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Review

A Comprehensive Review of Microgrid Energy Management Strategies Considering Electric Vehicles, Energy Storage Systems, and AI Techniques

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Abstract: The relentlessly depleting fossil-fuel-based energy resources worldwide have forbidden an imminent energy crisis that could severely impact the general population. This dire situation calls for the immediate exploitation of renewable energy resources to redress the balance between power consumption and generation. This manuscript confers about energy management tactics to optimize the methods of power production and consumption. Furthermore, this paper also discusses the solutions to enhance the reliability of the electrical power system. In order to elucidate the enhanced reliability of the electrical system, microgrids consisting of different energy resources, load types, and optimization techniques are comprehensively analyzed to explore the significance of energy management systems (EMSs) and demand response strategies. Subsequently, this paper discusses the role of EMS for the proper consumption of electrical power considering the advent of electric vehicles (EVs) in the energy market. The main reason to integrate EVs is the growing hazards of climate change due to carbon emissions. Moreover, this paper sheds light on the growing importance of artificial intelligence (AI) in the technological realm and its incorporation into electrical systems with the notion of strengthening existing smart grid technologies and to handle the uncertainties in load management. This paper also delineates the different methodologies to effectively mitigate the probability of facing cyber-attacks and to make the smart grids invulnerable.

Keywords: energy storage system; demand-side management; renewable energy resources; microgrid; smart grid; optimization algorithms; electric vehicles; artificial intelligence

Citation: Khan, M.R.; Haider, Z.M.; Malik, F.H.; Almasoudi, F.M.; Alatawi, K.S.S.; Bhutta, M.S. A Comprehensive Review of Microgrid Energy Management Strategies Considering Electric Vehicles, Energy Storage Systems, and AI Techniques. *Processes* **2024**, *12*, 270. https://doi.org/10.3390/pr12020270

Academic Editor: Peng Li

Received: 26 November 2023
Revised: 9 January 2024
Accepted: 13 January 2024
Published: 26 January 2024

1. Introduction

Energy systems are receiving widespread attention due to their significance in our daily lives. Most of our energy generation systems are based on fossil fuels, which are non-renewable and come with an inevitable concomitant—hazardous carbon emissions. The growing nuisance of carbon emissions is pivotal in intensifying global warming. There is an instant need to curtail this menacing phenomenon to forestall potential large-scale environmental catastrophes. These fossil fuels, including oil, coal, and gas, are continuously depleting at a baffling rate, raising a red flag for concerned scientists to cope with this issue instantly [1]. Moreover, the global shortage of fossil fuels consequently results in an excessive spike in its prices [2]. According to experts, the extensive dependence on fossil fuels can significantly impede the development process of countries and, sometimes, become the cause of an outright economic downturn that drags countries to the brink of an utter fiasco. In modern times, fossil-fuel-operated vehicles are being supplanted by high-tech electric vehicles that are environmentally friendly with zero tailpipe emissions. This rapid adaption of electric vehicles augurs well for the environment and the automobile industry. It has been made adequately practical by engineers to charge these electric vehicles using less expensive and more efficient electrical supply sources.

Furthermore, scientists are undertaking extensive research to fathom alternate energy resources to uproot the evil of carbon emissions and to satiate the incessantly amplifying energy demands across the globe. Some issues related to the energy system include fossil fuel depletion, relentlessly rising greenhouse gas (GHG) emissions, and a huge energy shortage [3]. It is a common belief amongst the experts that the significant utilization of renewable energy resources, to meet the growing energy demand, is the most suitable alternative available at the moment. In this regard, optimized energy management is imperative in order to yield maximum results from renewable resources, which can be achieved through microgrids. A microgrid is a decentralized, resilient energy system that facilitates the transition from fossil fuels to renewable energy. It integrates renewable sources, like solar and wind, reducing dependence on centralized infrastructure. Microgrids enhance grid resilience, promoting energy independence and optimizing management. The acute decline in energy reserves calls for the immediate formulation of requisite energy management strategies to rectify such widespread concerns. The panacea for all these thorny issues lies in effectively implementing a microgrid energy management system [4]. Contemporary study aims to showcase the effectiveness of microgrid energy management systems, and for this purpose, it incorporates different decisive determinants, such as phasor measurement units and sensor nodes [5]. Furthermore, in this regard, a unique decentralized controlling structure is also included to regulate the voltage and frequency variations in an AC microgrid (MG). In any microgrid management system, a sturdy energy management system underlies the smooth availability of electrical supply to consumers. For a better energy management system, a higher bandwidth control structure is more suitable than the conventional one, without any need for communication hardware. The approach mentioned above was employed by the set model of finite control that predicts the voltage converter's control at the primary level. On the other hand, a droop control can also be used to keep the frequency and voltage steady and maintain them at the secondary level of hierarchical control. The simulation results also verified the accurate voltage and frequency of restoration, as well as the swift and uninterrupted sharing of power during transient and steady-state behaviors [6]. In addition to the aforementioned facets of this study, Gaziantep Metropolitan Municipality Central Wastewater Treatment Plant is also employed to investigate urban wastewater using the new concept of the bio-gas plants, and simultaneously, different calculations were performed to analyze the output power ratio compared to the injected fuel [7]. Figure 1 depicts the smart grid (SG) system architecture.

Additionally, demand response energy management is a strategic approach to optimizing energy consumption by adjusting usage based on changing grid conditions, pricing signals, or environmental factors. It involves real-time monitoring and adaptive decision making using advanced technologies like smart meters, promoting a more resilient and sustainable energy infrastructure. A new energy management strategy through a fuzzy adaptive particle swarm optimization algorithm (PSO) was proposed to increase the efficiency and performance of microgrid systems by analyzing the losses. PSO optimized the demand response by identifying optimal energy consumption patterns through collective intelligence and dynamic particle adaption, consequently enhancing gird efficiency [8].

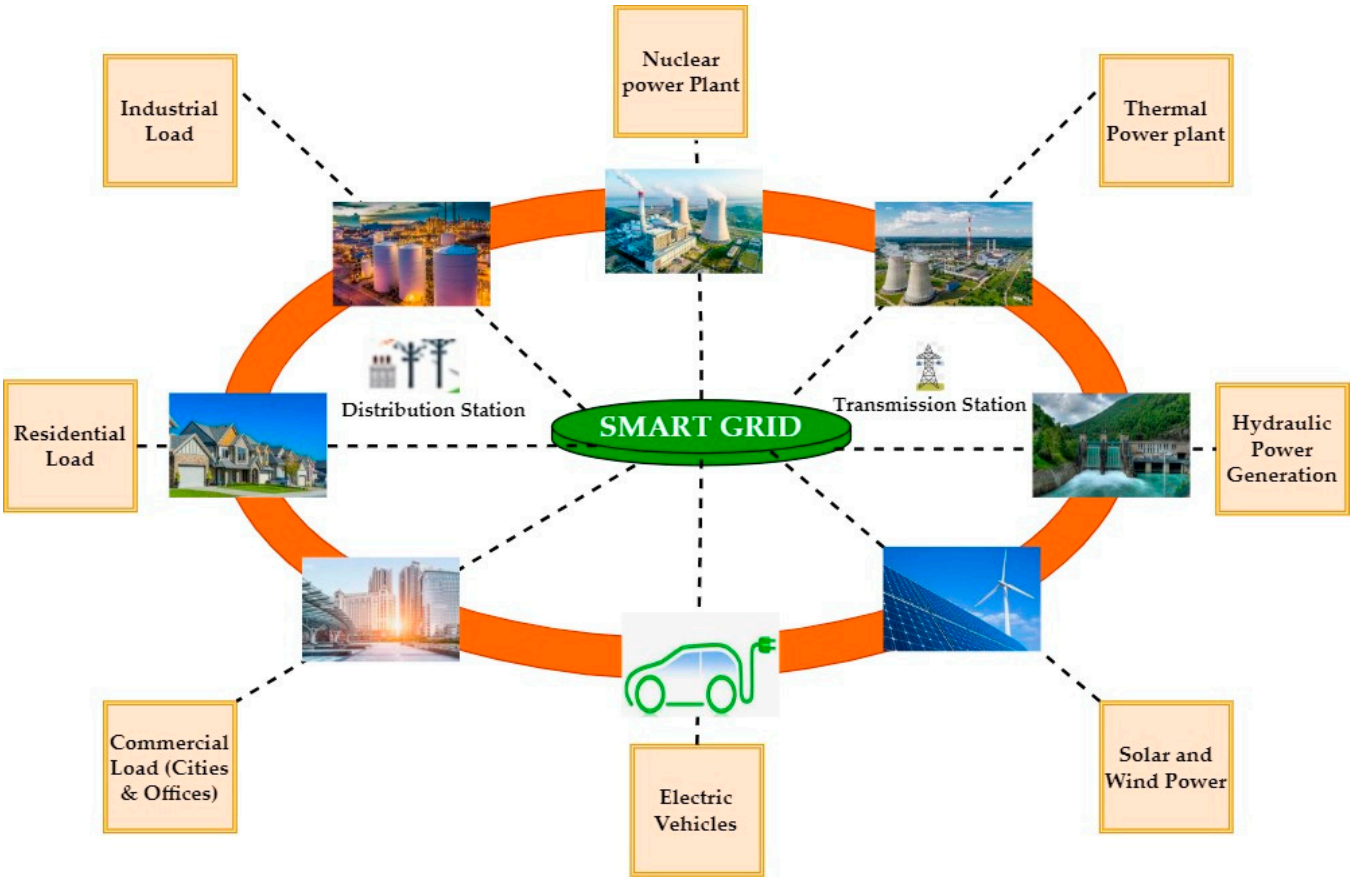

Figure 1. Smart grid system architecture.

Furthermore, the optimal dispatch of integrated energy systems in smart homes by combining heat, power, and batteries was also presented. The prime motive was to effectively mitigate the operation costs by implementing adequate energy routing and optimal energy scheduling during different time intervals. A considerable number of countries are promoting combined heat and power (CHP) and operations that are studied using an evolutionary algorithm. In this regard, a robust integrated energy system is preferred for optimized energy management. A typical integrated energy system consists of fuel cells, a thermal power plant, batteries, electricity loads, and natural gas resources connected to the electrical grid. The Harmony Search Algorithm (HSA) was used for proper energy routing and scheduling. The obtained results decreased the system operation cost [9]. The advanced energy management System (AEMS) facilitates the microgrid's energy flow. It also provides new techniques, algorithms, and new approaches to energy management like the block chain, artificial intelligence, or machine learning [10]. Table 1 shows the detailed study of 'Microgrids' energy management systems (EMSs).

Table 1. Details of Microgrid Energy Management System.

Ref.	Building Type	Integrated Components	Optimization Techniques	Load Types	Results
[9]	Large-sized building	Fuel cells, batteries, natural gas resources	Harmony Search Method Algorithm (HAS)	Thermal and electrical loads	System operational cost reduces as demand curves do not change

Table 1. *Cont.*

Ref.	Building Type	Integrated Components	Optimization Techniques	Load Types	Results
[11]	Campus Load of University of Engineering and Technology, Taxila, Pakistan	Photovoltaic panels, distributed generations (DGs), energy storage systems	Mathematical problem of optimal scheduling of DG and DR	Electrical Loads	System operations become cost-effective
[12]	A micro market design for the university	Controllable and uncontrollable loads, distributed generation (DG)	Self-Crossover Genetic Algorithm	Electrical Loads	Power system cost control, power system operation control
[13]	Smart house	Hybrid energy resources, battery energy storage system, Boiler	Real Coded Genetic Algorithm	Electrical loads, electrical vehicles	Optimal operational cost
[14]	Smart home	Photovoltaic (PV) generation, energy storage, grid energy exchange	Genetic Algorithm	Electrical appliances	Optimal energy scheduling and management
[15]	University smart grid	Photovoltaic panels, energy storage system, electric vehicles	Linear optimization problem solved by MATLAB	Electrical loads	Reduction in energy cost by 45.58% and reduction in load by 19.33%
[16]	Grid connected to microgrid	Solar cells and wind energy generation, Main Grid	Quantum Particle Swarm Optimization	Electrical loads	Reduction in energy cost 43.81% and reduction in load by 20%
[17]	Off-grid microgrid	Renewable energy generation and battery storage system	Convex optimization methods	Electrical loads	Microgrid operational cost reduction
[18]	Grid connect commercial microgrid	Solar cells and battery energy storage systems	Multi-Objective Particle Swarm Optimization	Electrical loads	Reduction in operational cost of system and resilience of System
[19]	Microgrid	Hybrid renewal system, battery energy storage system, electrical vehicle aggregator	Non-dominated sorting genetic algorithm-II	Electrical loads	Extension in battery life, optimal energy generation, and recharge cost of vehicles
[20]	Smart grid	Solar and battery storage system	Glow-Warm Swarm Optimization	Small-scale loads	Reduction in electricity tariff by 11.2% and reduction from 2.3 to 2.27 with load of 8.2 kWh/day
[21]	Commercial grid	Renewable energy resources and gridable Vehicles	Dynamic Stochastic Optimization	Commercial loads	Energy cost and CO_2 emission reduction and reliability system
[22]	Microgrid	Electric vehicle, main Grid	Elephant Herding Optimization	Commercial loads	Reduction in energy cost and stability enhancement of grid
[23]	Plug-in electric vehicles	Main grid with renewable energy systems and battery storage	Pontryagin's minimum principle and particle swarm optimization	Commercial loads	Cost minimization and extended battery life

Table 1. *Cont.*

Ref.	Building Type	Integrated Components	Optimization Techniques	Load Types	Results
[24]	Hybrid power plant	Renewable energy generation and Battery Storage	Risk-constrained optimization algorithms	Commercial electrical Loads	Low operating costs and reliable power generation
[25]	Multi-carrier energy hub	Dispersed generating system, combined heat and power units, battery storage system	Mixed-integer non-linear optimization	Electrical and thermal loads	Enhancement of economic operation of the system
[26]	Battery-flywheel compound energy storage system	Battery storage system	Optimization Method for Genetic Algorithms	Motor load	Recovered energy increased 1.17 times and decrease of 42.27% in charging current

According to the statistical study conducted by E. Wood on microgrids, the autonomous operational capability and sustainability of microgrids are predicted to grow significantly in the upcoming years on a global scale, especially in North America and the Asia–Pacific. From 2018 to 2027, grid capacity and spendings are predicted to rise by around five times [27]. The growth in microgrid capacity and spending over time is depicted in Figure 2.

