optimal price in advance involves considering various factors, including load forecasting, supply availability, climatic forecasting, and energy price forecasting

Table 14 Advancements in the day-ahead pricing mechanism

Years	References	AIM
January 2019	[387]	A multistage optimization model based on game theory has been suggested to concurrently establish dynamic pricing policies for both the ISO (independent system operator) and EV parking lots. The study focuses on reducing electricity expenses for EV owners while maintaining profitability for the ISO within a day-ahead pricing framework
January 2019	[386]	The authors have introduced an optimal hourly setup and a day-ahead pricing structure within a smart distribution system, accounting for the functionality of protective devices. They have applied a metaheuristic-based optimization model to reduce expenses such as purchasing power from the wholesale market, costs for distributed resource owners, power loss, switching actions, and implementation costs for demand response programs
January 2019	[347]	The authors have explored the viability of trading electrical power as a commodity within a day-ahead electricity market, shifting away from the typical energy trading approach. This study aims to address the common issue of imprecise discretization often encountered in wholesale energy markets
January 2019	[385]	The authors employed a dual-objective optimization model aiming to minimize electricity costs and decrease the combined peak demands of residential electric vehicles (EVs) within a day-ahead pricing framework

[402]. Robust optimization algorithms are necessary to handle these complexities effectively.

One potential challenge is that prices are set and communicated a day ahead, which may result in financial losses for the utility if the peak demand occurs during low-price periods [403]. To mitigate this risk, utilities need to carefully analyze historical data and demand patterns to improve their price-setting strategies. Additionally, advancements in forecasting technologies can help in making accurate predictions of energy demand and supply, reducing the likelihood of financial losses for energy providers.

Control topology

The researchers introduced a hierarchical and distributed congestion management concept for future distribution networks with large-scale distributed generation (DG) and other controllable resources in medium voltage (MV) and low voltage (LV) networks. The control strategy aims to minimize network costs while maintaining an acceptable network state, with three levels of control: primary controllers based on local measurements, secondary controllers optimizing primary controllers' set points in real-time, and tertiary control using load and production forecasts for network reconfiguration and market connection. The concept enables scalable active network management, utilizing existing control center software and distribution automation without requiring a complete system overhaul. It also integrates a flexibility market to real-time automation, ensuring compatibility and acceptance from all market participants. The control architecture is scalable, modular, and easily accommodates new DERs. Simulation results validate its effectiveness [404].

The study [405, 406] proposes a distributed, hierarchical control architecture for integrating renewable energy resources (RERs) into the smart grid. The architecture operates across three levels—primary, secondary, and tertiary—covering time scales from milliseconds to minutes. It combines decision-making, communication, and computation within a cyber–physical infrastructure to match energy supply and demand effectively.

The approach incorporates demand response (DR) models and distributed economic dispatch into the traditional automatic generation control (AGC) framework. This ensures frequency regulation, optimizes resource allocation, and accommodates the intermittency of RERs. The proposed system enhances grid stability while improving social welfare through efficient energy management.

The authors compared two control approaches for microgrids: hierarchical control and distributed control. Hierarchical control uses a central supervisor controller to manage and optimize the microgrid, with each resource having its own local controller. It is ideal for large microgrids with multiple distributed energy resources (DERs) and variable utility prices. It requires less communication and provides better optimization. On the other hand, distributed control allows each energy resource to communicate directly with others to achieve global goals. It offers a more reliable, simpler, and cost-effective solution, making it suitable for smaller microgrids. The case study shows that hierarchical control outperforms distributed control economically due to its centralized optimization. However, hierarchical control demands higher computational power, while distributed control is less computationally intensive and can be implemented on simpler control systems [404, 405].

Role of green IoT

Green IoT (green internet of things) provides a sustainable solution to rising electricity consumption and resource limitations by enabling efficient energy management and environmentally friendly practices. Leveraging technologies such as wireless sensor networks (WSN), cloud computing, machine-to-machine (M2M) communication, and advanced metering infrastructure, green IoT optimizes data processing, energy usage, and communication for smart grids.

This highlights advancements in energy-efficient communication protocols, renewable energy integration, demand response, and real-time monitoring. It emphasizes the role of edge and fog computing in enabling distributed intelligence, addressing challenges, and presenting case studies of successful green IoT applications. Emerging technologies like AI, IoT, and distributed computing to enhance energy efficiency and sustainability are observed. Collaboration among businesses, academia, and governments is essential for overcoming implementation challenges and fostering the development of smart grid solutions [128, 406].

Conclusion

In conclusion, this comprehensive review focused on various aspects of smart grids, including data management, cybersecurity, pricing modalities, demand response, renewable power integration, and reliability indices. The study shed light on the challenges and recent advancements in handling the massive amount of heterogeneous data generated by different components within a smart grid. Additionally, the potential cybersecurity threats and mathematical models to describe cyberattacks were highlighted, along with advancements in detection techniques. The pricing modalities discussed in this study mainly revolved around price-based or incentive-based schemes, providing consumers with limited choice once the tariff rate is agreed upon. However, with the expansion of advanced metering infrastructure, consumers are gaining more flexibility to control their energy consumption effectively. The presented study thoroughly examined various pricing mechanisms that can be utilized through demand response to optimize energy usage and encourage participation.

As smart grids continue to evolve and expand, ongoing research and development in data management, cybersecurity, and innovative pricing strategies will play a crucial role in building a resilient, efficient, and sustainable energy infrastructure for the future. This comprehensive review has emphasized the state-of-the-art advancements in the field, covering various aspects of smart grids. The demand response that takes an important role in facilitating the transition to smart grids was extensively discussed, highlighting its potential to engage end users in electricity bill management and enhance the efficiency of the electricity market. Moreover, the study suggests that the science of behavior could play a crucial role in unlocking the full potential of a successful smart grid transformation.

The review also delved into the emerging advances in demand response applications and emphasized the importance of integrating distributed generation (DG) and energy storage in smart grids. Recent applications in this area were briefly presented to showcase the ongoing developments. Additionally, the study offered a synopsis of the reliability indices associated with the deployment of DGs and demand response (DR) in smart grids, underlining the significance of ensuring grid stability and resilience. Overall, the review offers valuable insights into the current progress and potential future directions of smart grid technologies, particularly about demand response, distributed generation, and reliability indices. As smart grids continue to evolve, the knowledge shared in this study will play a crucial function in influencing the future of energy systems, enabling a more sustainable, efficient, and responsive grid infrastructure.

This review works on recent advances in smart grid and enhances few benefits like comprehensive insight: this review categorically and extensively explores many advantages in smart grid technologies also providing proper understanding the recent developments over last few decades.

Structured Knowledge: This paper organizes information into categories and subcategories, energy data management, different mechanisms in pricing, cybersecurity.

Application Oriented: This work highlights real-time applications of smart grid and its technologies, emphasizing different areas like demand response, distributed renewable generation and energy storage.

State-of-the-Art Challenges and Solutions: The review discusses the current challenges, like cybersecurity concerned along with data integrity issues, and presents state-of-the-art solutions for modernizing the power grid.

Promotes Sustainability: The work by addressing areas like renewable energy integration and energy efficiency and also supports sustainable energy practices.

Encourage Future Research: This paper finds the gaps and areas requiring further investigation, pays a way for the future studies. Here are some recommendations for the future work advanced data management, enhancement of cybersecurity, consumer centric pricing models, integration of renewable resources, behavioral science in demand response, reliability and resilience metrics, innovative control strategies, and cross-disciplinary research.

Abbreviations

AGC	Automatic generation control
AMI	Advanced metering infrastructure
AVR	Automatic voltage regulation
BESS	Battery energy storage system
CPP	Critical peak pricing
DCL	Direct control load
DER	Distributed energy resources
DMS	Distribution management system
DR	Demand response
DSM	Demand-side management
EMS	Energy management system
EPRI	Electric power research institute
FACTS	Flexible AC transmission system
FSS	Flywheel storage system
GIS	Geographical information system
ICL	Indirect control load
IEA	International energy agency
ISO	Independent system operator
LOLE	Loss of load expectation
MDM	Meter data management
MG	Microgrids
MPC	Model predictive control
NIST	National institute of standards and technologies
OMS	Outage management system
PCC	Point of common coupling

PMU	Phasor measurement units
RES	Renewable energy sources
SCADA	Supervisory control and data acquisition
SG	Smart grid
SMACK	Simplified mandatory access control kernel
TOU	Time of use
WAMS	Wide area management system

Acknowledgements
The authors acknowledge all the researchers who made their views in their contributions, which are helpful to developing this whole manuscript.

Author contributions
Each author has made a significant contribution to complete this review work in a proper manner.

Funding
The authors are not supported by any funding.

Availability of data and materials
Not applicable as it is a review paper.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 8 February 2024 Accepted: 16 February 2025
Published online: 25 March 2025

References

1. Muhammad Khalid A (2024) Smart grids and renewable energy systems: perspectives and grid integration challenges. Energy Strat Rev 51:101299. https://doi.org/10.1016/j.esr.2024.101299
2. Parhizi S, Lotfi H, Khodaei A, Bahramirad S (2015) State of the art in research on microgrids: a review. IEEE Access 3:890–925
3. Justo JJ, Mwasilu F, Lee J, Jung J-W (2013) AC-microgrids versus DC-microgrids with distributed energy resources: a review. Renew Sustain Energy Rev 24:387–405
4. Arunkumari T, Indragandhi V (2017) An overview of high voltage conversion ratio DC-DC converter configurations used in DC micro-grid architectures. Renew Sustain Energy Rev 77:670–687
5. Arbab-Zavar B, Palacios-Garcia E, Vasquez J, Guerrero J (2019) Smart inverters for microgrid applications: a review. Energies 12:840
6. Zhang Q, Callanan R, Das MK, Ryu S-H, Agarwal AK, Palmour JW (2010) SiC power devices for microgrids. IEEE Trans Power Electron 25:2889–2896
7. Blaabjerg F, Chen Z, Kjaer SB (2004) Power electronics as efficient interface in dispersed power generation systems. IEEE Trans Power Electron 19:1184–1194
8. Zhong Q-C, Weiss G (2011) Synchronverters: Inverters that mimic synchronous generators. IEEE Trans Ind Electron 58:1259–1267
9. El-hawary ME (2014) The smart grid—state-of-the-art and future trends. Electr Power Compon Syst 42:239–250
10. Nosratabadi SM, Hooshmand R-A, Gholipour E (2017) A comprehensive review of microgrid and virtual power plant concepts employed for distributed energy resources scheduling in power systems. Renew Sustain Energy Rev 67:341–363
11. Olivares DE, Mehrizi-Sani A, Etemadi AH, Cañizares CA, Iravani R, Kazerani M, Hajimiragha AH, Gomis-Bellmunt O, Saeedifard M, Palma-Behnke R et al (2014) Trends in microgrid control. IEEE Trans Smart Grid 5:1905–1919
12. Independence Energy. Security Act of 2007. Public law 110–140. In: 110th Congr. Congr. Rec. 2007, 153, pp 110–140
13. Bryson J, Gallagher PD (2012) NIST framework and roadmap for smart grid interoperability standards. In: Natl. Inst. Stand. Technol. NIST US Dep. Commer, p 227
14. Betis G, Cassandras CG, Nucci CA (2018) Smart cities [scanning the Issue]. Proc IEEE 106:513–517
15. Bi S, Zhang YJA (2017) Graph-based cyber security analysis of state estimation in smart power grid. IEEE Commun Mag 55:176–183
16. Tuballa ML, Abundo ML (2016) A review of the development of smart grid technologies. Renew Sustain Energy Rev 59:710–725
17. Siddiqui O (2008) Energy savings and carbon emissions reductions enabled by a smart grid. In: Electric Power research institute EPRI: Palo Alto, CA, USA, p 64
18. DECC (2009) Smarter grids: the opportunity. In: Department of energy & climate change: London, UK, p 18
19. Ardito L, Procaccianti G, Menga G, Morisio M (2013) Smart grid technologies in Europe: an overview. Energies 6:251–281
20. Farhangi H (2010) The path of the smart grid. IEEE Power Energy Mag 8:18–28
21. Cunjiang Y, Huaxun Z, Lei Z (2012) Architecture design for smart grid. Energy Procedia 17:1524–1528