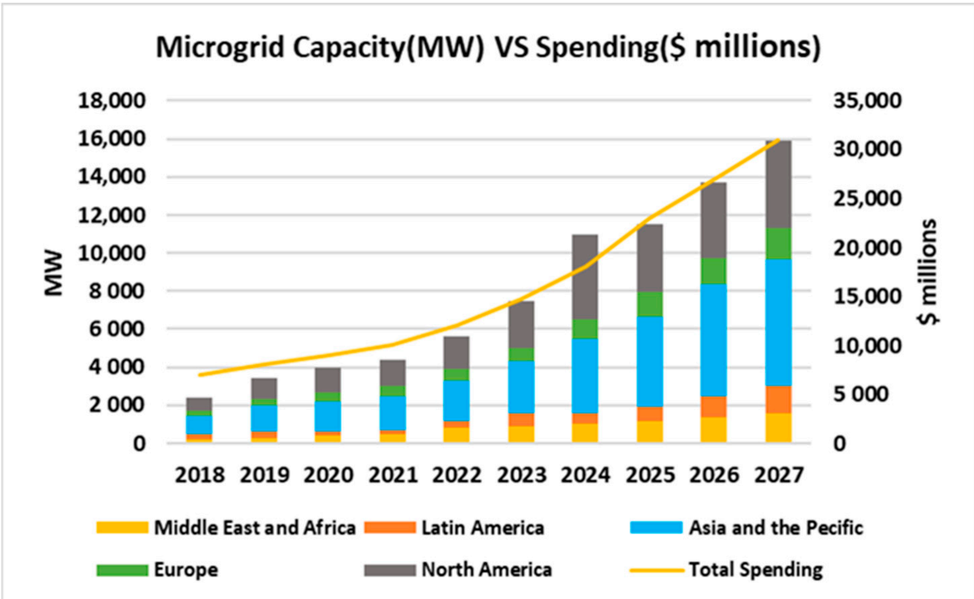

Figure 2. Microgrid capacity vs. spending graph.

This study is a comprehensive survey of the microgrid energy management system and can be classified in the following areas:

- Microgrid demand-side management (DSM)
- Demand response strategies
- Microgrid energy storage system
- Role of AI in smart grids
- Optimization techniques used for energy management systems
- Uncertainty handling in microgrid system
- Future scope and challenges in microgrid systems

This paper consists of various sections. Section 2 focuses on microgrid demand-side management, while Section 3 discusses demand response strategies. Section 4 highlights the microgrid energy storage system, and Section 5 explains the role of AI in smart grids. Sections 6–9 are dedicated to discussing uncertainty handling in microgrid systems' future scope and challenges, respectively.

2. Microgrid Demand-Side Management

Microgrid demand-side management optimizes electricity consumption within a microgrid to improve efficiency, reduce costs, and improve grid performance. It uses advanced technologies like smart meters, sensors, and automation to monitor usage patterns, implement demand response strategies, and promote sustainable energy practices.

There are two key factors that are taken into consideration when accessing a microgrid system: the cost and quality of service. Besides that, load-side or demand-side management is also an important factor that holds the ability to considerably enhance the quality of the power system network. Demand-side management (DSM) mitigates the effect of contingencies and the utilization of peak load management, considering the demand response (DR) techniques. Some existing studies are also presented here to explore the new paradigm in this domain, anatomizing the provision of electricity to remote areas with less cost and more reliability. In that context, objective functions were established as the cost of electricity (COE) and the probability of power supply loss (LPSP) [28]. Figure 3 shows a detailed picture of the energy management system covering utility-side, generation-side, and demand-side management.

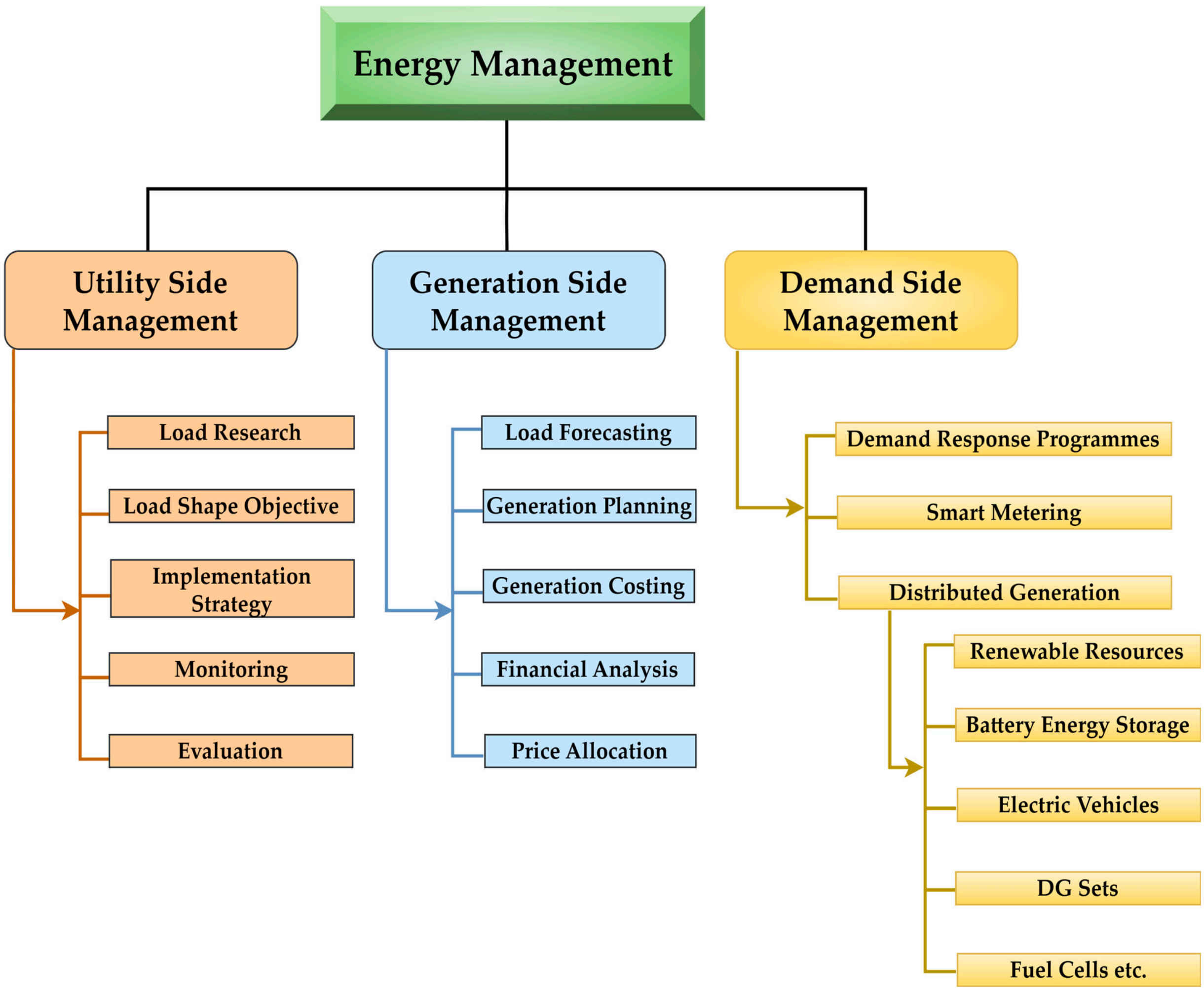

Figure 3. Demand-side management with other aspects.

Furthermore, the customer-oriented incentive charging scheme for electric vehicles (EVs) were established for communication between multiple microgrid regions. Initially, the respective implementation framework was incorporated into the system based on multi-regional charging coordination, and subsequently, the charging information was shared with the customers. Afterwards, by taking into the consideration the potential impacts of charging price, charging demand and customer charging demand models were formulated to amplify the interests of system operators. The algorithms used to solve the models included particle swarm optimization (PSO), which conspicuously improved the multi-grid system's operating revenue [29]. Table 2 shows the study of demand-side management of different types of loads considering the components installed.

Table 2. Demand-side management analysis of different types of loads.

Refs.	**Load Type**	**Components**										**Load Type**
		PV	**(BESS) (Battery Energy Storage System)**	**Wind**	**Biomass**	**DG** [1]	**MT** [2]	**EV** [3]	**SC** [4]	**FC** [5]	**CHP** [6]	**Residential/Commercial/Industrial**
[9]	Commercial building	☒	☑	☒	☒	☒	☒	☒	☒	☒	☑	Commercial
[11]	Campus building	☑	☑	☒	☒	☑	☒	☒	☒	☒	☒	Commercial microgrid
[30]	University building	☑	☒	☒	☒	☑	☒	☒	☒	☒	☒	Commercial microgrid
[12]	University building	☒	☒	☒	☒	☑	☒	☒	☒	☒	☒	Commercial Load
[14]	Smart house	☑	☑	☒	☒	☒	☒	☒	☒	☒	☒	Residential Load
[15]	University building	☑	☑	☒	☒	☒	☒	☑	☒	☒	☒	Commercial microgrid
[16]	Grid connected to microgrid	☑	☒	☑	☒	☑	☒	☒	☒	☒	☒	Commercial microgrid
[24]	Hybrid power plant	☑	☑	☑	☒	☒	☒	☒	☒	☒	☒	Commercial
[25]	Multi-carrier energy hub	☒	☑	☒	☒	☑	☒	☒	☒	☒	☑	Commercial Load

[1] DG denotes distributed generation. [2] MT denotes the microturbine. [3] EV denotes the electric vehicle. [4] SC denotes supercapacitor. [5] FC denotes fuel cells. [6] CHP denotes combined heat and power.

Microgrid energy management is a broadly deliberated technological strategy in the realm of electrical power management topic from the last few years because of the amplifying demand for electricity, climate change, and increasing electricity costs. To overcome these issues, densely populated countries are inching towards the utilization of renewable energy resources—by discarding the hitherto predominant utilization of fossil fuels. The installation of solar/PV panels is a widely preferred phenomenon that is a rich source of electrical energy in multiple highly luminous areas, offices, and institutes, and notably, almost 1–20% of renewable energy is being used to meet the electrical energy demand of the institutions [30]. In this day and age, existing energy systems primarily bank on fossils, but resultant emissions and unprecedented price hikes are the glaring undersides attached to such energy production phenomena. On the other hand, the systems operated by renewable energy resources are primarily cost-effective and environmentally friendly with virtually zero carbon emissions. To achieve the optimized flow of energy, energy management is mostly performed through renewable energy resources, DG generators, and energy storage systems, On the other hand, due to high load demand, electric power systems are becoming excessively intricate considering their stability and reliability [31].

To meet the energy demand and improve the efficiency, researchers are painstakingly working on multiple techniques of smart microgrid; one of them is the emergency energy demand response technique considering the decentralized approach for distribution-feeder load management based on decision-making techniques. The same approach not only relieved the system of undue burden, but also mitigated the demand rebound effect and provided efficient and clean energy without any hazardous impact on the climate [32]. Moreover, in terms of demand-side management, two factors are under consideration: one is power cost control, and the other is power system operation. The microgrid demand-side management optimization model is designed to acquire optimized system cost, load control, and micro-market operations. For the purpose of consequent analysis, self-crossover genetic algorithms were implemented to deduce the desired results. The primary aim of the study is to investigate and implement effective methods for managing unpredictable loads [12].

A microgrid is a feasible choice for a sustainable and reliable electrical energy supply system. The microgrid planning model developed through the MDS tool is divided into two sub-models: performance and economic models. Performance models are utilized to analyze energy and help appraise technical feasibility, and on the other hand, economic models are used to calculate the cash flow. Microgrid planning is a difficult task and sometimes requires government incentives to complete these tasks [33]. The power system faces challenges, such as inaccurate power sharing and the inability to extract maximum power from renewable energy resources. An optimal 3D droop method is proposed to address this issue [34]. Figure 4 represents various smart grid components.

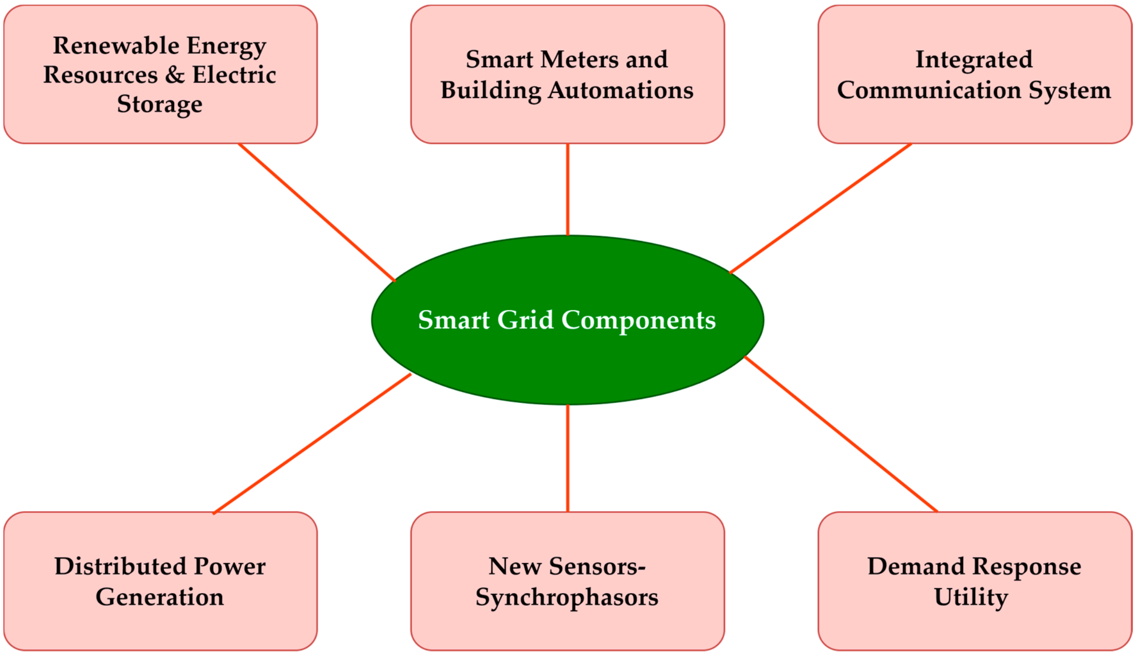

Figure 4. Smart grid integrated components.

In a comprehensive study regarding the interactive framework for improving resilience of power–water distribution systems with multiple microgrids, emergencies and microgrids provide the Distribution System Operator (DSO) with an energy block list. Subsequently, the DSO chooses a plan to reconnect the disconnected loads by assessing the inaccessibility values pertinent to the power and water distribution network damage. In this regard, the modified IEEE-30 bus system, including the microgrids, is used as a test, and the usefulness of the proposed strategy is confirmed [35]. Microgrids can significantly help in providing a clean and seamless energy supply to remote and far-flung areas with potentially no energy losses. Research conducted in the remote areas of Tanzia corroborates the aforementioned assertion. The microgrid included in the study generated 1000 kWh/day via HOMER Pro software and AHP-based multi-criteria decision making. Energy sources include PV, wind, micro-hydro, bio-gas generation, and battery storage. All sources were cost-effective and included in the design. Microgrid's levelized cost is 0.0694 USD/kWh via HOMER Pro. The results clearly showcased the effectiveness of microgrids in term of supplying energy to remote areas [36]. Moreover, in recent times, a highly productive model was introduced by researchers for interconnected microgrids to obtain 100% utilization of renewable energy resources named the Hybrid Information Gap Decision Theory (IGDT)/Stochastic approach. The model involved using trans-active technology to trade energy in a local market to maintain a dynamic energy balance. The system addressed the intermittency of RERs using information-gap decision and stochastic programming, incorporating risk-averse and risk-seeker schemes. The model was tested using the IEEE 14-bus model, which verified its effectiveness in achieving an 18.34% cost reduction compared to the base model [37]. Energy management (EM) is of paramount importance in microgrids (MGs) as it guarantees the secure and effective utilization of renewable energy resources (RERs). A smart microgrid, which consists of communication devices, electrical loads, electrical vehicle loads, and distributed energy resources (DERs), necessitates the implementation of all-encompassing approaches to tackle technical, environmental, and economic obstacles. A critical and comparative analysis of EM strategies in this context classifies EMS according to supervisory control, operating time platform, decision-making approach, and optimal decision making and demand response strategies. Diverse uncertainty quantification strategies for managing the intermittent character of renewable-based DERs are also emphasized. Considerations such as the objective function, practicability, suitability, and tractability influence the choice of decision-making approach. For quantifying uncertainty, scenario generation and reduction has become a widely adopted method. In the realm of demand response strategies, incentive-based DSM is the prevailing approach; however, price-based DSM distinguishes itself through its straightforward modeling and implementation. Furthermore, meta-heuristic algorithms and multi-agent-based approaches are superior in decentralized energy management, supporting precise scheduling and forecasting algorithms. Despite limitations in demand management and forecasting, they facilitate collaborative energy sharing in community microgrids, offering end-to-end energy [38].

Recognizing the pivotal role of energy management systems (EMSs), societies are increasingly prioritizing their development to achieve sustainable energy goals. Microgrids (MGs), owing to the stochastic nature of electrical loads and renewable sources, necessitate EMSs for optimized operations, planning, control, monitoring, and energy conservation. Over the period from 2009 to 2022, the focus on EMS strategies for MGs has encompassed diverse aspects. This includes database preparation, classification of EMS methods based on technique, control strategies, and structure, as well as discussions about potential directions for future studies. Industries and academia alike are directing their attention towards energy management research to enhance the efficiency, manageability, and sustainability of the energy sector [39].

Renewable energy systems have become increasingly significant due to the increasing global energy demand, which is primarily propelled by population growth and technological advancements. However, their intermittent nature complicates their design and operation. To address this, a sophisticated energy management strategy (EMS) is developed in [40] by the authors, with a real-time monitoring interface to optimize the functioning of a hybrid microgrid. It ensured stable voltage, balanced power supply, and frequency stability. Moreover, the system includes backup electrical infrastructure, AC/DC loads, hybrid sources, and a Li-ion battery storage system. The Python platform and GUI software facilitated efficient data analysis, demonstrating the effectiveness of the proposed EMS and monitoring interface. Few optimization techniques are also implemented within microgrids to tackle the challenges, such as mixed-integer programming, which is a frequently employed technique owing to its straightforwardness and power management solution [41].

3. Demand Response Strategies

Demand response (DR) strategies are dynamic methods used in energy management to optimize electricity consumption and improve grid reliability. They address challenges pertinent to peak demand, grid instability, and renewable energy integration. In DR mechanism, time-of-use pricing is a valuable factor that regulates consumers' energy consumption by shifting energy-intensive activities to off-peak hours, reducing grid strain. Critical peak pricing introduces higher rates during critical peak events, encouraging non-essential use. In order to automatically optimize energy consumption, automated demand response (ADR) is widely preferred, and it uses advanced automation systems to respond to grid signals, allowing real-time adjustments without human intervention. Load shifting involves transferring energy-intensive activities to off-peak hours, while incentive programs reward consumers for reducing consumption. Moreover, Vehicle-to-Grid technology allows electric vehicles to discharge stored energy back to the grid during peak demand. These strategies contribute to a more flexible and responsive energy system. In order to optimize electricity usage in response to grid conditions, pricing signals, and other considerations, demand response (DR) methods are essential parts of contemporary energy management systems. Improving grid resilience, controlling peak demand, and encouraging a more economical and ecological use of energy resources are all made possible by these tactics. Figure 5 shows the different types of demand response schemes. Demand response is becoming popular as it has been proven very useful in recent implementations, and its usefulness is now unquestionable. There is a need for more adequate approaches and models to address the small need of consumers and producers.

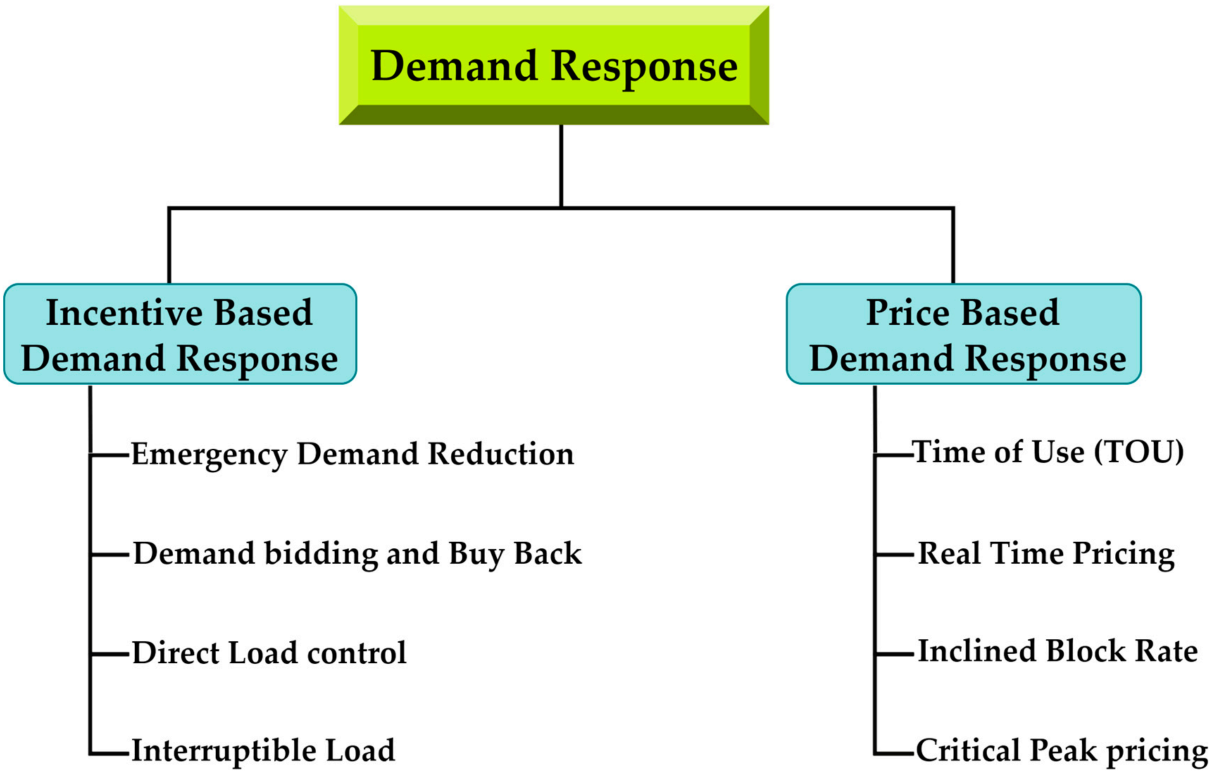

Figure 5. Types of demand response.

By using hourly pricing and peak-power-limiting techniques, a residential energy management system framework was created to optimize day-ahead appliance scheduling. All assets that can be controlled were modelled, such as distributed generation, electric cars, energy storage systems, thermostatically and non-thermostatically controlled appliances, and electric automobiles. In this regard, bidirectional energy flow was taken into consideration through improved choices for EV and ESS operation. A practical test case was showcased to examine the efficacy of the model, utilizing information, and much better results were found compared to previous energy utilization trends [42]. Dynamic pricing is real-time pricing (RTP) and mainly depends on two factors: one is efficient energy management, and the other is generic DR. There was an observation upon the RTP-based DR program that it decreased both the uncertainty in price and the electricity consumption [43].

Furthermore, collaboration of private microgrids (PMGs) with a robust decentralized model for a distribution company (DISCO) can also help handle uncertainty and operational cost. A test system of modified IEEE 33-buses, including the distribution network and three PMGs, is utilized to prove the usefulness of the proposed strategy [44]. Moreover, a flexible system of compressed air energy storage (CAES) can be a better choice due to its high ramp rate and reduced impact on the cost of the power system. Demand response programs are also deemed suitable solutions as part of practical approaches to deal with peak-demand challenges.

In conventional power system demand response, customers adjust their initial power consumption pattern in reaction to energy price or incentives in order to obtain additional advantages. The research on the effectiveness of multi-energy systems clearly delineated that their emergence enabled the integration of various sources of energy, such as electricity, heat, and natural gas. This integration allowed all energy consumers to actively engage in demand response, giving rise to the idea of integrated demand response (IDR). Within the IDR framework, energy users had the ability to respond by not just decreasing their energy usage or selecting to consume energy during non-peak hours, but also by altering the type of energy they consume. The research under discussion also provided an overview of the classic demand response in power systems [45].

Electrical heating devices solve the problem in the renewable energy system by modulating heat pumps. Furthermore, they can change their output according to the demand curves. Heuristic control techniques to modulate heat pumps can minimize heating costs and surplus energy. Compared to the other techniques, this strategy reduced heating costs by 4.1% and 13.3%, and the improvements in surplus energy were between 38.3% and 52.6%. A 40-building system was used for the test using a control and communication architecture to maintain inhabitants' privacy, and the results verified the strategy's importance [46].

The consumption of fossil fuels poses some environmental threats, such as global warming and CO_2 emissions. The prime purpose of using demand response programs (DRPs) is to reduce real-time pricing, peak-time pricing, incremental block rate, day-ahead pricing, etc. Furthermore, some challenges in implementing DRPs mainly include the willingness of customers to participate as they lose their comfort zone [47]. Artificial intelligence (AI) algorithms and battery banks can deal with peak-hour demand curves. The authors assessed the performance of different schemes in implementing the demand response algorithms in residential buildings. Two algorithms were implemented: one rule-based approach and another predictive-based approach to control a system with a thermal storage system and heat pumps. These algorithms assessed the demand response price scheme and observed the reduction in electricity end-user expenditure, such as 20.5% using a rule-based technique and about 41.8% using the predictive algorithm. Similarly, the utility generation-based cost was 18.8% using the rule-based technique and 39% using the predictive algorithm. An algorithm-based system was recommended due to its reliability and desired outcomes [48]. There is a gradual increase in demand for energy in the world, which forces us to opt for renewable energy resources. However, sometimes, in the case of renewables, variability and unpredictability in power generation unduly amplify. To solve these problems, customers approve the demand response (DR) mechanism worldwide. Besides that, due to the similarity of the gas system with the electricity network, the DR actions are applied to it. The proposed scheme involves management actions like balancing, pipeline congestion or shortage of underground storage, and the use of all DR products developed for power system and communication, and metering also needs to achieve optimum reliability in the gas sector [49].

3.1. Demand Response Strategies

In the DR program, incentive-based demand response (IBDR) is widely utilized in light of technological requisites. Some types of IBDR are direct load control, interruptible and manageable services, and demand bidding strategies [50], as well as optimal power flow (OPF) for IBDR, which reserves resources during normal and unusual conditions based on customer appliances. MG aims to improve security and reliability and maximize overall profit under normal and emergency operating conditions. There was a 4% and 2.7% increment in the profit of the operator, and the improvement in reliability indicator is recorded as 60% and 56%, respectively, by applying the IBDR model [51].