22. Irfan M, Iqbal J, Iqbal A, Iqbal Z, Riaz RA, Mehmood A (2017) Opportunities and challenges in control of smart grids—Pakistani perspective. Renew Sustain Energy Rev 71:652–674
23. Momoh JA (2009) Smart grid design for efficient and flexible power networks operation and control. In: Proceedings of the 2009 IEEE/PES power systems conference and exposition, Seattle, WA, USA, pp 1–8
24. Massoud Amin S (2011) Smart grid: overview, issues and opportunities. Advances and challenges in sensing, modelling, simulation, optimization and control. Eur J Control 17:547–567
25. Mei S, Chen L (2013) Recent advances on smart grid technology and renewable energy integration. Sci China Technol Sci 56:3040–3048
26. Pirak C, Sangsuwan T, Buayairaksa S (2014) Recent advances in communication technologies for smart grid application: a review. In: Proceedings of the 2014 international electrical engineering congress (iEECON), Chonburi, Thailand, pp 1–4
27. Xu Z, Xue Y, Wong KP (2014) Recent advancements on smart grids in China. Electr Power Compon Syst 42:251–261
28. Gharavi H, Ghafurian R (2011) Smart grid: the electric energy system of the future [scanning the Issue]. Proc IEEE 99:917–921
29. Mei S, Chen L (2012) Research focuses and advanced technologies of smart grid in recent years. Chin Sci Bull 57:2879–2886
30. Ismagilova E, Hughes L, Dwivedi YK, Raman KR (2019) Smart cities: advances in research—an information systems perspective. Int J Inf Manag 47:88–100
31. Hossain MR, Oo AMT, Ali ABMS (2013) Smart grid. In: Ali ABMS (ed) Smart grids: opportunities, developments, and trends green energy and technology. London, Springer, pp 23–44
32. Tariq F, Dooley LS (2013) Smart Grid communication and networking technologies: Recent developments and future challenges. In: Ali ABMS (ed) Smart grids: opportunities, developments, and trends green energy and technology. London, Springer, pp 199–213
33. Zahran M (2013) Smart grid technology, vision, management and control. WSEAS Trans J 12:12
34. Nambiar R, Shro R, Handy S (2018) Smart cities: challenges and opportunities. In: Proceedings of the 2018 10th international conference on communication systems networks (COMSNETS), Bengaluru, India, pp 243–250
35. Babu NR (2018) Smart grid systems: modeling and control. CRC Press, Boca Raton
36. 1854–2019—IEEE standards association guide for smart distribution applications guide. In: IEEE standards: Piscataway, NJ, USA, 2019; pp 1–65
37. Warren CA (2012) 1366-2012—IEEE guide for electric power distribution reliability indices. In: IEEE standards association: Piscataway, NJ, USA
38. 1250–2018—IEEE Guide for identifying and improving voltage quality in power systems. In: IEEE standards association: Piscataway, NJ, USA, 2018
39. IEEE Standards Committee IEEE Guide for Smart Grid Interoperability of Energy Technology and Information Technology Operation with the Electric Power System (EPS), End-Use Applications, and Loads. In: Inst. Electr. Electron. Eng. 2011
40. IEEE Standards Association IEEE Guide for Synchronization, Calibration, Testing, and Installation of Phasor Measurement Units (PMUs) for Power System Protection and Contro. IEEE Stand. C 2013, 37.
41. C37231–2006–IEEE Standards Committee IEEE Recommended Practice for Microprocessor-Based Protection Equipment Firmware Control; IEEE Standards Association: Piscataway, NJ, USA, 2007; pp. 1–25. Energies 2020, 13, 6269 26 of 41
42. IEEE Standards Committee IEEE Standard for Common Format for Naming Time Sequence Data Files (COMNAME); IEEE Std C37232–2011 Revis; IEEE Standards Association: Piscataway, NJ, USA, 2011; pp. 1–25.
43. IEEE Standards Committee IEEE Standard Profile for Use of IEEE 1588 Precision Time Protocol in Power System Applications. IEEE PC37238D212 2017, 1–40.
44. Sato, T.; Kammen, D.M.; Duan, B.; Macuha, M.; Zhou, Z.; Wu, J.; Tariq, M.; Asfaw, S.A. Smart Grid Standards: Specifications, Requirements, and Technologies; John Wiley & Sons: Hoboken, NJ, USA, 2015; ISBN 978–1–118–65369–2.
45. 19012–2013—Standard for Low Frequency (less than 500 kHz) Narrow Band Power Line Communications for Smart Grid Applications; IEEE Standards Association: Piscataway, NJ, USA, 2013; pp. 1–269.
46. Camacho, E.F.; Samad, T.; Garcia-Sanz, M.; Hiskens, I. Control for renewable energy and smart grids. Impact Control Technol. Control Syst. Soc. 2011, 69–88.
47. Sridhar S, Govindarasu M (2014) Model-based attack detection and mitigation for automatic generation control. IEEE Trans Smart Grid 5:580–591
48. Ou T-C, Tsao T-P, Hong C-M, Chen C-H (2013) Hybrid control system for automatic voltage regulator in smart grid. In: Proceedings of the 2013 international conference on machine learning and cybernetics Tianjin, China, 14–17 July 2013; 3, pp 1103–1108
49. Keyhani A, Chatterjee A (2012) Automatic generation control structure for smart power grids. IEEE Trans Smart Grid 3:1310–1316
50. Dirkman J (2013) Best practices for creating your smart grid network model. In: Schneider Electric Inc.: Fort Collins, CO, USA
51. Environmental Systems Research Institute (ESRI). Enterprise GIS and the Smart Electric Grid; ESRI: Redlands, CA, USA, 2009; p. 11.
52. Schneider Electric. GIS-Based Design for Effective Smart Grid Strategies; Schneider Electric Inc.: Fort Collins, CO, USA, 2012
53. Rahman F, Rehman S, Abdul-Majeed MA (2012) Overview of energy storage systems for storing electricity from renewable energy sources in Saudi Arabia. Renew Sustain Energy Rev 16:274–283
54. Samarakoon K, Ekanayake J, Jenkins N (2012) Investigation of domestic load control to provide primary frequency response using smart meters. IEEE Trans Smart Grid 3:282–292
55. Samarakoon K, Ekanayake J (2009) Demand side primary frequency response support through smart meter control. In: Proceedings of the 2009 44th international universities power engineering conference (UPEC), Glasgow, UK, pp 1–5

56. Yu S, Chau TK, Fernando T, Savkin AV, Iu HH-C (2017) Novel quasi-decentralized SMC-based frequency and voltage stability enhancement strategies using valve position control and FACTS device. IEEE Access 5:946–955
57. Shi Y, Tuan HD, Duong TQ, Poor HV, Savkin AV (2020) PMU placement optimization for efficient state estimation in smart grid. IEEE J Sel Areas Commun 38:71–83
58. Gharani Khajeh K, Bashar E, Mahboub Rad A, Gharehpetian GB (2015) Integrated model considering effects of zero injection buses and conventional measurements on optimal PMU placement. IEEE Trans Smart Grid 8:1006–1013
59. Esmaili M, Gharani K, Shayanfar HA (2013) Redundant observability PMU placement in the presence of flow measurements considering contingencies. IEEE Trans Power Syst 28:3765–3773
60. Ipakchi A, Albuyeh F (2009) Grid of the future. IEEE Power Energy Mag 7:52–62
61. Nafi NS, Ahmed K, Gregory MA, Datta M (2016) Asurvey of smart grid architectures, applications, benefits and standardization. J Netw Comput Appl 76:23–36
62. Fang X, Misra S, Xue G, Yang D (2012) Smart grid—the new and improved power grid: a survey. IEEE Commun Surv Tutor 14:944–980
63. Keeping S (2013) Carbon emission reductions by the implementation of a smart grid. In: NOJA power: Murarrie, Queensland, Australia
64. Chandan A, Potdar V, Nandi C (2018) Smart cities. Springer International Publishing AG, Cham, Switzerland
65. Wade NS, Taylor PC, Lang PD, Jones PR (2010) Evaluating the benefits of an electrical energy storage system in a future smart grid. Energy Policy 38:7180–7188
66. Li N, Ni Y, Sun S, Yao MQ (2010) Survey on smart grid and relevant key technologies. South Power Syst Technol 4:1–7
67. Borlase S (2013) Smart grids: infrastructure, technology, and solutions. CRC Press, Boca Raton
68. Xie, K.; Liu, Y.; Zhu, Z.; Yu, E. The vision of the future smart grid. Electr. Power 2008, 6.
69. Hamilton B, Summy M (2011) Benefits of the smart grid [in my view]. IEEE Power Energy Mag 9:102–104
70. Moslehi K, Kumar R (2010) A reliability perspective of the smart grid. IEEE Trans Smart Grid 1:57–64
71. Mehigan L, Deane JP, Gallachóir BPÓ, Bertsch V (2018) A review of the role of distributed generation (DG) in future electricity systems. Energy 163:822–836
72. Allan G, Eromenko I, Gilmartin M, Kockar I, McGregor P (2015) The economics of distributed energy generation: a literature review. Renew Sustain Energy Rev 42:543–556
73. Vahl FP, Rüther R, Casarotto Filho N (2013) The influence of distributed generation penetration levels on energy markets. Energy Policy 62:226–235
74. Kakran S, Chanana S (2018) Smart operations of smart grids integrated with distributed generation: a review. Renew Sustain Energy Rev 81:524–535
75. Abdmouleh Z, Gastli A, Ben-Brahim L, Haouari M, Al-Emadi NA (2017) Review of optimization techniques applied for the integration of distributed generation from renewable energy sources. Renew Energy 113:266–280
76. Paliwal P, Patidar NP, Nema RK (2014) Planning of grid integrated distributed generators: a review of technology, objectives and techniques. Renew Sustain Energy Rev 40:557–570
77. Ackermann T, Andersson G, Söder L (2001) Distributed generation: A definition. Electr Power Syst Res 57:195–204
78. Distributed Energy Resources (2017) North American electric reliability corporation (NERC): Atlanta, GA, USA, p 50
79. Bayod-Rújula AA (2009) Future development of the electricity systems with distributed generation. Energy 34:377–383
80. Chmutina K, Goodier CI (2014) Alternative future energy pathways: assessment of the potential of innovative decentralised energy systems in the UK. Energy Policy 66:62–72
81. Adil AM, Ko Y (2016) Socio-technical evolution of decentralized energy systems: a critical review and implications for urban planning and policy. Renew Sustain Energy Rev 57:1025–1037
82. Singh B, Sharma J (2017) A review on distributed generation planning. Renew Sustain Energy Rev 76:529–544
83. Kim W-W, Park J-K, Yoon Y-T, Kim M-K (2018) Transmission expansion planning under uncertainty for investment options with various lead times. Energies 11:2429
84. Howell S, Rezgui Y, Hippolyte J-L, Jayan B, Li H (2017) Towards the next generation of smart grids: semantic and holonic multi-agent management of distributed energy resources. Renew Sustain Energy Rev 77:193–214
85. Oliva HS (2017) Residential energy efficiency and distributed generation—natural partners or competition renew. Sustain Energy Rev 76:932–940
86. Pepermans G, Driesen J, Haeseldonckx D, Belmans R, D'haeseleer W (2005) Distributed generation: definition, benefits and issues. Energy Policy 33:787–798
87. William EL, Luke JR, Liam DW, Colin FA, Anthony RS (2012) An economic evaluation of the potential for distributed energy in Australia. Energy Policy 51:277–289
88. Rouhani A, Hosseini SH, Raoofat M (2014) Composite generation and transmission expansion planning considering distributed generation. Int J Electr Power Energy Syst 62:792–805
89. Khalid M, Ahmadi A, Savkin AV, Agelidis VG (2016) Minimizing the energy cost for microgrids integrated with renewable energy resources and conventional generation using controlled battery energy storage. Renew Energy 97:646–655
90. Labis PE, Visande RG, Pallugna RC, Caliao ND (2011) The contribution of renewable distributed generation in mitigating carbon dioxide emissions. Renew Sustain Energy Rev 15:4891–4896
91. Morstyn T, Savkin AV, Hredzak B, Tuan HD (2018) Scalable energy management for low voltage microgrids using multi-agent storage system aggregation. IEEE Trans Power Syst 33:1614–1623
92. Pesaran MHA, Huy PD, Ramachandaramurthy VK (2017) A review of the optimal allocation of distributed generation: objectives, constraints, methods, and algorithms. Renew Sustain Energy Rev 75:293–312
93. Khalid M (2012) An optimal operation of wind energy storage system for frequency control based on model predictive control. Renew Energy 48:127–132