3.2. Price-Based Demand Response

The price-based demand response scheme (PBDR) has numerous types, such as time of use (ToU), critical peak pricing (CPP), and real-time pricing (RTP). These are all based on the tariff variation throughout the day. The tariffs vary during peak and off-peak hours. After extensively reviewing the working mechanisms of PBDR, shortcomings such as poor quality turn out to be the main problem in the distribution network. To overcome the abovementioned problem, rooftop and on-load changing procedures are adopted for energy management. The on-load tap changer (OLTC) method minimizes the compensation cost of voltage management.

The modified particle swarm optimization algorithm (MPSO) switches combinations between household appliances and OLTC tap position DR integrated with OLTC. Additionally, effective improvements in network voltage and PV hosting capacity are also observed by using independent phase tap control. This scenario is applied on a low-voltage network. In the future, it can be applied to medium-voltage networks as well [52]. A virtual power player was introduced that efficiently reduces operational costs by considering the trend in consumption shifting. This methodology was tested on three different scenarios including 214 customers and four types of distributed generation systems for 96 periods. The results authenticated the usefulness of this novel approach [53]. The challenges were faced by electrical networks due to an increase in electricity demand and intermittent renewable energy resources like photovoltaic (PV) systems. The study proposed a methodology to encourage residential prosumers to use price-based demand-side management (DSM) techniques. The methodology was tested on a pilot network of 300 residential prosumers with PV systems on their roofs. The results showed a reduction in seasonal peak consumption ranging from 1.03% to 3.19% and a 2% reduction in total consumption. The analysis showed a net benefit of EUR 4.09 million for 15 years. This methodology can be universally applied to manage demand and address reliability and congestion issues in electrical networks [54].

4. Microgrid Energy Storage System

The role of battery storage systems in microgrids is to improve their reliability and operational cost. Proper location and size are also significant for achieving the desired outcome through BESS. Besides many other benefits, ESS is used for ancillary services, voltage regulation, frequency regulation, etc.

Lead acid and lithium-ion batteries are used by applying GA algorithms for optimal power flow. The results of the simulation showed that lithium-ion BESS was more reliable, and the results were tested with 1.2 MW and the expected case of 2.3 MW solar installation system expected if a reduction in the cost of lithium-ion BESS is expected in future [55]. Historical data of the real grid and generation capacity from renewable energy resources should be known to handle uncertainties. Proper planning and operation of the distribution network are also necessary. Total investment and operational costs are taken as the objective function, and different schemes are implemented into the distributed test system, and results prove that the joint utilization of EESs and RESs are useful for cost reduction and fluctuation handling [56]. Optimal energy management of electrical energy storage systems (ESSs) through a bi-level framework depends upon two factors, i.e., minimizing the cost and maximizing the profit and the charge/discharge scheduling of ESSs. The model provides the optimal operation strategies for both the ESS and the power system [57].

The battery is an essential part of microgrids that run independently off the grid because renewable energy sources have significantly shorter operational hours. To reduce the running expenses of MGs, the optimal battery energy system size must be determined. Convex optimization techniques are used to determine the BESS size in a two-step cost-based approach. In the first step, a unit commitment (UC) issue is determined. The second phase was determining the BESS size while keeping operational and physical constraints using convex optimization and relaxation techniques. The aforementioned issue was resolved using MATLAB's CVX toolbox, and the outcome was better than the PSO and GA methods [17]. A rise in the popularity of photovoltaic (PV) systems, wind turbines, and battery energy storage systems (BESS) can be attributed to the increasing need for electricity, the rapid depletion of fossil fuels, and their harmful environmental effects. Due to its rapid responsiveness, controllability, adaptability, eco-friendliness, and geographical independence, the BESS is more attractive. The authors investigated the BESS in addition to the need for optimal BESS sizing approaches.

Future research should be conducted to build productive, efficient, long-lasting, and effective battery energy storage for a sustainable environment [58]. To manage renewable energy sources in microgrids, researchers suggest using battery energy storage systems (BESSs) due to their efficiency and adaptability. However, the BESS is grid-connected and requires a local voltage source (VS) as a reference to function. The study proposes a solution to operate the BESS at the local VS reference when the grid and renewable sources are unavailable by using the Simulink/MATLAB platform. Simulation results show that a seamless power supply (UPS) with 30–45% BESS capacity can be used for VS during 150–200% overload scenarios [59].

State of charge (SoC) is necessary because sometimes it becomes very difficult to control renewable energy sources in microgrids. To resolve this issue, a battery as an energy storage device is offered as a solution because of its versatility, efficiency, and high energy density. In contrast, BESS is a grid-connected system that cannot function without the local voltage source (VS), which functions as a reference. Using the Simulink/MATLAB platform, a method for operating the BESS at local VS in the absence of the grid and renewable energy sources is described. Simulation results indicate that a backup power supply (UPS) with 30-45% capacity of the BESS can be selected for VS under 150-200% overload scenarios. There was a need for a constant state of charge for all battery energy storage systems (BESSs) to prevent excessive use of some BESS units and extend BESSs' life. SoC-based droop control was analyzed on a multi-agent system, a proportional integral (PI) with the average SoC employed in P-f droop for the regulation of charging and discharging BESS units. Consequently, regardless of the size of the BESS units, the SoC progresses toward equalization. The effectiveness of the proposed technique was evaluated based on a variety of case scenarios, and the outcomes met with approval [60]. To ensure business continuity during a grid outage, a grid-connected Microgrid (GCMG) with a photovoltaic (PV) system and a battery energy storage system (BESS) was designed. The system employed a novel multi-objective strategy for optimal GCMG operation considering operational cost and system robustness. Optimization was achieved through multi-objective particle swarm optimization (MOPSO), which considered electricity cost and power outage during a grid outage as resilience indices. Numerical simulation and Pareto solutions were used to locate the optimal cost-to-resilience ratio. This approach proved effective in ensuring optimal GCMG performance [18].

The smooth operation of an isolated microgrid system requires a plan for generation scheduling and demand-side control. Electric car aggregators, hybrid renewable energy sources, solar panels, wind turbines, battery banks, and conventional generators were studied as system components. A multi-objective optimization model was suggested for such a system, with battery life extension on one side, energy generation cost of sources and recharge cost of a vehicle on the other, and demand-side management (DSM) introduced via plug-in electric vehicles (PEVS). Using a non-dominated Sorting Genetic Algorithm-II (NSGA-II), optimal operating circumstances and results validated the validity of this technique [19]. Nowadays, the world is focusing on economic power generation and renewable energy resources that play a key role in it. Due to the limitations of transmission lines, the cost and scarcity of fossil fuels force us to look for uninterrupted power sources by using battery banks and renewable energy systems in smart grids. In Ref. [61], the authors concentrate on the technology, size, efficiency, cost, and recycling of batteries utilized as prime energy storage devices. Optimization and probabilistic methods in battery sizing are observed, considering elements such as deterioration rate, battery placement, and reliability, which produce a cost-effective solution for the smart grid system. In addition, the researchers explain the batteries' potential to be recycled and their environmental impact. Energy storage (ES) has emerged as a crucial component of energy systems and is crucial in advanced smart grids. Smart grids share ES to strengthen the resilience and dependability of the energy system. Improved utilization of ES requires energy storage design and control mechanisms instead of standard sharing approaches.

A detailed survey encompassed all the research methodologies proposed in the previous decade for ES sharing and described their potential and adoption challenges [62]. The authors focused on battery storage device technology, size, efficiency, cost, and recycling in their research. Optimization and probabilistic methods in battery sizing, considering factors such as deterioration rate, battery placement, and dependability, resulted in a cost-effective solution for the smart grid system. Energy storage (ES) has been developed as an integral part of energy systems and is critical in advanced smart grids. Smart grids share ES to increase the energy system's resilience and dependability. Enhanced utilization of ES necessitates design and control methods for energy storage instead of typical sharing approaches. A comprehensive survey of all research approaches developed in the preceding decade for ES sharing and describing their potential and adoption problems was given [63]. Additionally, a distributed cooperative control technique for freestanding DC microgrids (DCMGs) is necessary when coupled with several photovoltaic (PV) energy systems attached to the DCMGs. This technology mitigates intermittent power swings by providing steady power generation from PV systems. It also contributes to cost reduction by monitoring and evaluating energy sources to reduce the quadratic cost function. By minimizing charging stress, the effectiveness of the suggested solution increases the lifespan of battery energy storage systems (BESSs) [64].

The resilient power supply supplies electricity during natural disasters and grid failures by utilizing a redundant structure and predictive control strategy, attracting the attention of the power system. As power outages can result in provider losses, incorporating renewable energy sources, natural gas networks, and electrical grid supply and control techniques into a microgrid can make a system more resilient. This study describes a controller based on artificial intelligence and simulates the information and communication technology (ICT) system as an uninterruptible power supply in emergencies. Its potential is evaluated by improving its resilience in terms of survival time under defective conditions [65]. An optimal battery energy storage system (BESS) design and virtual energy storage system (VESS) can significantly achieve microgrid stability and cost savings. The appropriate energy size of a two-layer BESS in a smart microgrid with a high penetration of solar systems is examined. The initial BESS size is determined based on the VESS role in the first layer. In the second layer, the optimal dispatch of energy resources is computed based on the optimal BESS size and system limitations. Markowitz's mean-variance theory was utilized to evaluate the risk of system cost variability with load fluctuation ranging from 70% to 130% and PV generation from 40% to 100%; resultantly, it was established that the BESS was less impacted by PV generation [66].

Due to the scarcity of fossil fuels and the attendant environmental concerns, the generation has shifted towards renewable energy technologies. Microgrids with scattered generation and interconnected loads will be helpful in locations where grid functionality cannot be expanded. The ideal scheduling of an interconnected 82 kW load with microgrid and distributed generation is shown to reduce fuel expenditures. The literature describes numerous optimization procedures, such as particle swarm optimization (PSO), Whale Optimization Algorithms (WOA), Grey Wolf Optimization (GWO), and Modified Grey Wolf Optimization (MGWO). MGWO resulted in superior cost optimization compared to all other algorithms and conventional methods [67]. In general, there is always an approximate match between power generation and consumption, and with the development of battery storage technologies, the power system needs BES. The analysis of technical and economic benefits renders deep insights into the effects of BES on the load factor, voltage index, and network losses in power systems. The optimal power flow (OPF) model is also suggested for sizing and placing a battery bank in a power system. The model's efficacy and availability are evaluated through its application in a model [68]. For optimal energy management, various simulation tools were used and some of them are mentioned in Table 3.

Table 3. Simulation tools used in the energy management system of microgrids.

References	Tools	Objectives and Applications
[11,15,17,59,69–77]	MATLAB/Simulink	MATLAB is a powerful mathematical computing platform with a wide range of toolboxes for scientific and engineering applications, including BESS. It can be used for modeling battery behavior, analyzing system performance, and developing control algorithms.
[24]	HOMER Pro	Simulation software, optimizing microgrids, evaluating renewable energy sources, selecting energy storage systems, and analyzing microgrid performance and economics.
[76]	MAGNET—Infolytica	MAGNET—Infolytica is a comprehensive software suite for designing and analyzing electromagnetic devices, including batteries. Understanding the strengths and limitations of each tool can help make an informed decision and leverage their capabilities to design and optimize effective BESS solutions.
[78]	GAMS	GAMS is a high-level optimization modeling language used for solving complex problems in various domains, including BESS design. It has powerful optimization capabilities, flexible model formulation, and integration with other software tools.
[79]	PSCAD	PSCAD is a power system simulation software designed for analyzing the dynamics and stability of electrical grids. It has highly accurate simulations and detailed modeling capabilities, but it may not be suitable for the economic or design aspects of BESS.

The sturdy correlation between the Micro Gas Turbine Generation System (MTGS) and the battery energy storage is crucial to the system's stability in an isolated system. In another study, a control approach based on the rapid reaction of the battery is proposed. A seamless switching control strategy is presented for MTGS and battery storage power sources to prevent voltage quality issues during the load changeover between supplies. A PSCAD simulation validated the proposed technique, and the result matched the description [79]. The economic advantages of solar and wind energy are gaining traction, but operational issues in grid-connected systems require coordination between solar and battery storage. To address this, a maximum power point tracking (MPPT) controller is used to regulate solar generation. This model is simulated in MATLAB-Simulink for two scenarios: constant load with variable irradiation and changeable load with variable irradiance. The results demonstrate the model's effectiveness in maintaining voltage, power balance, and frequency in the system [72]. The power quality (PQ) of a microgrid combining a photovoltaic (PV) system and a battery storage system (BSS) is improved by using the shunt hybrid active filter in a three-phase system with a PV system and a BSS shunt hybrid active filter (SHAF). The proposed technique was used to eliminate harmonics, regulate reactive power in the system, and maximize the PV array's power output. SHAF uses the maximized M. Kalman filter for reference current control and hysteresis of the current control (HCC) while generating switching signals [73]. Moreover, for multi-carrier energy hubs, three sources are included in the optimal scheduling: distributed generating systems (DGs), considered to be micro-combined heat and power (MCHP) units; battery electrical storage systems (ESSs) and electrical heaters; absorption chillers; and heat pumps. A mixed-integer non-linear optimization problem was used to describe the optimal management and scheduling of energy resources in exchange with distribution networks. The optimum operating points of DG units and ESSs were determined using a cost-effective scheme. In addition, the cost reduction in ESSs was studied for short-term scheduling. The simulation findings demonstrate that utilizing optimal scheduling with energy storage options improves the economic operation of the system by meeting all of its needs [25]. Microgrids (MGs) are increasingly popular due to their ability to deliver reliable and robust power when combined with battery energy storage systems and renewable energy sources. Current reliability measures, like expected energy not supplied (EENS) and loss of load expectation (LOLE), may not provide a comprehensive assessment of MGs' dependability and robustness. Additionally, three new indices for MGs were introduced: (1) Microgrid Resiliency Index (MRI); (2) Microgrid Renewable Energy Availability Index (MREAI); and (3) Microgrid Renewable Expected Energy Index (MREEI). These indices provide additional data beyond EENS and EENS, highlighting the impact of renewable energy sources on energy losses and availability in MGs [80]. The growing use of intermittent renewable energy resources presents challenges for traditional bulk power systems and microgrids. To address this, flexible components like demand response and battery energy storage systems are integrated using a mixed-integer programming strategy in [81]. Moreover, an incentive-based demand response model and comprehensive model is presented to enhance the vanadium redox battery's efficacy and dependability. Simulation outcomes are compared with a genetic algorithm approach to confirm the reliability. In microgrids, the battery energy storage system (BESS) is an indispensable energy storage technology; however, frequent replacements are financially burdensome due to its short lifecycle and substantial cost. To overcome this issue, a method for optimizing capacity and cost analysis is taken into account in [82] to increase the lifespan of the BESS. To estimate the lifetime of the BESS, the weighted throughput method is utilized to optimize the battery capacity, and the particle swarm optimization algorithm is also implemented. The optimal adjusting factor of 1.761 produces the lowest total net present value of 200,653 USD, thereby reducing overall operation expenses for the duration of the project. A new methodology is tested in [83] for using battery storage units (BSUs) in microgrids (MGs) to perform energy arbitrage and supply/demand matching. The goal to reduce power discrepancies between demand and renewable energy systems (RESs) and gas emissions is addressed by the authors. The study considered uncertainties in wind speed, solar irradiance, and temperature from RESs' stochastic output. Two metaheuristic optimization algorithms, Moth-Flame Optimization (MFO) and Hybrid Firefly and particle swarm optimization, are used to resolve the issue.

4.1. Flywheel Energy Storage System

For energy storage types, the flywheel energy storage system is based on rotational energy. The rotational stored energy converts into electrical energy. In the microgrid energy system, flywheel attracts many users due to its prominent characteristics. Different types of technologies utilized in flywheel energy storage systems (FESSs) are discussed. The materials used in producing FESSs and an overview of the uses of FESSs in grid leveling are also discussed. Using the above discussion, the implementations for cost reduction in permanent magnet synchronous machines and the operational temperature for these machines can also be analyzed. Similarly, using renewable energy resources like wind generation, solar generation, ocean wave energy generation, and geothermal energy has an environmentally friendly nature and is a cost-effective solution [84].

It also posed some problems to the grid, such as generation fluctuations in weather, environmental conditions, destabilization of the grid, grid error, and grid collapse. Flywheel energy storage systems are used in microgrids as a regulation element. The results confirmed the role of the FESS, its governing principles in the microgrid, and its indispensable role in science and technology [85]. The authors introduced energy-saving methods for a particular duty cycle and effective estimation-related issues with flywheel energy storage systems in pillar rolling mills. By calculating loss components in electric motors and knowing the dependency of motor losses on the moment of inertia, the analysis of flywheel usefulness is made, and the results declare that the implementation of a flywheel system will reduce the losses of energy in heavy load charts. The analysis used the function of dependency on the losses in electric motors, both electrical and mechanical, considering the moment of inertia as a function [86].

The development of a digitalized vector control system for FESSs employing permanent magnet-assisted synchronous reluctance machines (PMA-SynRM) has been accomplished. A proposed filter was implemented to remove offset and dead zone effects from current sensor signals while maintaining their amplitude. The efficacy of the adapted FESS drive control system was confirmed through simulations and experimental outcomes [87]. Similarly, optimization and analysis of a flywheel energy storage system that acts as a dynamic voltage regulator (DVR) were also carried out. The primary objectives were to design an FESS with a natural resonance frequency within the operational frequency range and to demonstrate a matrix converter structure for bidirectional power conversion. To achieve this, a specific motor or generator design is required, with a permanent magnet synchronous motor (PMSM) being the preferred choice. Frequency analysis was performed using SolidWorks, and a PMSM was constructed using MATLAB-Simulink and MAGNET-Infolytica to match the matrix voltage level [80]. Some energy storage systems are shown in Figure 6.

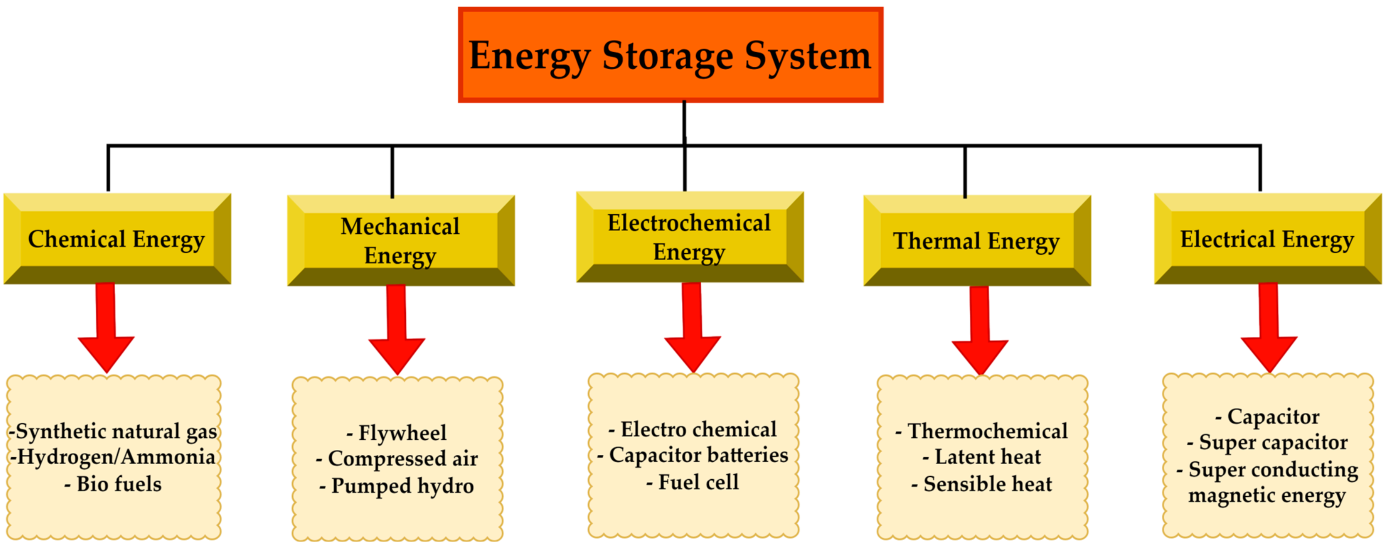

Figure 6. Types of energy storage system.

The battery flywheel compound energy system models were developed by taking into account the battery's state of charge (SOC) and open-circuit voltage (OCV), along with the flywheel's rotational speed and motor speed, as well as heat loss. Energy optimization in GA is used to determine the appropriate electric braking torque for recovered braking energy under varied scenarios. A double neural-network-based adaptive PI vector control approach was implemented to govern the flywheel's rotational speed. The acquired results demonstrated a 1.17-fold increase in recovered energy, a 42.27 percent decrease in the maximum charging current, and an improvement in the flywheel's stability, which gave references for designing energy management systems for electric vehicles [88]. In peak shaving services, the authors proposed a concept of FESS deployed at the transformer substation. The power set points of the flywheel were determined via a lexicographic optimization approach that minimized power losses and transformer power restriction violations. In addition, the maximum power was determined and integrated using the convex functions of the flywheel's power losses. In this regard, two-level hierarchical control architecture was devised for the transformer flywheel system to address model flaws and predictive mistakes. At a higher level, linear programming was used to solve the lexicographic optimization technique, while at a lower level, real-time measurements were used to correct the power set points. The proposed controllers are integrated into the experimental test setup using a software platform to demonstrate their efficacy. Simulation and experimental findings substantiated the flywheel system's modeling, control, identification, and operation for peak shaving services [89]. Table 4 shows the comparison of energy storage system used for the optimization of smart microgrids.

Table 4. Comparison of energy storage system.

References	Energy Storage System	Pros	Cons	Reliability	Cost	Challenges	Applications
[90,91]	Lithium-ion Batteries	High density of energy	Shortened lifecycle	High	Medium to high	Fire risks, resource availability, scalability	Energy storage system in grids, portable electronics, electric vehicles, telecommunications, backup power
[91]	Lead-acid batteries	Low price	Low density of energy	Moderate	Low to medium	Maintenance and limited lifecycle	Emergency lightening, automotive starting batteries, uninterruptible power supplies (UPS), solar energy storage
[92]	Flow batteries	Long lifecycle and scalability	Lower density of energy compared to Li-ion	Moderate	Medium to high	Efficiency and complex system design	Microgrid support, renewable integration, electric-vehicle-charging infrastructure, islanded power systems
[93]	Pumped hydro storage	High effectiveness	Site-specific (needs variations in elevation)	Moderate	Medium to high	Environmental impact, limited use in terms of geography	Emergency power backup, load balancing, peak load shifting
[94–97]	Compressed air energy storage (CAES)	High efficiency and Scalability	Site-specific (needs appropriate underground formations)	Moderate	Medium to high	Energy losses, geographical restrictions	Grid energy storage, peak shaving, grid balancing and frequency regulation, transmission and distribution Support

Table 4. *Cont.*

References	Energy Storage System	Pros	Cons	Reliability	Cost	Challenges	Applications
[95,97]	Flywheel energy storage	High density of power	Limited time for energy storage	High	High	Cost, high rotational speeds	Grid stabilization, microgrid Support, frequency regulation, power quality improvement
[95,98–100]	Thermal energy storage	Potential for inexpensive materials and long-duration storage	Reduced round-trip efficiency in relation to alternative technologies	High	Medium to high	Thermal losses, material selection	Solar thermal power plants, industrial processes, district heating
[95,101,102]	Supercapacitors	Quick charging and discharging	Less energy density compared to batteries	Moderate	High	Limited density of energy, cost	High-power applications, regenerative braking in vehicles, power tools and portable electronics, backup power for communication systems

4.2. Role of Electrical Vehicles in Storage Systems

In consideration of the system consisting of the energy storage system (ESS), electric vehicle (EV), and solar generation to fulfill energy demand, an optimal energy management system (EMS) for effective energy harvesting from available energy resources was proposed. MATLAB was used for linear optimization problems, and the simulations results showed a reduction of 45% in operational costs and a decrease of 45.58% in energy consumption costs and 19.33% in load [103]. Hybrid electric vehicles (HEVs) and plug-in HEVs (PHEVs) are advancements in the intelligent transportation system (ITS) and allow performance improvement in energy management systems (EMSs). The descriptive analysis of EMSs highlights the main differences between HEVs/PHEVs and internal combustion engine (ICE) vehicles. The structure of EMSs is categorized into three instances: single-vehicle, two-vehicle, and multiple-vehicle instances. Hence, eco-driving is a feature used by vehicles to communicate with Vehicle to Infrastructure (V2I) technologies [104]. The article also presents a unique hybrid control system that uses the battery's state of charge (SOC) and hydrogen level. The interconnection and damping assignment passivity-based control (IDA-PBC) technique was used to develop this strategy for load power sharing between sources. The PBC non-linear powerful technique, artificial neural networks (ANNs), and system energy information were used as references to validate the proposed approach. The article provides modeling, control, simulation stability proof, and experimental authentication of the entire solution, with testing results confirming the effectiveness of the proposed method [105]. It can be referred to as the urbanization of smart cities and the shift toward electric vehicles (EVs) as alternate transportation. It significantly reduces greenhouse gas emissions, so the smart grids with renewable energy resources (RESs) with their charging structure are eligible for a smart solution. The article discusses EVs and microgrids powered by renewable energy sources. The section on EVs covers the development of EV-charging infrastructure and innovative applications, such as Vehicle-to-Grid (V2G) and Vehicle-to-Home (V2H) technologies. The authors also introduced an energy management system (EMS) that enhances the dependability of the charging infrastructure. A real-time stochastic optimization technique was developed to reduce cost emissions and maximize the utilization of clean energy resources in a smart power grid with grid-capable vehicles (GVs) and renewable energy resources [106].

Dynamic stochastic optimization (DSO) was found to be effective in assuming the grid-capable vehicle as a small portable power plant (SP3) and the smart parking lot as a virtual power plant (VPP). This approach led to cost and emission reduction, an increase in the reserve and dependability of the smart grid, and a levelized load demand curve when millions of GVs were integrated [21].

A technique for optimizing energy management was implemented, which uses plug-in electric vehicles and dispersed energy sources as inputs. To avoid overcharging and over-discharging, the model uses the engine's fuel consumption, battery charge and discharge, and battery state of charge as constraints. The model is solved using a multi-objective optimization approach and is compared with other methods, such as particle swarm optimization and traditional grey wolf techniques. The results of the abovementioned study showed that electric vehicles can be more advantageous in an energy-based economy under certain circumstances [107]. Electric vehicles (EVs) and renewable energy (RE) sources can dramatically reduce carbon emissions from the transportation and electricity sectors. Additionally, another literature assessment of the power grid is offered, integrating renewable energy sources and electric vehicles. With economic and environmental analysis, the presence of EVs can reduce grid effects, the ability of EVs to integrate the RER, and excessive RE power generated on the grid. In the Vehicle-to-Grid (V2G) concept, the vehicle can be considered a load or a distribution energy source. Utilizing V2G can improve efficiency, performance, dependability, and stability [108].