94. Zhuo W, Savkin AV, Meng K (2019) Decentralized optimal control of a microgrid with solar PV. BESS Therm Control Loads Energ 12:2111
95. Huda ASN, Živanovi´c R (2017) Large-scale integration of distributed generation into distribution networks: Study objectives, review of models and computational tools. Renew Sustain Energy Rev 76:974–988
96. Kiani Rad H, Moravej Z (2017) Coordinated transmission substations and sub-transmission networks expansion planning incorporating distributed generation. Energy 120:996–1011
97. L'Abbate A, Fulli G, Starr F (2007) European commission. In: Distributed power generation in Europe: technical issues for further integration; EUR 23234 EN-2007; European Commission: Brussels, Belgium
98. Carley S (2009) Distributed generation: an empirical analysis of primary motivators. Energy Policy 37:1648–1659
99. Heo J-H, Kim M-K, Park G-P, Yoon YT, Park JK, Lee S-S, Kim D-H (2011) A reliability-centered approach to an optimal maintenance strategy in transmission systems using a genetic algorithm. IEEE Trans Power Deliv 26:2171–2179
100. Khatamianfar A, Khalid M, Savkin AV, Agelidis VG (2013) Improving wind farm dispatch in the Australian electricity market with battery energy storage using model predictive control. IEEE Trans Sustain Energy 4:745–755
101. Khalid M, AlMuhaini M, Aguilera RP, Savkin AV (2018) Method for planning a wind–solar–battery hybrid power plant with optimal generation-demand matching. IET Renew Power Gener 12:1800–1806
102. Khalid M (2019) Wind power economic dispatch—Impact of radial basis functional networks and battery energy storage. IEEE Access 7:36819–36832
103. Morstyn T, Hredzak B, Agelidis VG (2018) Control strategies for microgrids with distributed energy storage systems: an overview. IEEE Trans Smart Grid 9:3652–3666
104. Saad W, Han Z, Poor H, Basar T (2012) Game-theoretic methods for the smart grid: an overview of microgrid systems, demand-side management, and smart grid communications. IEEE Signal Process Mag 29:86–105
105. Morstyn T, Demetriades GD, Agelidis VG (2015) Unified distributed control for DC microgrid operating modes. IEEE Trans Power Syst 31:802–812
106. Global DER Deployment Forecast Database (2017) Navigant research: Boulder, CO, USA, p 40
107. Distributed Energy Resources: Technical Considerations for the Bulk Power System (2018) Federal energy regulatory commission (FERC): Washington, DC, USA, p 47
108. Han J, Ouyang L, Xu Y, Zeng R, Kang S, Zhang G (2016) Current status of distributed energy system in China. Renew Sustain Energy Rev 55:288–297
109. Albasrawi MN, Jarus N, Joshi KA, Sarvestani SS (2014) Analysis of reliability and resilience for smart grids In: Proceedings of the 2014 IEEE 38th annual computer software and applications conference, Vasteras, Sweden, pp 529–534.
110. Xu S, Qian Y, Hu RQ (2015) On the reliability of smart grid neighbourhood area networks. IEEE Access 3:2352–2365
111. Bose A (2010) Models and techniques for the reliability analysis of the smart grid. In: Proceedings of the IEEE PES general meeting, providence, RI, USA, pp 1–5
112. Ilie I, Hernando-Gil I, Collin AJ, Acosta JL, Djokic SZ (2011) Reliability performance assessment in smart grids with demand-side management. In: Proceedings of the 2011 2nd IEEE PES international conference and exhibition on innovative smart grid technologies, Manchester, UK, pp. 1–7
113. Karki R, Billinton R, Verma AK (2014) Reliability modeling and analysis of smart power systems; Springer India Private Limited: New Delhi, India, 2014; ISBN 978–81–322–1798–5. Energies 2020, 13, 6269 29 of 41
114. Moslehi K, Kumar R (2010) Smart Grid—A reliability perspective. In: Proceedings of the 2010 innovative smart grid technologies (ISGT), Gothenburg, Sweden, pp 1–8
115. Marashi K, Sarvestani SS (2014) Towards comprehensive modelling of reliability for smart grids: Requirements and challenges. In: Proceedings of the 2014 IEEE 15th international symposium on high-assurance systems engineering, Miami Beach, FL, USA, pp 105–112
116. Liu, Y.; Deng, L.; Gao, N.; Sun, X. A reliability assessment method of cyber physical distribution system. Energy Procedia 2019, 158, 2915–2921.
117. Kazemi S (2011) Reliability evaluation of smart distribution grids; Aalto University, School of Electrical Engineering: Espoo, Finland
118. Chren S, Rossi B, Bühnova B, Pitner T (2018) Reliability data for smart grids: where the real data can be found. In Proceedings of the 2018 Smart City Symposium Prague (SCSP), Prague, Czech Republic, pp 1–6
119. Aravinthan V, Balachandran T, Ben-Idris M, Fei W, Heidari-Kapourchali M, Hettiarachchige-Don A, Jiang JN, Lei H, Liu C-C, Mitra J et al. (2018) Reliability modeling considerations for emerging cyber-physical power systems. In: Proceedings of the 2018 IEEE international conference on probabilistic methods applied to power systems (PMAPS), Boise, ID, USA, pp 1–7
120. Wadi M, Baysal M, Shobole A, Tur MR (2018) Reliability evaluation in smart grids via modified monte carlo simulation method. In: Proceedings of the 2018 7th international conference on renewable energy research and applications (ICRERA), Paris, France, pp 841–845
121. Kornatka, M. (2017) Distribution of SAIDI and SAIFI indices and the saturation of the MV network with remotely controlled switches. In Proceedings of the 2017 18th international scientific conference on electric power engineering (EPE), Kouty nad Desnou, Prague, Czech Republic, pp 1–4
122. Brown R (2008) Electric power distribution reliability, Second Edition; Power engineering (Willis); CRC Press: Boca Raton, FL, USA, 2008; Vol. 20081087, ISBN 978-0-8493-7567-5
123. Billinton R (1989) Distribution system reliability indices. IEEE Trans Power Deliv 4:561–568
124. EPRI. (2016) Electric power system resiliency: challenges and opportunities. In: Electric Power Research Institute: Palo Alto, CA, USA, p 56
125. Amini F, Ghassemzadeh S, Rostami N, Tabar VS (2023) Electrical energy systems resilience: a comprehensive review on definitions, challenges, enhancements and future proceedings. IET Renew Power Gener 17:1835–1858. https://doi.org/10.1049/rpg2.12705
126. Raoufi H, Vahidinasab V, Mehran K (2020) Power systems resilience metrics: a comprehensive review of challenges and outlook. Sustainability 12:9698. https://doi.org/10.3390/su12229698

127. Bhusal N, Abdelmalak M, Kamruzzaman M, Benidris M (2020) Power system resilience: current practices, challenges, and future directions. IEEE Access 8:18064–18086. https://doi.org/10.1109/ACCESS.2020.2968586
128. Pandiyan P, Saravanan S, Kannadasan R, Krishnaveni S, Alsharif MH, Kim MK (2024) A comprehensive review of advancements in green IoT for smart grids: paving the path to sustainability. Energy Rep 11:5504–5531
129. Escalera A, Hayes B, Prodanovi´c, M. (2018A) survey of reliability assessment techniques for modern distribution networks. Renew Sustain Energy Rev 91:344–357
130. Allan RN, Billinton R (1996) Reliability evaluation of power systems. Springer, Boston
131. Dialynas EN, Allan RN (1986) Local generating facilities in the reliability evaluation of power distribution systems. IEEE Trans Power Syst 1:62–67
132. Bae I, Kim J (2007) Reliability evaluation of distributed generation based on operation mode. IEEE Trans Power Syst 22:785–790
133. Billinton R (2001) Reliability benefit analysis of adding WTG to a distribution system. IEEE Trans Energy Convers 16:134–139
134. Wang P, Billinton R (2001) Time-sequential simulation technique for rural distribution system reliability cost/worth evaluation including wind generation as alternative supply. Transm Distrib IEEE Proc Gener 148:355–360
135. Atwa YM, El-Saadany EF (2009) Reliability evaluation for distribution system with renewable distributed generation during islanded mode of operation. IEEE Trans Power Syst 24:572–581
136. Conti S, Rizzo SA (2015) Monte carlo simulation by using a systematic approach to assess distribution system reliability considering intentional islanding. IEEE Trans Power Deliv 30:64–73
137. Celli G, Ghiani E, Pilo F, Soma GG (2013) Reliability assessment in smart distribution networks. Electr Power Syst Res 104:164–175
138. Guo H, Levi V, Buhari M (2015) Reliability assessment of smart distribution networks. In: Proceedings of the 2015 IEEE innovative smart grid technologies—Asia (ISGT ASIA), Bangkok, Thailand, pp 1–6
139. Fotuhi-Firuzabad M, Rajabi-Ghahnavie A (2005) An analytical method to consider DG impacts on distribution system reliability. In: Proceedings of the 2005 IEEE/PES transmission distribution conference exposition: Asia and Pacific, Dalian, China, pp 1–6
140. Conti S, Nicolosi R, Rizzo SA (2012) Generalized systematic approach to assess distribution system reliability with renewable distributed generators and microgrids. IEEE Trans Power Deliv 27:261–270
141. Al-Muhaini M, Heydt GT (2013) Evaluating future power distribution system reliability including distributed generation. IEEE Trans Power Deliv 28:2264–2272
142. Conti S, Rizzo SA (2013) Modelling of microgrid-renewable generators accounting for power-output correlation. IEEE Trans Power Deliv 28:2124–2133
143. Zou K, Agalgaonkar AP, Muttaqi KM, Perera S (2014) An analytical approach for reliability evaluation of distribution systems containing dispatchable and nondispatchable renewable DG units. IEEE Trans Smart Grid 5:2657–2665
144. Chen C, Wu W, Zhang B, Singh C (2015) An analytical adequacy evaluation method for distribution networks considering protection strategies and distributed generators. IEEE Trans Power Deliv 30:1392–1400
145. Conti S, Faraci G, La Corte A, Nicolosi R, Rizzo SA, Schembra G (2016) Effect of islanding and telecontrolled switches on distribution system reliability considering load and green-energy fluctuations. Appl Sci 6:138
146. De Castro CLC, Rodrigues AB, Silva MG (2004) Reliability evaluation of radial distribution systems considering voltage drop constraints in the restoration process. In: Proceedings of the 2004 international conference on probabilistic methods applied to power systems, Ames, IA, USA, pp 106–111
147. Neto, A.C.; Da Silva, M.G.; Rodrigues, A.B. Impact of distributed generation on reliability evaluation of radial distribution systems under network constraints. In: Proceedings of the 2006 international conference on probabilistic methods applied to power systems, Stockholm, Sweden, 11–15 June 2006; pp 1–6
148. Da Silva AML, Nascimento LC, Da Rosa MA, Issicaba D, Lopes JAP (2012) Distributed energy resources impact on distribution system reliability under load transfer restrictions. IEEE Trans Smart Grid 3:2048–2055
149. Abdullah MA, Agalgaonkar AP, Muttaqi KM (2014) Assessment of energy supply and continuity of service in distribution network with renewable distributed generation. Appl Energy 113:1015–1026
150. Michael L, Aslam O, Foster B, Kathan D, Kwok J, Medearis L, Palmer R, Sporborg P, Tita M (2013) Assessment of demand response and advanced metering. Fed. Energy Regul. Comm. Tech Rep 2013.
151. Yan X, Ozturk Y, Hu Z, Song Y (2018) A review on price-driven residential demand response. Renew Sustain Energy Rev 96:411–419
152. Gelazanskas L, Gamage KAA (2014) Demand side management in smart grid: A review and proposals for future direction. Sustain Cities Soc 11:22–30
153. Strüker J, Dinther C (2012) Demand response in smart grids: research opportunities for the IS discipline. In: Proceedings of the Americas conference on information systems (AMCIS), Seattle, WA, USA, Vol 7
154. Good N, Ellis KA, Mancarella P (2017) Review and classification of barriers and enablers of demand response in the smart grid. Renew Sustain Energy Rev 72:57–72
155. Deng R, Yang Z, Chow M-Y, Chen J (2015) A survey on demand response in smart grids: mathematical models and approaches. IEEE Trans Ind Inform 11:570–582
156. Zhu Q, Sauer P, Ba¸sar T (2013) Value of demand response in the smart grid. In: Proceedings of the 2013 IEEE power and energy conference at Illinois (PECI), Champaign, IL, USA, pp 76–82
157. Warren P (2014) A review of demand-side management policy in the UK. Renew Sustain Energy Rev 29:941–951
158. Wu Y-K, Tang K-T (2019) Frequency support by demand response—Review and analysis. Energy Procedia 156:327–331
159. Albadi MH, El-Saadany EF (2007) Demand response in electricity markets: an overview. In Proceedings of the 2007 IEEE power engineering society general meeting, Tampa, FL, USA, 24–28 June 2007; pp 1–5
160. Mohagheghi S, Yang F, Falahati B (2011) Impact of demand response on distribution system reliability. In: Proceedings of the 2011 IEEE power and energy society general meeting, Detroit, MI, USA, 24–28 July 2011; pp 1–7
161. Safdarian A, Degefa MZ, Lehtonen M, Fotuhi-Firuzabad M (2014) Distribution network reliability improvements in presence of demand response. Transm Distrib IET Gener 8:2027–2035

162. Xie H, Bie Z, Hua B, Li G (2013) Reliability assessment of distribution power systems considering the TOU pricing. In: Proceedings of the 2013 IEEE international conference of IEEE region 10 (TENCON 2013), Xi'an, China, 23–25 October 2013; pp 1–4
163. Zeng B, Wu G, Wang J, Zhang J, Zeng M (2017) Impact of behavior-driven demand response on supply adequacy in smart distribution systems. Appl Energy 202:125–137
164. Syrri ALA, Mancarella P (2020) Reliability and risk assessment of post-contingency demand response in smart distribution networks. Sustain. Energy Grids Netw. 2016, 7, 1–12. Energies 2020, 13, 6269 31 of 41
165. Syrri ALA, Mancarella P (2014) Reliability evaluation of demand response to increase distribution network utilisation. In: Proceedings of the 2014 international conference on probabilistic methods applied to power systems (PMAPS), Durham, UK, 7–10 July 2014; pp 1–6
166. Drysdale B, Wu J, Jenkins N (2015) Flexible demand in the GB domestic electricity sector in 2030. Appl Energy 139:281–290
167. Jin X, Mu Y, Jia H, Wu J, Jiang T, Yu X (2016) Dynamic economic dispatch of a hybrid energy microgrid considering building based virtual energy storage system. Appl Energy 194:386–398
168. Cheng M, Sami SS, Wu J (2017) Benefits of using virtual energy storage system for power system frequency response. Appl Energy 194:376–385
169. Cheng M, Wu J, Ekanayake J, Coleman T, Hung W, Jenkins N (2013) Primary frequency response in the Great Britain power system from dynamically controlled refrigerators. In: Proceedings of the 22nd international conference and exhibition on electricity distribution (CIRED 2013, Institution of engineering and technology, Stockholm, Sweden, 10–13 June 2013; p. 507.
170. Short JA, Infield DG, Freris LL (2007) Stabilization of grid frequency through dynamic demand control. IEEE Trans Power Syst 22:1284–1293
171. Cheng M, Wu J, Galsworthy SJ, Ugalde-Loo CE, Gargov N, Hung WW, Jenkins N (2016) Power system frequency response from the control of bitumen tanks. IEEE Trans Power Syst 31:1769–1778
172. Elamari, K.; Lopes, L.A.C.; Tonkoski, R. Using Electric Water Heaters (EWHs) for Power Balancing and Frequency Control in PV-Diesel Hybrid Mini-Grids. In Proceedings of the World Renewable Energy Congress—Sweden, Linköping, Sweden, 8–13 May 2011; pp. 842–850.
173. Tokudome M, Tanaka K, Senjyu T, Yona A, Funabashi T, Kim C-H (2009) Frequency and voltage control of small power systems by decentralized controllable loads. In: Proceedings of the 2009 international conference on power electronics and drive systems (PEDS), Taipei, Taiwan, 2–5 November 2009; pp 666–671
174. Cheng M, Wu J, Galsworthy S, Jenkins N, Hung W (2014) Availability of load to provide frequency response in the Great Britain power system. In: Proceedings of the 2014 power systems computation conference, Wroclaw, Poland, 18–22 August 2014; pp 1–7
175. Yao Y, Zhang P, Wang Y (2018) A two-layer control method for thermostatically controlled loads to provide fast frequency regulation. Proc Chin Soc Electr Eng 38:4987–4998
176. Yan S, Wang M-H, Yang T-B, Hui SYR (2016) Instantaneous frequency regulation of microgrids via power shedding of smart load and power limiting of renewable generation. In: Proceedings of the IEEE energy conversion congress and exposition (ECCE), Milwaukee, WI, USA, 18–22 September 2016
177. Pourmousavi SA, Nehrir MH (2012) Real-time central demand response for primary frequency regulation in microgrids. IEEE Trans Smart Grid 3:1988–1996
178. Liu H, Hu Z, Song Y, Wang J, Xie X (2015) Vehicle-to-grid control for supplementary frequency regulation considering charging demands. IEEE Trans Power Syst 30:3110–3119
179. Palizban O, Kauhaniemi K (2016) Energy storage systems in modern grids—Matrix of technologies and applications. J Energy Storage 6:248–259
180. Faisal M, Hannan MA, Ker PJ, Hussain A, Mansor MB, Blaabjerg F (2018) Review of energy storage system technologies in microgrid applications: issues and challenges. IEEE Access 6:35143–35164
181. Mwasilu F, Justo JJ, Kim E-K, Do TD, Jung J-W (2014) Electric vehicles and smart grid interaction: a review on vehicle to grid and renewable energy sources integration. Renew Sustain Energy Rev 34:501–516
182. Zhang W, Qiu M, Lai X (2008) Application of energy storage technologies in power grids. Power Syst Technol 7:3–9
183. Carpinelli G, Celli G, Mocci S, Mottola F, Pilo F, Proto D (2013) Optimal integration of distributed energy storage devices in smart grids. IEEE Trans Smart Grid 4:985–995
184. Akinyele DO, Rayudu RK (2014) Review of energy storage technologies for sustainable power networks. Sustain Energy Technol Assess 8:74–91
185. Guney MS, Tepe Y (2017) Classification and assessment of energy storage systems. Renew Sustain Energy Rev 75:1187–1197
186. Khodadoost Arani AAB, Gharehpetian G, Abedi M (2019) Review on energy storage systems control methods in microgrids. Int J Electr Power Energy Syst 107:745–757
187. Khalid M (2019) A review on the selected applications of battery-supercapacitor hybrid energy storage systems for microgrids. Energies 12:4559
188. Bragard M, Soltau N, Thomas S, Doncker RWD (2010) The balance of renewable sources and user demands in grids: power electronics for modular battery energy storage systems. IEEE Trans Power Electron 25:3049–3056
189. Griths BW (2019) Reducing emissions from consumer energy storage using retail rate design. Energy Policy 129:481–490
190. Terlouw T, AlSkaif T, Bauer C, Van Sark W (2019) Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies. Appl Energy 239:356–372
191. Anderson K, Rajagopal R, Gamal AE (2019) Coordination of distributed energy storage under spatial and temporal data asymmetry. IEEE Trans Smart Grid 10:1184–1194
192. Sadat SA, Dai R, Charkhgard H (2018) Bi-objective mixed integer program for energy storage sharing considering storage lifetime maintenance. In: Proceedings of the IEEE power and energy society general meeting, Portland, OR, USA