Hybrid energy storage systems (HESSs) are related to energy management (EM) methods, configurations related to HESSs, and numerous tactics utilized for electric vehicles (EVs). In addition, research was conducted on the performance evaluation of EM methods for HESS setup. The HESS EM topologies have been evaluated for EV predicated on their performance. The performance depended on the lowering of the EVs' battery peak current, with the regenerative braking power comparison being considered. System design and voltage variation were offered as a path for EV researchers to follow [109]. A two-stage model was designed for managing a microgrid with renewable sources and EVs, aiming to minimize operation costs and emissions. The model uses an Improved Shuffled Frog Leaping Algorithm (ISFLA) to optimize the objective function, focusing on managing variations in wind turbine and photovoltaic (PV) management. Subsequently, simulation results show the algorithm's superiority over conventional approaches [110]. Moreover, mixed-integer linear programming (MILP) should be utilized to optimize the cost of energy demand. The cost function was solved with real and altered data to explore the bidirectional PEV effects on the load of a flexible building, and the distribution system's optimized DERs were investigated. The purpose was to highlight the importance of a comprehensive approach for determining the most appropriate PEV strategies. Simulation findings proved the method's effectiveness by lowering expenses and voltage variations relative to slower PEV activities.

EV scheduling requires robust optimization techniques, such as Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) strategies, for the integration of electric vehicles (EVs) with smart grids [78]. The study under discussion addressed clean energy resources and reduced air pollution due to internal combustion engines. Similarly, some of the energy storage devices discussed were required for EVs. The use of plug-in electric vehicles (PEVs) is the most effective technique to minimize carbon emissions and is a prerequisite for developing green transportation services. The advantages of PEVs are significant because they can operate as an energy buffer by enhancing the energy network's stability, affordability, and dependability through storage.

Vehicle-to-Building (V2B) technology is a highly auspicious energy management system, which enables the optimized regulation of energy between vehicles and buildings. The study under observations extensively discusses the uses and reviewed energy management techniques with respect to V2B integration. In this regard, recent battery storage capacity findings delineate the result by explaining bidirectional power flow and more discharging cycles using V2B [111]. Due to the reported mismanagement by the government of Pakistan, power plants are erected to combat a power shortfall; nevertheless, there is now more generative capacity than is required, and plants are not operating, but incurring fixed costs. The transportation of fossil fuels degraded the quality of the air. Since 2020, three scenarios with 30%, 50%, and 70% EV sales have been thoroughly examined, and on the account of the previous scenarios, it has been established that in 2024, with 70% EV sales, EVs added up to 1250 MW, and with peak demand, they would be in a position to surpass the generating level [112]. In order to amplify the feasibility regarding EV, the analysis was proposed for using railway infrastructure for highway charging stations so electric vehicles could go great distances. The growing economic, security, and environmental concerns provide a strong impetus to transform the existing transportation system into an advanced electrified system. Using the Sim Power system in MATLAB/Simulink to model and simulate a *25kV supply to feed the railway, a feasible option utilizing the railway line was shown. The results proved the scheme's effectiveness in real-world circumstances [79]. Electric vehicles, which utilize electric fuel cells and hybrid energy resources such as batteries and ultra-capacitors, were discussed to satisfy the dynamic requirements of electric motors and auxiliary systems. New technologies and DC/DC converters were suggested for further research, along with the most recent fuel cell electric car advancements and concepts. An analysis of the advantages and disadvantages was conducted using rule-based, optimization-based, and learning-based approaches. Researchers could now work on the software side to create control techniques utilizing artificial intelligence [113].

The electrification of automobiles necessitates fast-charging facilities, resulting in an electric power shortage in conventional networks. Electric vehicle (EV) fast-charging research is provided to examine the problems of power design, energy storage, microgrid control techniques, and energy management optimization. A hierarchical control system for decoupled control in EV charging with the various microgrid system levels is also described. For the optimal performance of EV-charging stations, several control mechanisms and future research topics were discussed [114]. Electric vehicles are the primary solution to the economic and environmental problems posed by internal combustion engines. With the improvement in electric vehicle power drive and battery-charging technologies, Vehicle-to-Grid (V2G) topology is the primary rationale for EV integration in smart grids, as it enables the integration of renewable energy systems into the power grid. The topologies for charging EVs, the effects of EVs, and the smart grid with the V2G scheme are discussed. The study identified some major issues in the EV sector and the direction of future research [115]. Microgrids are a solution to decentralize electrical grids and improve distributed energy resource usage. However, all active players within a microgrid can be computationally expensive. An optimal scheduler is essential for electric-vehicle -charging stations (EVCSs) to meet demands without wasting electricity and flatten peak load on the main power grid. In [116], the authors introduced two novel microgrid models that combine energy generated by a DER, storage with an energy storage system (ESS), EVCS, and electricity trading with the MPG. These models effectively shift load from the MPG while maintaining customer satisfaction and throughput, despite costs incurred by the DER. Real data are used to ensure robustness, and reinforcement learning is implemented to find the optimal scheduler. The COVID-19 pandemic has prompted the energy industry to prioritize renewable energy sources, particularly microgrid systems, to address environmental concerns and establish a sustainable future. A comprehensive assessment of microgrid systems, focusing on optimal design, control systems, and energy management, is provided by the authors in [117]. Key findings include the importance of effective design and control strategies; the integration of renewable energy sources and energy storage systems; advanced control techniques and optimization algorithms; and the application of cutting-edge trends like artificial intelligence, data analysis, and blockchain. A novel MG sizing method is developed in [118] to incorporate metaheuristics into a particle swarm optimization algorithm. The authors considered optimal demand response capacity from EV-charging loads, ensuring reliable electrical load supply in areas far from the grid. An advanced EV-charging demand response program is also incorporated in the proposed strategy. Comprehensive statistics-based performance evaluations indicated that new metaheuristics have the potential to outperform the PSO by up to 6% in MG sizing applications. It indicates the potentially significant implications of using advanced metaheuristics for improving the economics and rollout of capital-intensive grid-isolated 100% renewable MGs. It is anticipated that the exponential growth of electric vehicles (EVs) will make a substantial impact on the transportation sector, given the diminishing efficiency of fossil fuels and the emission of greenhouse gases. Developed and developing nations are concentrating on intelligent charging solutions to satisfy the demand for EV charging. In order to enhance the design and implementation of charging station infrastructure, researchers are additionally analyzing the EV-charging control, EV variants, global charging standards, and AC-DC and DC-DC converter architectures. Furthermore, examining the impact of electric vehicle (EV) collectors and EV penetration on the integration of renewable energy sources into electric energy systems. Increasing demand is being placed on charging technology and power converters that offer a versatile, dependable, and cost-effective charging environment. The researchers are investigating various facets and frameworks of electric vehicle (EV) charging, encompassing charging current, charging duration, charging site, alternating voltage power supply, charging power, battery capacity, industry standards, and charging methods (onboard and offboard). For widespread EV charging, the use of noise filters and semiconductor devices will substantially improve the ability to regulate converter power, and new methods to enhance power quality and grid stability are required [119].

5. Role of Artificial Intelligence in Smart Grid

AI technologies applied to smart grids provide a broader view of how to control and improve smart grids, even if they provide security from hackers, with multiple pricing methods like (ToU) or real-time pricing improve efficiency [120]. Further use of artificial intelligence (AI) in smart grids is necessary to build a criterion for better control and monitoring. Due to the interconnection of networks like the internet, false data detection is important because manipulation and physical change in data can lead one the wrong way; that is why measuring the accuracy of the IEEE 14 bus system is used to judge different scenarios and to compare with previous historical data based on under-concept drift and without-concept drift. A principal component analysis (PCA) test was carried out to measure data accuracy. Furthermore, the effectiveness was checked using the KNN algorithm [121]. Demand response is widely discussed nowadays due to electricity distribution. A scheduling strategy for demand response management provides benefits in terms of cost, reliability, and functionality.

Multiple household scenarios were tested in MATLAB to obtain the confirmation of solutions and particle swarm optimization (PSO) for load management. A cost saving of 39.1% was achieved through the proposed methodology. A plug-in hybrid electric vehicle (PHEV) capable of storing energy and the concept of selling excess energy back to the grid can be incorporated into the system [122]. Figure 7 shows the various domains where AI is used.

Optimal home energy management system (HEMS) scheduling is necessary to decrease the load demand. For this purpose, a multi-objective optimization-based solution is used to shift the electricity load from peak demand hours to non-peak hours by defining the load pattern. For real-time rescheduling, the home appliance coordinated with each other in this study. The scheduler will receive help with the optimal scheduling of the ON/OFF timing of appliances, and it will avoid the waiting time of appliances. Various optimization techniques, such as binary multi-objective bird swarm optimization, a combination of birds' swarm and cuckoo search algorithms, can be combined to achieve the desired outcomes and reduce the cost of electricity bills [123]. Traditional model-based algorithms must be more efficient to address the issues related to renewable energy resources like analysis, control, and scheduling. As such, artificial intelligence is used to deal with massive amounts of data and non-linear problems. There are three different sections into which the whole discussion is divided: (i) optimization control of the power and energy system by AI; (ii) fault detection, state estimation, and parameter identification of power systems by AI; and (iii) forecasting of renewable energy system generation by AI [124]. Different types of AI techniques are represented in Figure 8.

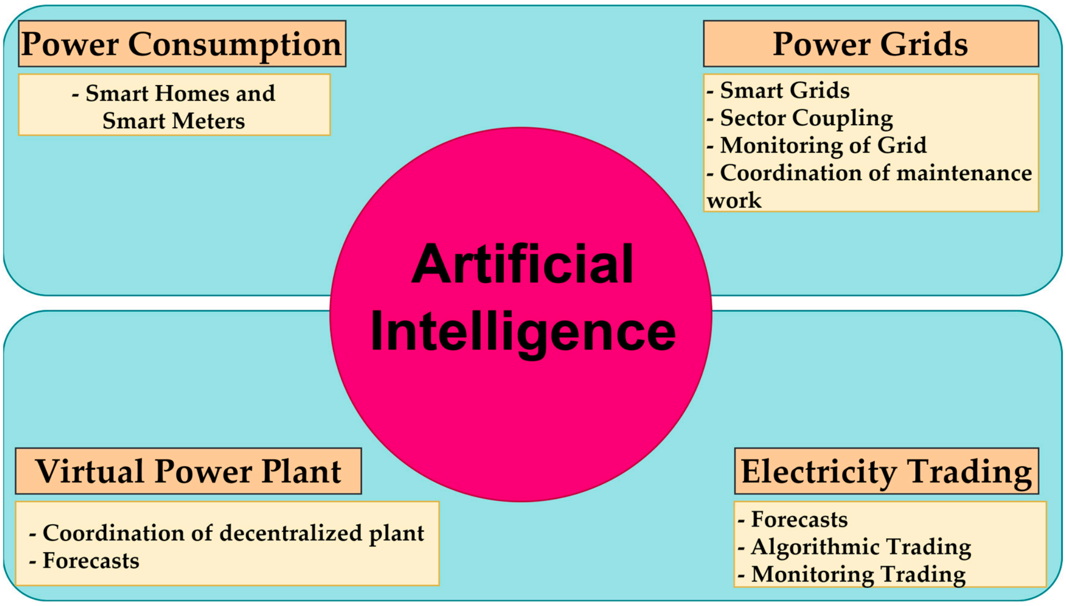

Figure 7. Application Domains of Artificial Intelligence.

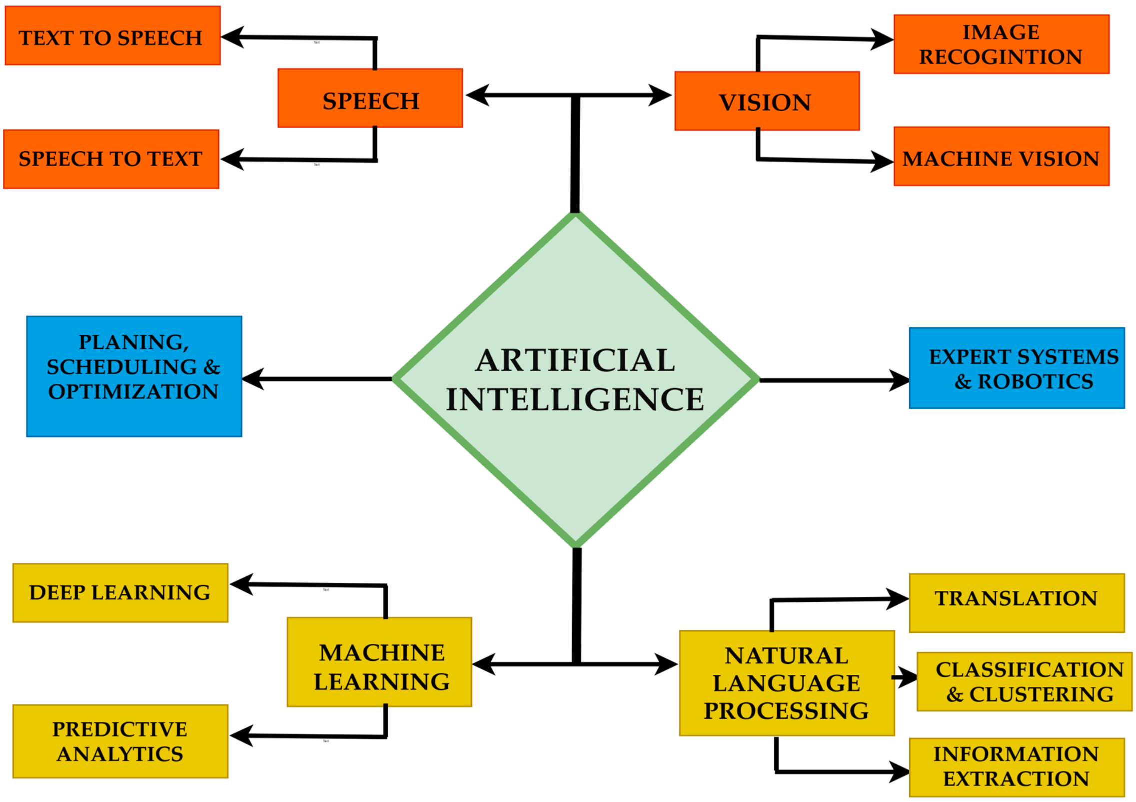

Figure 8. Types of AI techniques.

Another AI-based framework has been developed for uncertainty forecasting and management in smart grids with information analysis functions, data processing, and uncertainty management. Specifically, uncertainties from electric load, solar, and electric vehicles (EV) were modeled. Using improvised-quintile regression neural network (IRNN) probabilistic load forecasting and for handling the missing data, a novel multivariate solar data imputation method was proposed. It outperforms the imputation methods with up to 28% lower mean-squared errors. An uncertain EV-charging management system was distributed, and a multi-agent method was used for uncertainty management in smart grids to achieve 92% less computational time. By this proposed strategy, uncertain smart grid control was achieved by using uncertainty qualification and adequate control strategies [125]. Smart grids rely heavily on artificial intelligence (AI) solutions due to the data-handling limitations of conventional modeling and control approaches. A review of artificial intelligence techniques for load forecasting, power grid stability evaluation, problem identification, and smart grid security challenges has been carried out. Furthermore, the challenges of integrating AI approaches to completely materialize smart grid systems and the prospects for AI applications in smart grids were also examined. The study concluded that smart grid system dependability and resiliency could be improved by employing AI approaches [126]. Grid decentralization is a crucial solution to meet global energy demand by incorporating renewables at the distributed level. Microgrids are driving this decentralization, and an intelligent and reliable energy management system (EMS) is essential for optimal resource utilization. Artificial intelligence (AI) can provide resilient, efficient, reliable, and scalable solutions. In this context, the existing conventional and AI-based techniques for energy management systems in microgrids include analyzing methods for centralized, decentralized, and distributed microgrids. Machine learning techniques, like ANNs, federated learning, LSTMs, recurrent neural networks (RNNs), and reinforcement learning, are summarized for EMS objectives like economic dispatch, optimal power flow, and scheduling. AI can enhance performance efficiency and reliability in managing energy resources, but challenges like data privacy, security, and scalability need to be addressed. Future research directions should explore AI-based EMSs' potential in real-world applications [127]. The integration of energy management systems (EMSs) in microgrids is developed in [128] to optimize energy scheduling, control, and operation. The proposed architecture used the proximal policy optimization (PPO) algorithm for learning stability and complexity. A novel performance metric, namely the burden of load and generation (BoLG), is proposed by the authors to evaluate energy management performance. The BoLG is incorporated into reward settings for optimizing multi-action controls like load shifting, energy charging–discharging, and transactions. As a result, the proposed architecture could improve energy management performance with a proper trade-off between stability and profitability, compared to dynamic programming and double deep Q-network-based operation. The implementation of renewable energy sources (RESs) in remote and rural regions is becoming increasingly prevalent due to its sustainability and dependability. The intermittent nature of hybrid RESs, nevertheless, poses obstacles. A variety of systems, schemes, requirements, microgrid communication challenges, and the application of artificial intelligence are examined by the authors in [129], and it was found that they pertain to the integration of RESs. In addition, potential obstacles and control strategies, optimization methods, and approaches to enhance the performance of the electrical grid are addressed with the help of the efficacy of artificial intelligence in integrating RESs. Rechargeable batteries are crucial for energy storage, but traditional methods often face time and resource constraints. Artificial intelligence (AI), particularly machine learning (ML), has rapidly grown in recent years, enabling the classification and regression of various battery research fields. The authors provided a comprehensive review in [130] of the various fields in which AI has been utilized in rechargeable battery research, including the concept of ML, prediction of battery states and parameters, discovery of key materials for rechargeable batteries, and their use in energy storage charging protocols. The review also highlighted the potential for developing AI's new elements, machine vision, and digital twins in battery research.

Problems, trends, and cybersecurity issues in smart grid (SG) critical infrastructure for big data and artificial intelligence were described, and some combined known and unknowns were proposed. The SG architecture and functionalities are described along with the electrical network's reliability, safety, and efficiency. Furthermore, security countermeasures are exposed, and the cybersecurity assessment method for supervisory control and data acquisition of smart grids is presented [131]. Electric vehicle (EV) adoption, along with the smart grid, has many benefits, like reducing CO_2 emissions, and it also poses some problems that need to be addressed. The concern is to design an algorithm for the cost reduction in EV-charging batteries and to avoid users from being stranded. Artificial intelligence is used to render EVs and systems to avoid the collectives of smarter EVs, and the comparison of different techniques was also presented [132].

Artificial intelligence techniques have mostly been developed in recent decades, and it has applications in power electronics, power engineering, and industrial systems. AI application in smart grid (SG) and renewable energy systems (RESs) is presented [133]. The research explores how AI is used in areas such as health monitoring, wind generation, smart grid system control, and simulating operating conditions. It specifically focuses on optimizing automated generation control (AGC) in multi-area and multi-machine power systems using various AI models, including those for solar irradiance prediction, PV power generation, and power system frequencies. The study proposes a distributed and parallel security-constrained optimal power flow (SCOPF) algorithm for large power networks and evaluates it on an experimental platform consisting of a real-time simulator, weather station, and phasor measuring devices and suggests that these approaches could be applied to other technological domains [134]. In [135], the authors developed an evolutionary reinforcement learning method to address the problem of energy resource management in microgrids and to enhance the share of renewable energy resources in the power grid. The proposed approach employed reinforcement learning and neuro-evolution techniques to find the optimal policy. Therefore, it is more efficient in high-dimensional and continuous action spaces.

5.1. Role of Machine Learning in Smart Grids

An optimal way can be achieved using machine learning techniques to run the grid with analysis and proper decision making. Connectivity and communication are the core parts of any smart grid because massive data are required for decision making. The big data we obtained from the microgrid needs unique analysis techniques to extract the data and handling of the data [136]. The smart grid has transformed the electricity industry with communication technology and sensors, enabling improved generation, monitoring, distribution, and control. To enhance demand-side management (DSM) on the Internet of Things (IoT)-enabled grid, machine learning can be applied. The success of DSM depends on priorities, and a robust model has been developed to control smart grid incursions. Simulation results show that the proposed technique is less effective for incursion but more effective for reducing smart grid power consumption [137]. Figure 8 shows the branches of AI linked with machine learning that is applied in the MG-based EMS.

Demand response (DR) has proven to be highly effective in enhancing the flexibility and dependability of the energy system, and it is increasingly utilized in smart grid energy systems. Artificial intelligence (AI) and machine learning are used to accomplish difficult tasks in DR machine learning (ML). AI addresses all issues associated with the DR, such as the optimal selection of consumers, dynamic pricing, scheduling, device control, and the means to motivate customers fairly and economically. Based on 160 articles, 40 companies, and 21 large-scale initiatives, a summary of the AI technique for DR applications is provided. It outlines the benefits and limits of each technique and provides recommendations for future research [50]. Figure 9 shows the branches of AI linked with machine learning, which is applied in the microgrid-based EMS

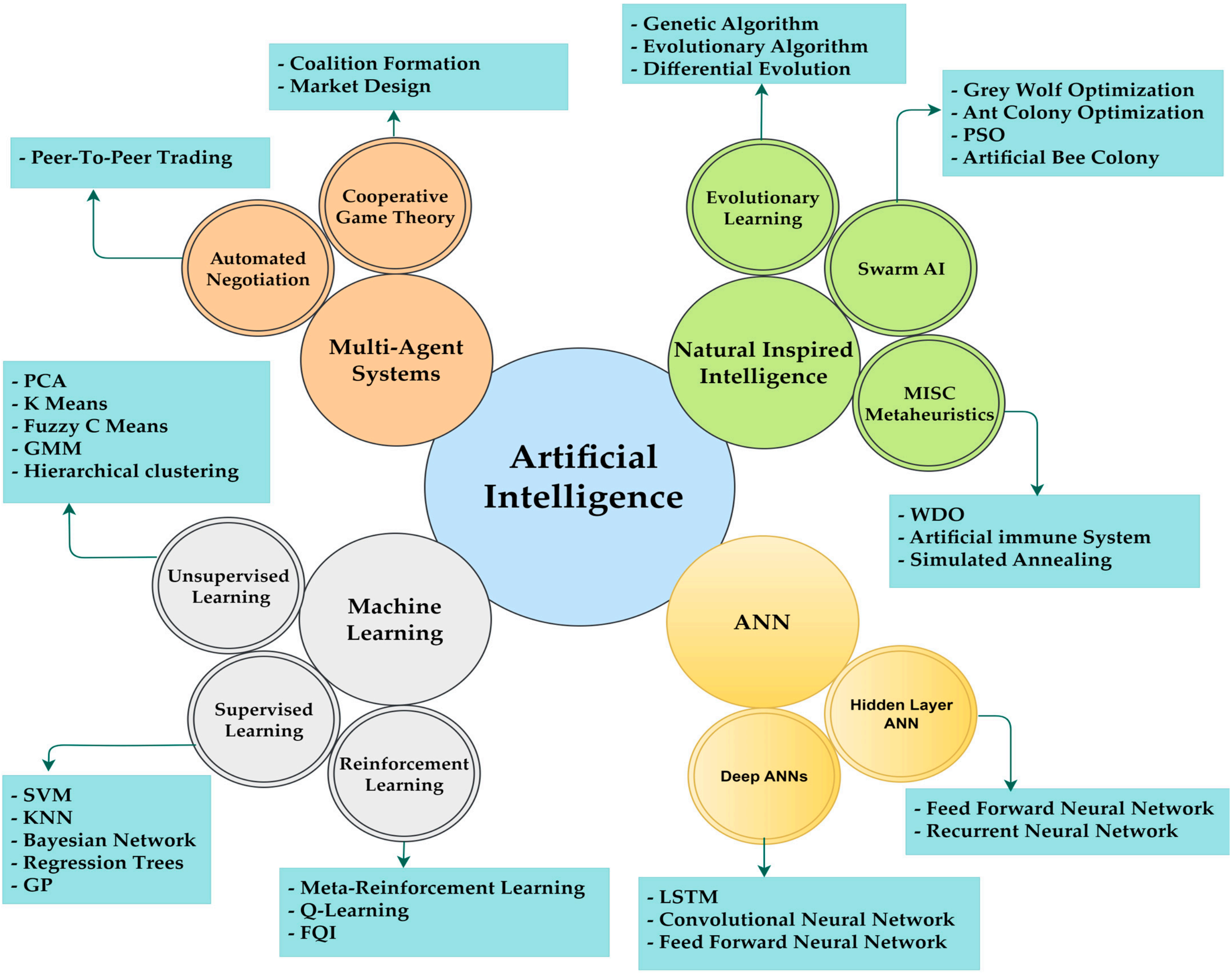

Figure 9. Branches of AI techniques.

The ideal power flow to meet the growing energy demand in the intelligent microgrid is provided. Introducing a blockchain-based predictive energy trading platform enables real-time energy consumption monitoring and the management and production of scattered energy generation resources. Predictive analysis based on historical energy use data was also performed to make better selections. To statistically analyze the predictive model's success, machine learning models also evaluate blockchain platforms based on consumer–supplier service quality and resource utilization [138]. A technique for evaluating cooling load (CL) and heating load (HL) in buildings using multiple forecast models is described. The technique uses a hybrid machine learning approach that combines group methods of data handling (GMDH) and Support Vector Regression (SVR) models with Back-Propagation Neural Networks (BPNNs), Elastic Net Regression (ENR), Partial Least-Squares Regression (PLSR), K-Nearest Neighbors (KNN), and general regression neural networks (GRNNs). The results show a high correlation coefficient (R) of 99.92% for CL forecasting and 99.99% for HL forecasting with minimal statistical error [139]. Implementing prediction and optimization models based on machine learning yielded impressive results. The algorithm's implementation of this concept consists of four steps. The initial and second stages work on the day's pricing before the market, which is completed by the higher performance of neural network design. The support-vector-based architecture of the consumer is also offered for orders of 1 MWh. In the final stage, reinforcement learning architecture based on Q learning is implemented to optimize the economics of electricity transactions. In the third stage, SAM NREL simulates commercial-scale PV connected to a microgrid with a capacity of 600 kW; in the final stage, reinforcement learning architecture based on Q learning is implemented to optimize the economics of electricity transactions. The total Python code is provided as a framework that fosters the renewable portfolio by reducing its reliance on supportive federal and state laws [140]. There is a possibility of false data incursion on the large data sources in the smart grid (SG), posing a significant threat and having serious consequences for the system. Various machine learning (ML) methodologies were developed, and their progress was assessed. The architecture of SG is examined in light of fake data assaults defined based on security requirements. ML techniques are then characterized based on detection situations, such as technical loss, load forecasting, and state estimation. The study suggests future research directions to address the limitations of the current machine-learning-based approach [141].

5.2. Cybersecurity Threats and Their Remedial Measures in Smart Grid

Power grid monitoring and control rely on communication networks. Still, the scourge of false data injection (FDI), which insidiously creeps into the network systems at times, can undermine the seamless working of power grids. Nonetheless, networks can control it by pre-empting the origination of errors through state estimation with SE variables relative to the actual values. The test system of IEEE 14-bus is primarily utilized to anatomize different scenarios in power grids [142]. The most forbidding impediment in establishing an innovative smart grid is to formulate its robust and unbreachable security mechanism, as cybercriminals, hackers, and terrorists usually exploit the vulnerability of open networks. The cardinal notions behind directing this analysis are to examine and adopt tried-and-tested methodologies for successfully averting cyber-attacks and uproot them to gain utter control over networks. The aforementioned notion of purging smart grids of the recurring cyber-attacks can only be materialized by smartening up the security mechanisms [143]. Figure 10 shows the vital role of cybersecurity in a smart grid.