193. Lee HC, Kim H, Yoon YT (2018) Optimal ESS investment strategies for energy arbitrage by market structures and participants. J Electr Eng Technol 13:51–59
194. Akram U, Khalid M (2018) A coordinated frequency regulation framework based on hybrid battery-ultracapacitor energy storage technologies. IEEE Access 6:7310–7320
195. Canevese S, Gatti A, Micolano E, Pellegrino L, Rapizza M (2017) Battery energy storage systems for frequency regulation: Simplified aging evaluation. In: Proceedings of the 6th international conference on clean electrical power (ICCEP), Santa Margherita Ligure, Italy, pp 291–297
196. Fang J, Tang Y, Li H, Li X (2018) A Battery/ultracapacitor hybrid energy storage system for implementing the power management of virtual synchronous generators. IEEE Trans Power Electron 33:2820–2824
197. Kumar KN, Vijayakumar K, Kalpesh C (2018) Virtual energy storage capacity estimation using ANN-based kWh modelling of refrigerators. IET Smart Grid 1:31–39
198. Díaz-González F, Sumper A, Gomis-Bellmunt O, Villafáfila-Robles R (2012) A review of energy storage technologies for wind power applications. Renew Sustain Energy Rev 16:2154–2171
199. Guerrero JM, Loh PC, Lee T, Chandorkar M (2013) Advanced control architectures for intelligent microgrids—part II: Power quality, energy storage, and AC/DC microgrids. IEEE Trans Ind Electron 60:1263–1270
200. Chapaloglou S, Nesiadis A, Iliadis P, Atsonios K, Nikolopoulos N, Grammelis P, Kakaras E (2019) Smart energy management algorithm for load smoothing and peak shaving based on load forecasting of an island's power system. Appl Energy 238:627–642
201. Taylor Z, Akhavan-Hejazi H, Cortez E, Alvarez L, Ula S, Barth M, Mohsenian-Rad H (2019) Customer-side SCADA-assisted large battery operation optimization for distribution feeder peak load shaving. IEEE Trans Smart Grid 10:992–1004
202. Yang H, Zhang Y, Ma Y, Zhou M, Yang X (2019) Reliability evaluation of power systems in the presence of energy storage system as demand management resource. Int J Electr Power Energy Syst 110:1–10
203. Khan KA, Khalid M (2019) Hybrid energy storage system for voltage stability in a DC microgrid using a modified control strategy. In: Proceedings of the 2019 IEEE innovative smart grid technologies—Asia (ISGT Asia), Chengdu, China, pp 2760–2765
204. Li Y, Yang Z, Li G, Zhao D, Tian W (2018) Optimal scheduling of an isolated microgrid with battery storage considering load and renewable generation uncertainties. IEEE Trans Ind Electron 66:1565–1575
205. Morstyn T, Hredzak B, Agelidis VG (2015) Communication delay robustness for multi-agent state of charge balancing between distributed AC microgrid storage systems. In: Proceedings of the 2015 IEEE conference on control applications (CCA), Sydney, Australia, 21–23 September 2015; pp 181–186
206. Feltes JW, Grande-Moran C (2008) Black start studies for system restoration. In: Proceedings of the 2008 IEEE power and energy society general meeting—conversion and delivery of electrical energy in the 21st century, Pittsburgh, PA, USA, pp 1–8
207. Khalid M, Savkin AV (2010) A model predictive control approach to the problem of wind power smoothing with controlled battery storage. Renew Energy 35:1520–1526
208. Saez-de-Ibarra A, Milo A, Gaztañaga H, Etxeberria-Otadui I, Rodríguez, P, Bacha S, Debusschere V (2013) Analysis and comparison of battery energy storage technologies for grid applications. In: Proceedings of the 2013 IEEE grenoble conference, Grenoble, France, 16–20 June 2013; pp. 1–6.
209. Leou R-C (2012) An economic analysis model for the energy storage system applied to a distribution substation. Int J Electr Power Energy Syst 34:132–137
210. Hill CA, Such MC, Chen D, Gonzalez J, Grady WM (2012) Battery energy storage for enabling integration of distributed solar power generation. IEEE Trans Smart Grid 3:850–857
211. Morstyn T, Hredzak B, Agelidis VG (2016) Cooperative multi-agent control of heterogeneous storage devices distributed in a DC microgrid. IEEE Trans Power Syst 31:2974–2986
212. Morstyn T, Savkin AV, Hredzak B, Agelidis VG (2018) Multi-agent sliding mode control for state of charge balancing between battery energy storage systems distributed in a DC Microgrid. IEEE Trans Smart Grid 9:4735–4743
213. Li C, Dragicevic T, Plaza MG, Andrade F, Vasquez JC, Guerrero JM (2014) Multiagent based distributed control for state-of-charge balance of distributed energy storage in DC microgrids. In: Proceedings of the IECON 2014—40th annual conference of the IEEE industrial electronics society, Dallas, TX, USA, pp 2180–2184
214. Mohd A, Ortjohann E, Schmelter A, Hamsic N, Morton D (2008) Challenges in integrating distributed Energy storage systems into future smart grid. In: Proceedings of the 2008 IEEE international symposium on industrial electronics, Cambridge, UK, 30 June–2 July 2008; pp 1627–1632
215. Zhou Y, Li X (2015) Vehicle to grid technology: a review. In: Proceedings of the 2015 34th Chinese control conference (CCC), Hangzhou, China, 28–30 July 2015; pp 9031–9036
216. Wenzel G, Negrete-Pincetic M, Olivares DE, MacDonald J, Callaway DS (2018) Real-time charging strategies for an electric vehicle aggregator to provide ancillary services. IEEE Trans Smart Grid 9:5141–5151
217. Aldik A, Al-Awami AT, Sortomme E, Muqbel AM, Shahidehpour M (2018) A planning model for electric vehicle aggregators providing ancillary services. IEEE Access 6:70685–70697
218. Cheng M, Sami SS, Wu J (2016) Virtual energy storage system for smart grids. Proc Energy Procedia 88:436–442
219. Kim Y, Raghunathan V, Raghunathan A (2017) Design and management of battery-supercapacitor hybrid electrical energy storage systems for regulation services. IEEE Trans Multi-Scale Comput Syst 3:12–24
220. Lucas A, Chondrogiannis S (2016) Smart grid energy storage controller for frequency regulation and peak shaving, using a vanadium redox flow battery. Int J Electr Power Energy Syst 80:26–36
221. Morstyn T, Hredzak B, Agelidis VG (2015) Distributed cooperative control of microgrid storage. IEEE Trans Power Syst 30:2780–2789
222. Wang R, Wang D, Jia H, Yang Z, Qi Y, Fan M, Sheng W, Hou L (2015) A coordination control strategy of battery and virtual energy storage to smooth the micro-grid tie-line power fluctuations. Zhongguo Dianji Gongcheng Xuebao Proceedings Chin. Soc. Electr. Eng. 35:5124–5134
223. Rohit AK, Devi KP, Rangnekar S (2017) An overview of energy storage and its importance in Indian renewable energy sector: part I—technologies and comparison. J Energy Storage 13:10–23

224. Alotaibi I (2018) A Hybridized SMES/BESS optimal storage system. Master's, Thesis, King Fahd University of petroleum and minerals, Dhahran
225. Avendano-Mora Mn, Camm EH (2015) Financial assessment of battery energy storage systems for frequency regulation service. In: Proceedings of the 2015 IEEE power energy society general meeting, Denver, CO, USA, 26–30 July 2015; pp. 1–5
226. Potdar V, Chandan A, Batool S, Patel N (2018) Big energy data management for smart grids—Issues, challenges and recent developments. In: Smart Cities, pp 177–205
227. Ahsan U, Bais A (2017) Distributed big data management in smart grid. In: Proceedings of the 2017 26th wireless and optical communication conference (WOCC), Newark, NJ, USA, pp 1–6
228. Daki H, Hannani AE, Aqqal A, Haidine A, Dahbi A (2017) Big Data management in smart grid: concepts, requirements and implementation. J Big Data 4:13
229. Diamantoulakis PD, Kapinas VM, Karagiannidis GK (2015) Big data analytics for dynamic energy management in smart grids. Big Data Res 2:94–101
230. Gungor VC, Sahin D, Kocak T, Ergut S, Buccella C, Cecati C, Hancke GP (2011) Smart grid technologies: communication technologies and standards. IEEE Trans Ind Inform 7:529–539
231. Zhou K, Fu C, Yang S (2016) Big data driven smart energy management: from big data to big insights. Renew Sustain Energy Rev 56:215–225
232. Zaballos A, Vallejo A, Selga JM (2011) Heterogeneous communication architecture for the smart grid. IEEE Netw 25:30–37
233. Yin J, Kulkarni A, Purohit S, Gorton I, Akyol B (2011) Scalable real time data management for smart grid. In: Proceedings of the middleware 2011 industry track workshop, Lisbon, Portugal, 7–11 December 2011; p 1
234. Hashem IAT, Chang V, Anuar NB, Adewole K, Yaqoob I, Gani A, Ahmed E, Chiroma H (2016) The role of big data in smart city. Int J Inf Manag 36:748–758
235. Vojdani A (2008) Smart integration. IEEE Power Energy Mag 6:71–79
236. He X, Ai Q, Qiu RC, Huang W, Piao L, Liu H (2017) A big data architecture design for smart grids based on random matrix theory. IEEE Trans Smart Grid 8:674–686
237. Stimmel CL (2014) Big data analytics strategies for the smart grid. CRC Press, Boca Raton
238. Gharaibeh A, Salahuddin MA, Hussini SJ, Khreishah A, Khalil I, Guizani M, Al-Fuqaha A (2017) Smart cities: a survey on data management, security, and enabling technologies. IEEE Commun Surv Tutor 19:2456–2501
239. Uludag S, Lui K, Ren W, Nahrstedt K (2016) Secure and scalable data collection with time minimization in the smart grid. IEEE Trans Smart Grid 7:43–54
240. Australian Bureau of Statistics Dwelling Type (2017) Greater sydney. In: Id Popul Experts; Available online: http://profile.id.com.au/australia/dwellings?WebID=250. Accessed 21 Jan 2019
241. Huang H, Savkin AV (2017) An energy efficient approach for data collection in wireless sensor networks using public transportation vehicles. AEU Int J Electron Commun 75:108–118
242. Li X, Lv Z, Hu J, Zhang B, Shi L, Feng S (2015) XEarth: a 3D GIS platform for managing massive city information. In: Proceedings of the 2015 IEEE international conference on computational intelligence and virtual environments for measurement systems and applications (CIVEMSA), Shenzhen, China, 12–14 June 2015; pp 1–6
243. Domínguez J, Amador J (2007) Geographical information systems applied in the field of renewable energy sources. Comput Ind Eng 52:322–326
244. Huang H, Savkin AV (2017) Viable path planning for data collection robots in a sensing field with obstacles. Comput Commun 111:84–96
245. Liu N, Chen J, Zhu L, Zhang J, He Y (2013) A key management scheme for secure communications of advanced metering infrastructure in smart grid. IEEE Trans Ind Electron 60:4746–4756
246. Uludag S, Zeadally S, Badra M (2015) Techniques, taxonomy, and challenges of privacy protection in the smart grid. In: Privacy in a digital, networked world; Zeadally, S., Badra, M., Eds.; Springer International Publishing: Cham, Switzerland, pp. 343–390. ISBN 978–3–319–08469–5
247. Fouda MM, Fadlullah ZM, Kato N, Lu R, Shen XS (2011) A lightweight message authentication scheme for smart grid communications. IEEE Trans Smart Grid 2:675–685
248. Bekara C, Luckenbach T, Bekara K (2019) A privacy preserving and secure authentication protocol for the advanced metering infrastructure with non-repudiation service. In: Proceedings of the second international conference on smart grids, St. Maarten, The Netherlands, p 9
249. Abbasinezhad-Mood D, Nikooghadam M (2018) An ultra-lightweight and secure scheme for communications of smart meters and neighborhood gateways by utilization of an ARM Cortex-M microcontroller. IEEE Trans Smart Grid 9:6194–6205
250. Kim Y, Kolesnikov V, Kim H, Thottan M (2011) SSTP: a scalable and secure transport protocol for smart grid data collection. In: Proceedings of the 2011 IEEE international conference on smart grid communications (SmartGridComm), Brussels, Belgium, pp 161–166
251. Saputro N, Akkaya K (2017) Investigation of smart meter data reporting strategies for optimized performance in smart grid AMI networks. IEEE Internet Things J 4:894–904
252. Cody R (2017) Cody's Data Cleaning Techniques Using SAS. In Cody's Data Cleaning Techniques Using SAS, 3rd ed.; SAS Institute Inc.: Cary, NC, USA, 2017; p. 23. ISBN 978–1–63526–069–4
253. Chu X, Ilyas IF (2016) Qualitative data cleaning. Proc VLDB Endow 9:1605–1608
254. Sagiroglu S, Terzi R, Canbay Y, Colak I (2016) Big data issues in smart grid systems. In: Proceedings of the 2016 IEEE international conference on renewable energy research and applications (ICRERA), Birmingham, UK, 20–23 November 2016; pp 1007–1012
255. Dellino G, Laudadio T, Mari R, Mastronardi N, Meloni C, Vergura S (2015) Energy production forecasting in a PV plant using transfer function models. In: Proceedings of the 2015 IEEE 15th international conference on environment and electrical engineering (EEEIC), Rome, Italy, pp 1379–1383
256. Xie S, Chen Z (2017) Anomaly detection and redundancy elimination of big sensor data in internet of things. arXiv 2017, arXiv:1703.03225.

257. Lee K, Kim D, Shin I (2017) REboost: Improving throughput in wireless networks using redundancy elimination. IEEE Commun Lett 21:160–163
258. Chen W, Zhou K, Yang S, Wu C (2017) Data quality of electricity consumption data in a smart grid environment. Renew Sustain Energy Rev 75:98–105
259. Aiello M, Pagani GA (2014) The smart grid's data generating potentials. In: Proceedings of the 2014 federated conference on computer science and information systems, Warsaw, Poland, 7–10 September 2014; pp 9–16
260. Li F, Luo B, Liu P (2010) Secure information aggregation for smart grids using homomorphic encryption. In: Proceedings of the first IEEE international conference on smart grid communications, Gaithersburg, MD, USA, pp 327–332
261. Uddin F (2017) Energy-Aware optimal data aggregation in smart grid wireless communication networks. IEEE Trans Green Commun Netw 1:358–371
262. Groat MM, HeyW, Forrest S (2011) KIPDA: K-indistinguishable privacy-preserving data aggregation in wireless sensor networks. In: Proceedings of the IEEE INFOCOM, Shanghai, China, 10–15 April 2011; pp. 2024–2032
263. Rottondi C, Verticale G, Krauss C (2013) Distributed privacy-preserving aggregation of metering data in smart grids. IEEE J Sel Areas Commun 31:1342–1354
264. Li F, Luo B (2012) Preserving data integrity for smart grid data aggregation. In: Proceedings of the 2012 IEEE Third international conference on smart grid communications (SmartGridComm), Tainan, Taiwan, 5–8 November 2012; pp 366–371
265. Guerrero JI, García A, Personal E, Luque J, León C (2017) Heterogeneous data source integration for smart grid ecosystems based on metadata mining. Expert Syst Appl 79:254–268
266. Alahakoon D, Yu X (2016) Smart electricity meter data intelligence for future energy systems: a survey. IEEE Trans Ind Inform 12:425–436
267. Jurado S, Nebot À, Mugica F, Mihaylov M (2017) Fuzzy inductive reasoning forecasting strategies able to cope with missing data: a smart grid application. Appl Soft Comput 51:225–238
268. Qiu RC, Antonik P (2017) Smart Grid using big data analytics: a random matrix theory approach. In: Smart grid using big data analytics; JohnWiley & Sons, Ltd.: Chichester, UK, 2017; pp. 1–575. ISBN 978–1–118–71677–9
269. Sigeru O, Sara R (2017) Distributed Computing and Artificial Intelligence, 14th International Conference. Springer International Publishing AG, Cham
270. Virgilio RD (2017) Smart RDF data storage in graph databases. In: Proceedings of the 2017 17th IEEE/ACM international symposium on cluster, Cloud and Grid Computing (CCGRID), Madrid, Spain, 14–17 May 2017; pp 872–881
271. Bruno S, Dellino G, Scala ML, Meloni C (2020) A microforecasting module for energy consumption in smart grids. In: Proceedings of the 2018 IEEE international conference on environment and electrical engineering and 2018 IEEE industrial and commercial power systems Europe (EEEIC/I&CPS Europe), Palermo, Italy, 12–15 June 2018; pp. 1–6. Energies 2020, 13, 6269 36 of 41
272. Monika, Srinivasan D, Reindl T (2015) Real-time display of data from a smart-grid on geographical map using a GIS tool and its role in optimization of game theory. In: Proceedings of the 2015 IEEE innovative smart grid technologies—Asia (ISGT ASIA), Bangkok, Thailand, 3–6 November 2015; pp. 1–6.
273. Stefan M, Lopez JG, Andreasen MH, Olsen RL (2017) Visualization techniques for electrical grid smart metering data: A survey. In: Proceedings of the 2017 IEEE third international conference on big data computing service and applications (BigDataService), San Francisco, CA, USA, 6–9 April 2017; pp 165–171
274. Yu M, Hong SH (2016) A real-time demand-response algorithm for smart grids: a Stackelberg game approach. IEEE Trans Smart Grid 7:879–888
275. Siano P (2014) Demand response and smart grids—a survey. Renew Sustain Energy Rev 30:461–478
276. Colson CM, Nehrir MH (2013) Comprehensive real-time microgrid power management and control with distributed agents. IEEE Trans Smart Grid 4:617–627
277. Ashok A, Hahn A, Govindarasu M (2014) Cyber-physical security of wide-area monitoring, protection and control in a smart grid environment. J Adv Res 5:481–489
278. Aloul F, Al-Ali AR, Al-Dalky R, Al-Mardini M, El-Hajj W (2012) Smart grid security: Threats, vulnerabilities and solutions. Int J Smart Grid Clean Energy 1:1–6
279. Ding D, Han Q-L, Xiang Y, Ge X, Zhang X-M (2018) A survey on security control and attack detection for industrial cyber-physical systems. Neurocomputing 275:1674–1683
280. Gupta A, Anpalagan A, Carvalho GH, Guan L, Woungang I (2019) Prevailing and emerging cyber threats and security practices in iot-enabled smart grids: a survey. J Netw Comput Appl 132:118–148
281. Peng C, Sun H, Yang M, Wang Y-L (2019) A survey on security communication and control for smart grids under malicious cyber attacks. IEEE Trans Syst Man Cybern Syst 49:1554–1569
282. Li B (2019) Detection of False data injection attacks in smart grid cyber-physical systems. Ph.D. Thesis, Nanyang Technological University, Singapore
283. Li X, Liang X, Lu R, Shen X, Lin X, Zhu H (2012) Securing smart grid: Cyber attacks, countermeasures, and challenges. IEEE Commun Mag 50:38–45
284. Wang W, Lu Z (2013) Cyber security in the smart grid: survey and challenges. Comput Netw 57:1344–1371
285. Liu J, Xiao Y, Li S, Liang W, Chen CP (2012) Cyber security and privacy issues in smart grids. IEEE Commun Surv Tutor 14:981–997
286. Khurana H, Hadley M, Lu N, Frincke DA (2010) Smart-grid security issues. IEEE Secur Priv 8:81–85
287. Liang G, Zhao J, Luo F, Weller SR, Dong ZY (2017) A review of false data injection attacks against modern power systems. IEEE Trans Smart Grid 8:1630–1638
288. Giraldo J, Sarkar E, Cardenas AA, Maniatakos M, Kantarcioglu M (2017) Security and privacy in cyber-physical systems: a survey of surveys. IEEE Des Test 34:7–17
289. Baig ZA, Szewczyk P, Valli C, Rabadia P, Hannay P, Chernyshev M, Johnstone M, Kerai P, Ibrahim A, Sansurooah K (2017) Future challenges for smart cities: cyber-security and digital forensics. Digit Investig 22:3–13
290. Zhang K, Ni J, Yang K, Liang X, Ren J, Shen XS (2017) Security and privacy in smart city applications: challenges and solutions. IEEE Commun Mag 55:122–129

291. Boroojeni KG, Amini MH, Iyengar SS (2017) Smart grids: security and privacy issues. Springer, Cham
292. Liang G, Weller SR, Zhao J, Luo F, Dong ZY (2017) The 2015 Ukraine blackout: Implications for false data injection attacks. IEEE Trans Power Syst 32:3317–3318
293. Wang D, Wang Z, Shen B, Alsaadi FE, Hayat T (2016) Recent advances on filtering and control for cyber-physical systems under security and resource constraints. J Frankl Inst 11:2451–2466
294. Li X, Scaglione A (2013) Robust decentralized state estimation and tracking for power systems via network gossiping. IEEE J Sel Areas Commun 31:1184–1194
295. Pang ZH, Liu GP, Dong Z (2011) Secure networked control systems under denial of service attacks. IFAC Proc 44:8908–8913
296. Shoukry Y, Tabuada P (2016) Event-triggered state observers for sparse sensor noise/attacks. IEEE Trans Autom Control 61:2079–2091
297. Amin S, Schwartz GA, Shankar Sastry S (2013) Security of interdependent and identical networked control systems. Automatica 49:186–192
298. Befekadu GK, Gupta V, Antsaklis PJ (2015) Risk-sensitive control under Markov modulated denial-of-service (DoS) attack strategies. IEEE Trans Autom Control 60:3299–3304
299. Zhang X-M, Han Q-L, Seuret A, Gouaisbaut F (2017) An improved reciprocally convex inequality and an augmented Lyapunov-Krasovskii functional for stability of linear systems with time-varying delay. Automatica 84:221–226
300. Wang J, Zhang X, Han Q (2016) Event-triggered generalized dissipativity filtering for neural networks with time-varying delays. IEEE Trans Neural Netw Learn Syst 27:77–88
301. Chenine M, Ullberg J, Nordström L, Wu Y, Ericsson GN (2014) A framework for wide-area monitoring and control systems interoperability and cybersecurity analysis. IEEE Trans Power Deliv 29:633–641
302. Lee P, Clark A, Bushnell L, Poovendran R (2014) A passivity framework for modeling and mitigating wormhole attacks on networked control systems. IEEE Trans Autom Control 59:3224–3237
303. Ding D, Wang Z, Han Q, Wei G (2018) Security control for discrete-time stochastic nonlinear systems subject to deception attacks. IEEE Trans Syst Man Cybern Syst 48:779–789
304. Ding D, Wang Z, Ho DWC, Wei G (2017) Observer-based event-triggering consensus control for multiagent systems with lossy sensors and cyber-attacks. IEEE Trans. Cybern. 47:1936–1947
305. Singh SK, Khanna K, Bose R, Panigrahi BK, Joshi A (2018) Joint-transformation-based detection of false data injection attacks in smart grid. IEEE Trans Ind Inform 14:89–97
306. Rai A, Ward D, Roy S, Warnick S (2012) Vulnerable links and secure architectures in the stabilization of networks of controlled dynamical systems. In: Proceedings of the 2012 American control conference (ACC), Montreal, QC, Canada, 27–29 June 2012; pp 1248–1253
307. Chen J, Abur A (2006) Placement of PMUs to enable bad data detection in state estimation. IEEE Trans Power Syst 21:1608–1615
308. Ashok A, Govindarasu M, Ajjarapu V (2018) Online detection of stealthy false data injection attacks in power system state estimation. IEEE Trans Smart Grid 9:1636–1646
309. Hao J, Piechocki RJ, Kaleshi D, Chin WH, Fan Z (2015) Sparse malicious false data injection attacks and defense mechanisms in smart grids. IEEE Trans Ind Inform 11:1–12
310. Tommaso AOD, Favuzza S, Genduso F, Miceli R, Galluzzo GR (2010) Development of diagnostic systems for the fault tolerant operation of Micro-Grids. In: Proceedings of the SPEEDAM, Pisa, Italy, pp 1645–1650
311. Kailkhura B, Han YS, Brahma S, Varshney PK (2015) Distributed bayesian detection in the presence of byzantine data. IEEE Trans Signal Process 63:5250–5263
312. Kailkhura B, Han YS, Brahma S, Varshney PK (2015) Asymptotic analysis of distributed bayesian detection with byzantine data. IEEE Signal Process Lett 22:608–612
313. Rawat AS, Anand P, Chen H, Varshney PK (2011) Collaborative spectrum sensing in the presence of byzantine attacks in cognitive radio networks. IEEE Trans Signal Process 59:774–786
314. Deng R, Xiao G, Lu R (2017) Defending against false data injection attacks on power system state estimation. IEEE Trans Ind Inform 13:198–207
315. Huang Y, Tang J, Cheng Y, Li H, Campbell KA, Han Z (2016) Real-time detection of false data injection in smart grid networks: an adaptive CUSUM method and analysis. IEEE Syst J 10:532–543
316. Hug G, Giampapa JA (2012) Vulnerability assessment of AC state estimation with respect to false data injection cyber-attacks. IEEE Trans Smart Grid 3:1362–1370
317. Liu L, Esmalifalak M, Ding Q, Emesih VA, Han Z (2014) Detecting false data injection attacks on power grid by sparse optimization. IEEE Trans Smart Grid 5:612–621
318. Manandhar K, Cao X, Hu F, Liu Y (2014) Detection of faults and attacks including false data injection attack in smart grid using Kalman filter. IEEE Trans Control Netw Syst 1:370–379
319. Mo Y, Chabukswar R, Sinopoli B (2014) Detecting integrity attacks on SCADA systems. IEEE Trans Control Syst Technol 22:1396–1407
320. Ao W, Song Y, Wen C (2016) Adaptive cyber-physical system attack detection and reconstruction with application to power systems. IET Control Theory Appl 10:1458–1468
321. Pasqualetti F, Dörfler F, Bullo F (2013) Attack detection and Identification in cyber-physical systems. IEEE Trans Autom Control 58:2715–2729
322. Sun C-C, Hahn A, Liu C-C (2018) Cyber security of a power grid: state-of-the-art. Int J Electr Power Energy Syst 99:45–56
323. Ericsson GN (2007) Toward a framework for managing information security for an electric power utility—CIGRÉ experiences. IEEE Trans Power Deliv 22:1461–1469
324. Kushner D (2013) The real story of stuxnet. IEEE Spectr 50:48–53
325. Falliere N, Murchu LO, Chien E (2008) W32. Stuxnet Dossier. White Pap. Symantec Corp Secur. Response 2011, 5, 69. 323. Ten, C.; Liu, C.; Manimaran, G. Vulnerability assessment of cybersecurity for SCADA systems. IEEE Trans. Power Syst. 2008, 23, pp 1836–1846

326. Namboodiri V, Aravinthan V, Mohapatra SN, Karimi B, Jewell W (2014) Toward a secure wireless-based home area network for metering in smart grids. IEEE Syst J 8:509–520
327. Liang X, Li X, Lu R, Lin X, Shen X (2013) UDP: Usage-based dynamic pricing with privacy preservation for smart grid. IEEE Trans Smart Grid 4:141–150
328. Sahoo S, Nikovski D, Muso T, Tsuru K (2015) Electricity theft detection using smart meter data. In: Proceedings of the 2015 IEEE power energy society innovative smart grid technologies conference (ISGT), Washington, DC, USA, pp 1–5
329. Bishop AN, Savkin AV (2013) Set-valued state estimation and attack detection for uncertain descriptor systems. IEEE Signal Process Lett 20:1102–1105
330. Yang Y, McLaughlin K, Sezer S, Littler T, Im EG, Pranggono B, Wang HF (2014) Multiattribute SCADA-specific intrusion detection system for power networks. IEEE Trans Power Deliv 29:1092–1102
331. McLaughlin S, Holbert B, Fawaz A, Berthier R, Zonouz S (2013) A multi-sensor energy theft detection framework for advanced metering infrastructures. IEEE J Sel Areas Commun 31:1319–1330
332. Liu Y, Hu S, Ho T (2016) Leveraging strategic detection techniques for smart home pricing cyberattacks. IEEE Trans Depend Secure Comput 13:220–235
333. Liu X, Zhu P, Zhang Y, Chen K (2015) A collaborative intrusion detection mechanism against false data injection attack in advanced metering infrastructure. IEEE Trans. Smart Grid 6:2435–2443
334. BerthierR, Sanders WH (2011) Specification-based intrusion detection for advanced metering infrastructures. In: Proceedings of the IEEE 17th Pacific Rim international symposium on dependable computing, Pasadena, CA, USA, 12–14 December 2011; pp 184–193
335. Zhang Y, Wang L, Sun W, RCG II, Alam M (2011) Distributed intrusion detection system in a multi-layer network architecture of smart grids. IEEE Trans. Smart Grid 2:796–808
336. Yang Y, McLaughlin K, Littler T, Sezer S, Pranggono B, Wang HF (2013) Intrusion detection system for IEC 60870-5-104 based SCADA networks. In: Proceedings of the IEEE power energy society general meeting, Vancouver, BC, Canada, 21–25 July 2013; pp 1–5
337. Fan Y, Zhang Z, Trinkle M, Dimitrovski AD, Song JB, Li H (2015) A cross-layer defense mechanism against GPS spoofing attacks on PMUs in smart grids. IEEE Trans Smart Grid 6:2659–2668
338. Wu J, Xiong J, Shil P, Shi Y (2014) Real time anomaly detection in wide area monitoring of smart grids. In: Proceedings of the IEEE/ACM international conference on computer-aided design (ICCAD), San Jose, CA, USA, 2–6 November 2014; pp 197–204
339. Mitchell R, Chen I (2013) Behavior-rule based intrusion detection systems for safety critical smart grid applications. IEEE Trans Smart Grid 4:1254–1263
340. Ten C, Hong J, Liu C (2011) Anomaly detection for cybersecurity of the substations. IEEE Trans Smart Grid 2:865–873
341. Hahn A, Govindarasu M (2013) Model-based intrustion detection for the smart grid (MINDS). In: Proceedings of the eighth annual cyber security and information intelligence Research Workshop, New York, NY, USA, 8–10 January 2013; pp 27:1–27:4
342. Hong J, Liu C, Govindarasu M (2014) Integrated anomaly detection for cyber security of the substations. IEEE Trans. Smart Grid 5:1643–1653
343. Yang Y, Xu H, Gao L, Yuan Y, McLaughlin K, Sezer S (2017) Multidimensional intrusion detection system for IEC 61850-based SCADA networks. IEEE Trans Power Deliv 32:1068–1078
344. Premaratne UK, Samarabandu J, Sidhu TS, Beresh R, Tan J (2010) An intrusion detection system for IEC61850 automated substations. IEEE Trans Power Deliv 25:2376–2383
345. Min C-G, Park J, Hur D, Kim M-K (2015) The economic viability of renewable portfolio standard support for off shore wind farm projects in Korea. Energies 8:9731–9750
346. Pultarova T (2016) Cyber security—Ukraine grid hack is wake-up call for network operators [News Briefing]. Eng Technol 11:12–13
347. Philipsen R, Morales-España G, DeWeerdt M, De Vries L (2019) Trading power instead of energy in day-ahead electricity markets. Appl Energy 233–234:802–815
348. Moghimi H, Ahmadi A, Aghaei J, Rabiee A (2013) Stochastic techno-economic operation of power systems in the presence of distributed energy resources. Int J Electr Power Energy Syst 45:477–488
349. Jain S, Kalambe S, Agnihotri G, Mishra A (2017) Distributed generation deployment: state-of-the-art of distribution system planning in the sustainable era. Renew Sustain Energy Rev 77:363–385
350. Nwaeze ET (2009) Deregulation of the electric power industry: The earnings, risk, and return effects. J. Regul. Econ. p 19
351. Kirschen D, Strbac G (2004) Fundamentals of Power System Economics: Kirschen/Power System Economics. John Wiley & Sons, Chichester
352. Min C-G, Kim M-K (2017) Impact of the complementarity between variable generation resources and load on the flexibility of the Korean power system. Energies 10:1719
353. Cory B (2002) Power system restructuring and deregulation: trading, performance and information technology. John Wiley Sons, Chichester, Vol. 16
354. Abhyankar AR, Khaparde SA (2013) Introduction to deregulation in power industry. In: Indian Institute of Technology: Mumbai, India, 2013; p 28
355. Khalid M, Aguilera RP, Savkin AV, Agelidis VG (2018) A market-oriented wind power dispatch strategy using adaptive price thresholds and battery energy storage. Wind Energy 21:242–254
356. Ko W, Park J-K, Kim M-K, Heo J-H (2017) A multi-energy system expansion planning method using a linearized load-energy curve: a case study in South Korea. Energies 10:1663
357. Balijepalli VSKM, Pradhan V, Khaparde SA, Shereef RM (2011) Review of demand response under smart grid paradigm. In: Proceedings of the ISGT2011, Kollam, Kerala, India, 1–3 December 2011; pp 236–243
358. Cavoukian A, Polonetsky J, Wolf C (2010) SmartPrivacy for the Smart Grid: embedding privacy into the design of electricity conservation. Identity Inf Soc 3:275–294

359. Li R, Wang Z, Gu C, Li F, Wu H (2016) A novel time-of-use tari design based on Gaussian Mixture Model. Appl Energy 162:1530–1536
360. Herter K, McAulie P, Rosenfeld A (2007) An exploratory analysis of California residential customer response to critical peak pricing of electricity. Energy 32:25–34
361. Khalid A, Javaid N, Mateen A, Ilahi M, Saba T, Rehman A (2019) Enhanced time-of-use electricity price rate using game theory. Electronics 8:48
362. Celebi E, Fuller JD (2012) Time-of-use pricing in electricity markets under different market structures. IEEE Trans Power Syst 27:1170–1181
363. Ali SQ, Maqbool SD, Ahamed TPI, Malik NH (2013) Load scheduling with maximum demand and time of use pricing for microgrids. In: Proceedings of the 2013 IEEE Global humanitarian technology conference: South Asia Satellite (GHTC-SAS), Trivandrum, India, 23–24 August 2013; pp 234–238
364. Liu H, Mahmoudi N, Chen K (2018) Microgrids real-time pricing based on clustering techniques. Energies 11:1388
365. Caramanis MC, Bohn RE, Schweppe FC (1982) Optimal spot pricing: Practice and theory. IEEE Trans Power Appar Syst PAS 101:3234–3245
366. Tang Q, Yang K, Zhou D, Luo Y, Yu F (2016) A real-time dynamic pricing algorithm for smart grid with unstable energy providers and malicious users. IEEE Internet Things J 3:554–562
367. Anees A, Chen Y-PP (2016) True real time pricing and combined power scheduling of electric appliances in residential energy management system. Appl Energy 165:592–600
368. Farrokhifar M, Momayyezi F, Sadoogi N, Safari A (2018) Real-time based approach for intelligent building energy management using dynamic price policies. Sustain Cities Soc 37:85–92
369. Eissa MM (2018) First time real time incentive demand response program in smart grid with "i-Energy" management system with different resources. Appl Energy 212:607–621
370. Kim S, Giannakis GB (2014) Real-time electricity pricing for demand response using online convex optimization. In: Proceedings of the ISGT, Washington, DC, USA, 19–22 February 2014; pp 1–5
371. Mohsenian-Rad A, Leon-Garcia A (2010) Optimal residential load control with price prediction in real-time electricity pricing environments. IEEE Trans. Smart Grid 1:120–133
372. Li P, Wang H, Zhang B (2019) A distributed online pricing strategy for demand response programs. IEEE Trans Smart Grid 10:350–360
373. Oldewurtel F, Ulbig A, Parisio A, Andersson G, Morari M (2010) Reducing peak electricity demand in building climate control using real-time pricing and model predictive control. In: Proceedings of the 49th IEEE conference on decision and control (CDC), Atlanta, GA, USA, 15–17 December 2010; pp 1927–1932
374. Lujano-Rojas JM, Monteiro C, Dufo-López R, Bernal-Agustín JL (2012) Optimum residential load management strategy for real time pricing (RTP) demand response programs. Energy Policy 45:671–679
375. Zhu H, Gao Y, Hou Y, Wang Z, Feng X (2019) Real-time pricing considering different type of smart home appliances based on Markov decision process. Int J Electr Power Energy Syst 107:486–495
376. Wang Y, Li L (2016) Critical peak electricity pricing for sustainable manufacturing: modeling and case studies. Appl Energy 175:40–53
377. Park SC, Jin YG, Song HY, Yoon YT (2015) Designing a critical peak pricing scheme for the profit maximization objective considering price responsiveness of customers. Energy 83:521–531
378. Kato T, Tokuhara A, Ushifusa Y, Sakurai A, Aramaki K, Maruyama F (2016) Consumer responses to critical peak pricing: impacts of maximum electricity-saving behavior. Electr J 29:12–19
379. Javaid N, Ahmed A, Iqbal S, Ashraf M (2018) Day ahead real time pricing and critical peak pricing based power scheduling for smart homes with different duty cycles. Energies 11:1464
380. Bagher Sadati SM, Moshtagh J, Shafie-khah M, Rastgou A, Catalão JPS (2019) Operational scheduling of a smart distribution system considering electric vehicles parking lot: A bi-level approach. Int J Electr Power Energy Syst 105:159–178
381. Zhang Y, Islam MM, Sun Z, Yang S, Dagli C, Xiong H (2018) Optimal sizing and planning of onsite generation system for manufacturing in Critical Peaking Pricing demand response program. Int J Prod Econ 206:261–267
382. Osorio GJ, Shafie-Khah M, Soares NGS, Catalao JPS (2018) Optimal dynamic tariffs for flexible ramp market in the presence of wind power generation and demand response. In: Proceedings of the IEEE international conference on environment and electrical engineering and IEEE industrial and commercial power systems Europe (EEEIC/I&CPS Europe), Palermo, Italy, 12–15 June 2018; pp 1–5
383. Doostizadeh M, Ghasemi H (2012) A day-ahead electricity pricing model based on smart metering and demand-side management. Energy 46:221–230
384. Joe-Wong C, Sen S, Ha S, Chiang M (2012) Optimized day-ahead pricing for smart grids with device-specific scheduling flexibility. IEEE J Sel Areas Commun 30:1075–1085
385. Zhang Q, Raman G, Peng JC-H (2019) EV charging optimization based on day-ahead pricing incorporating consumer behavior. arXiv 2019, arXiv:190104675
386. Esmaeili S, Anvari-Moghaddam A, Jadid S, Guerrero JM (2019) Optimal simultaneous day-ahead scheduling and hourly reconfiguration of distribution systems considering responsive loads. Int J Electr Power Energy Syst 104:537–548
387. Subramanian V, Das TK (2019) A two-layer model for dynamic pricing of electricity and optimal charging of electric vehicles under price spikes. Energy 167:1266–1277
388. Jang D, Eom J, Kim MG, Rho JJ (2015) Demand responses of Korean commercial and industrial businesses to critical peak pricing of electricity. J Clean Prod 90:275–290
389. Min C-G, Kim YC, Kim D-H, Kim M-K, Park J-K (2011) A study on coordinated generation maintenance scheduling in competitive electricity markets. J Int Counc Electr Eng 1:169–174
390. Kii M, Sakamoto K, Hangai Y, Doi K (2014) The effects of critical peak pricing for electricity demand management on home-based trip generation. IATSS Res 37:89–97
391. Zhuo W, Savkin AV (2019) Profit maximizing control of a microgrid with renewable generation and BESS based on a battery cycle life model and energy price forecasting. Energies 12:2904

392. Khalid M, Aguilera RP, Savkin AV, Agelidis VG (2018) On maximizing profit of wind-battery supported power station based on wind power and energy price forecasting. Appl Energy 211:764–773
393. Kim M-K (2017) Dynamic market-clearing model in a hybrid power market using parallel processing. J. Energy Eng 143:04016033
394. Yang Y, Wang M, Liu Y, Zhang L (2018) Peak-of-peak load shifting: Are public willing to accept the peak and off-peak time of use electricity price? J Clean Prod 199:1066–1071
395. de Sá Ferreira R, Barroso LA, Lino PR, Carvalho MM, Valenzuela P (2013) Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: a stochastic optimization approach. IEEE Trans Smart Grid 4(4):2285–2295
396. Yang P, Tang G, Nehorai A (2013) A game-theoretic approach for optimal time-of-use electricity pricing. IEEE Trans Power Syst 28:884–892
397. Nge CL, Ranaweera IU, Midtgård O-M, Norum L (2019) A real-time energy management system for smart grid integrated photovoltaic generation with battery storage. Renew Energy 130:774–785
398. Herter K (2007) Residential implementation of critical-peak pricing of electricity. Energy Policy 35:2121–2130
399. Centolella P (2010) The integration of price-responsive demand into regional transmission organization (RTO) wholesale power markets and system operations. Energy 35:1568–1574
400. Aalami HA, Moghaddam MP, Yousefi GR (2010) Demand response modelling considering interruptible/curtailable loads and capacity market programs. Appl Energy 87:243–250
401. Moghaddam MP, Abdollahi A, Rashidinejad M (2011) Flexible demand response programs modelling in competitive electricity markets. Appl Energy 88:3257–3269
402. Bruno S, Dellino G, La Scala M, Meloni C (2019) A microforecasting module for energy management in residential and tertiary buildings. Energies 12:1006
403. Hwang S-H, Kim M-K, Ryu H-S (2019) Real levelized cost of energy with indirect costs and market value of variable renewables: a study of the Korean power market. Energies 12:2459
404. Moreno A, Alonso M, Al-Jassim Z, Mehmedalic J, Amaris H, Repo S, Kulmala A (2016) Hierarchical and Distributed Control Concept for Distribution Network Congestion Management. IET Gener Transm Distrib. https://doi.org/10.1049/iet-gtd.2016.0500
405. Feng X, Shekhar A, Yang F, Hebner R, Bauer P (2017) Comparison of hierarchical control and distributed control for microgrid. Electric Power Compon Sys 45:1043–1056. https://doi.org/10.1080/15325008.2017.1318982
406. A Kiani, Annaswamy A (2012) Distributed hierarchical control for renewable energy integration in a Smart Grid. In: 2012 IEEE PES innovative smart grid technologies (ISGT), Washington, DC, USA, 2012, pp. 1-8, https://doi.org/10.1109/ISGT.2012.6175710

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