Smart metering inventory (SMI) or advanced metering infrastructure (AMI) provides a secure connection between users and suppliers through two-way communication. It sharply monitors data at the consumer end, e.g., time of use (ToU), real-time pricing (RTP), critical peak pricing (CPP), and transmits feedback to database management systems (DBMs) through SMS or signal. This paper extensively sheds light on the hazards that originate from lax cybersecurity surveillance, often leading to dire ramifications. Nonetheless, the paper also analyzes the remedial measures to forestall such threats [144]. The prime motive of this paper is to provide a well-conceived protective mechanism and to build an impregnable safety wall against all types of hackers and attackers. Cybersecurity is a confronting issue today because the smart grid's considerable data are shared through communication networks and can be secretly accessed by hackers. Smart grids should be capable of identifying and classifying threats and protecting the confidentiality, integrity, and availability of information resources against hackers to uproot the menace concerning cyber-attacks [145].

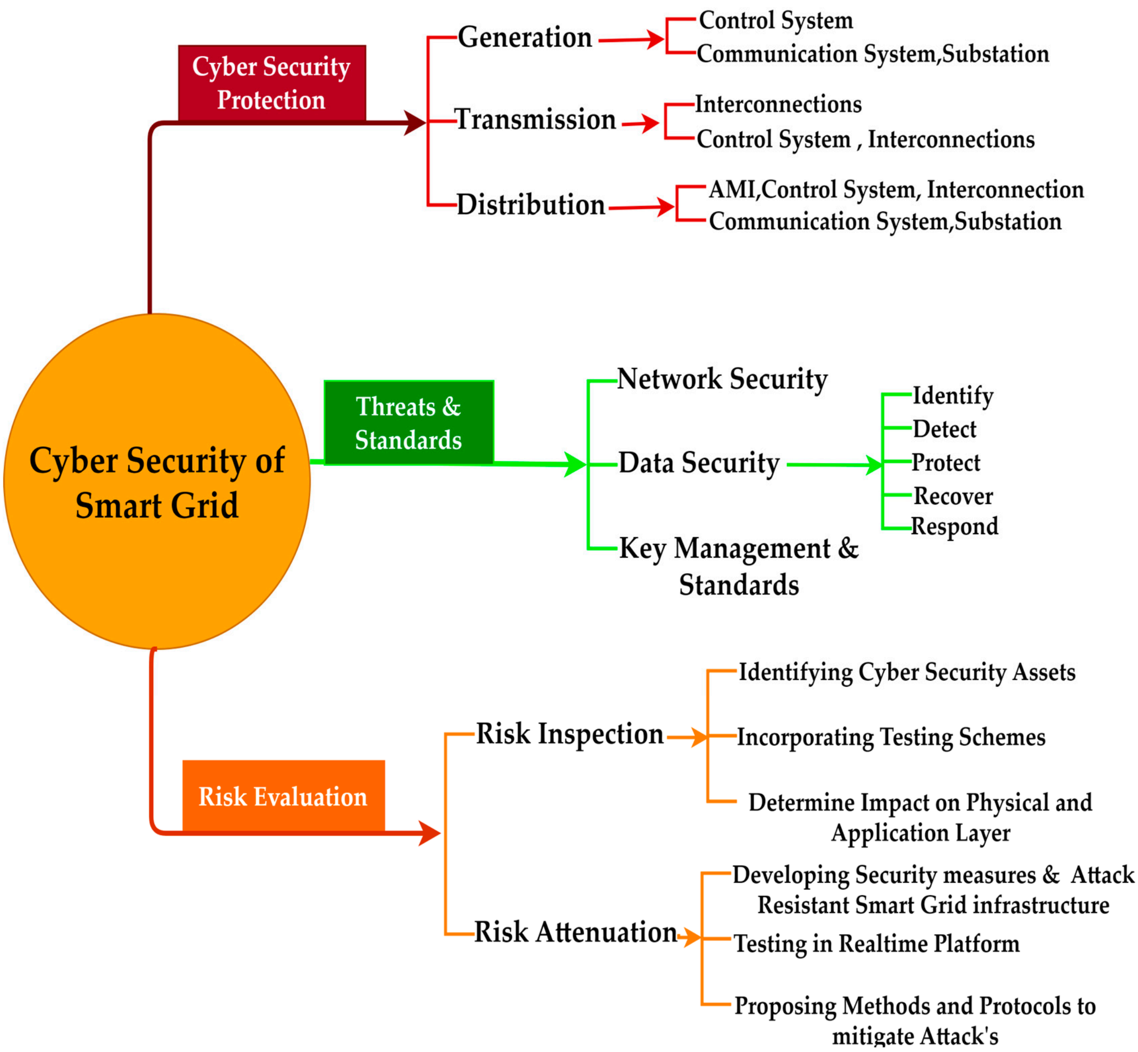

Figure 10. Role of cybersecurity in smart grid.

6. Greenhouse Gas Emission Reduction

The rampant amplification of pollution worldwide raises a red flag for scientists and is seemingly dragging scientific society toward the brink of an utter fiasco. Carbon emissions are an inevitable concomitant of the fossil-fuel-based energy generation system. So, integrating renewable energy resources is an optimal solution to resolve this issue effectively. In order to significantly subside the proliferation of carbon emissions, the optimal allocation of renewable energy resources and their capability to inject active and reactive powers into distribution networks are indispensable. The fundamental ambition was to reduce the power loss current between the reference buses and the buses where distributed generation systems (DGSs) are meant to be installed. This method was prudently tested on numerous buses of radial distribution networks to find ways to reduce energy loss. The developed modus operandi was applied on the bus network (IEEE69 and 39 Buses), and subsequently, definitive results were generated [146]. The proposed model in another research comprised resources being used, such as combined cooling, heating, power, gas, and water-based MG, where water would be extracted from a well during different intervals. In the previously mentioned scenario, power demand increased, and a stochastic optimization model seemed perfectly adequate to minimize the uncertainty concerning electric load and operating and emission costs [147]. The microgrid is an effective resource for introducing distributed energy resources (DERs) into the existing grid supply. Microgrids with DERs, electrical vehicles (EVs), and electrical storage systems (ESSs) are compared with the conventional power network and, subsequently, are analyzed to ascertain the results. The mechanism of a microgrid is elaboratively delineated with this control strategy. Some issues concerning power quality (PQ) and energy management strategies by the DER-based microgrid are also addressed. The simulation was performed to gauge the effectiveness of solar, wind, ESS, and EVs on microgrid frequency response. Additionally, the reliability of the microgrid was also estimated with the help of connected DER systems, ESSs, and EVs [148].

There is an unprecedented increment in the popularity and usage of renewable energy sources (RESs) in microgrids owing to their power generation capacity and environmentally friendly power generation capability. Unfortunately, the reliability and security of the system are compromised due to the integration of RESs. There is a requirement for an optimized control strategy to ensure efficient and secure power transfer. The discussion of optimized control strategies for the microgrids consisting of RESs based on structure, characteristics, operation, function, and pros and cons was emphasized. A rigorous review concluded that the optimized control schemes could increase the efficiency of the operation of RESs into microgrids. Some of the strategies are constricted to simulation only, so there is a genuine need to undertake extensive research in this field [149]. Global energy awareness was instrumental in shifting the focus towards the smart grid with solar systems and battery storage. Demand-side management (DSM) plays an essential role in smart grid operation, so in this study, a combination of Glow-Worm Swarm Optimization (GSO) and Support Vector Machine (SVM) is proposed to subside the electricity tariff. GSO is utilized to discover the optimum solution for power scheduling to reduce the cost significantly and to find the optimized range of battery storage energy. SVM uses that data set to find the in/out power from the battery for price minimization. The electricity tariff owing to this strategy plummeted by 11.2% as the reduction transpired from 2.3 to 2.27 at a load of 8.2 kWh/day, and consequently, it resulted in a shift in policies toward demand-side actions for system stability [20]. Furthermore, the mixed-integer linear programming method was used to transform a bi-objective optimization into a single-objective approach. The model was tested on a microgrid comprising 1000 smart homes with various DSM levels. Simulation results indicated that this model was cost-effective and an optimal way to plan and operate the system while considering economic and environmental factors [150].

Economic, environmental, and cost-effective energy supply and storage systems provided in the ship are proposed using a fuzzy self-adaptive meta-heuristic algorithm. Optimal solutions and better convergence characteristics were used using traditional methods like fuzzy-based particle swarm optimization (FPSO) algorithms. The fundamental purpose was to provide an integrated electric propulsion system, energy storage system, and shore power supply facility to ships [151].

7. Uncertainty Handling in Microgrid System

The high cost of energy and greenhouse gas emissions are ongoing challenges that renewable energy sources can help. In [152], a stochastic framework is proposed to optimize microgrid scheduling and prevent load shedding due to unpredictability while maximizing profit. The stochastic multi-objective model is also suggested to reduce planning costs and increase resilience during natural disasters [153,154].

The reliance of solar cells on irradiance level and partial shade condition (PSC) necessitates the utilization of the maximum power point tracking (MPPT), which delivers the maximum power point under PSC. A method for determining the MPP under uniform irradiance conditions (UICs) and PSC was investigated using the mathematical formulas of PV system behavior. In terms of tracking speed, low sampling time, and stable steady-state conditions, simulation and experiments improved the performance of the proposed method [155,156]. To optimize energy market profit, it is proposed to schedule Hybrid Thermal–Energy Storage (HTES) generation. In HTES, the energy storage system (ESS) is physically linked to the thermal units in order for ESS charging to be possible. Similarly, mixed-integer programming is used to formulate the proposed resilient optimization architecture, which can account for market unpredictability (MIP). The problem was resolved using the GAMS (General Algebraic Modelling System) program [82].

Recent research completed with the software HOMER pro discusses the numerous solutions for meeting the mine's Western Australian electricity needs. A risk-constrained optimization technique is developed using Monte-Carlo uncertainty models to provide optimal scheduling, cost, and conditional value at risk (CVaR) [24]. A risk-constrained optimization technique using Monte-Carlo uncertainty models is developed for optimal scheduling and cost analysis of Western Australian mine's electricity needs. A risk-constrained stochastic algorithm for resilient microgrid operation using demand-side management is also beneficial [157,158]. While a multi-objective bidding method for wind–thermal–photovoltaic systems in the deregulated power market to reduce costs and emissions. These studies demonstrate the importance of utilizing renewable energy sources and optimizing energy systems for economic and environmental benefits [159,160].

Hybrid power producers (HPPs) consist of concentrated solar power plants (CSPPs), wind turbines, demand response systems (DRSs), and compressed air energy storage (CAES) units. The research studies focus on optimizing the performance of the HPP and minimizing risk through the use of various techniques. Another technique introduces a distinct model for achieving optimal behavior of CSPP-based hybrid power producers (HPP) in day-ahead (DA) and intraday markets using a three-stage architecture. To compare different techniques for the same challenges, by applying conditional value at risk (CVaR) based on the GBP constraint technique, the utilization of CSPP-based HPP reduces the associated risk making it advantageous [161,162]. In a separate piece of research, a hybrid power production system consisting of a concentrated solar system, a storage system, a wind turbine, and a demand response provider was designed to operate in energy markets. The study developed a mixed stochastic–interval model using stochastic and interval parameters to address the uncertainties of demand response and solar energy. The proposed model was optimized with boundary intersection and lexicographic optimization and demonstrated that the model satisfies all its requirements [163,164]. A risk-averse stochastic bi-level programming method for a retailer's competitive market decision making. The method utilized electric vehicles and sensitive loads to monitor real-time prices and identify the most cost-effective vendors. The non-linear stochastic model was converted into an equivalent linear single-level program using Karush–Kuhn–Tucker optimality constraints and duality theory. The study demonstrated the applicability of the proposed model in real-world settings [165].

The autonomous operation of hybrid microgrids (HMGs) utilizing the unified interphase power controller (UIPC) to integrate AC and DC subsystems, which maintains bidirectional power flow using Model Reference Adaptive Control (MRAC). A new structural scheme for the UIPC's power converter and a harmonic-based modeling technique are introduced, and simulation results corroborate the acceptable islanding performance of HMG's proposed design [166]. A hierarchical stochastic management system is also proposed to manage interconnected grids, with a central entity responsible for connectivity and power reference values exchanged with microgrids for both the main and within the grid. Predictive control is derived from chance-constrained models for the local operation management of microgrids, taking into account system component unpredictability [167]. A discussion of the optimal scheduling approach for reconfigurable microgrids, taking into account the islanded capacity constraint and the probability of islanding operation (PIO) indicator, which assesses the likelihood of islanding. To address the non-linearity of the PIO issue and the error in the generation forecast, the 13-interval approximation technique is used. To validate the findings, a 10-bus radial reconfigurable microgrid that includes PV systems, wind turbines, batteries, and microturbines with varying levels of PIO is used as a test system [168]. An effective optimization framework is also discussed based on opportunity-constrained constraints for the optimal management system consisting of electrical load, heating load, cooling demand, and renewable energy generation. Energy hub (EH) operators use the proposed scheme for optimal decision making. Despite the unpredictability of renewable power supply and hourly demand, a strong opportunity-constrained model simulating real time is implemented. Some operators are accountable for the optimal operation of the hub's assets using day-ahead scheduling. A numerical stability test is conducted on the step time size to validate the time resolution independence of the solution [169].

8. Optimization Techniques Used for Energy Management System

For effective scheduling of distributed energy resources (DERs) in the system, a transactive energy (TE) strategy may be considered. The microgrid participates in energy exchange not only to meet the demand of the primary grid, but also to create a profit. Dynamic balancing and energy supply management facilitated by TE can also produce the similar results. Due consideration was given to commercial five-grid participation in the day-ahead market using an IEEE 10-bus test system to validate applicability and performance. The collected results demonstrated that by scheduling DERs using the proposed method, we could receive the greatest possible profit [170]. Controlled microgrids can reduce the complexity of distribution networks, which are growing increasingly intricate to meet energy demands and consumer satisfaction. A facility for testing hybrid microgrids was shown, demonstrating the high-efficiency distribution architecture that incorporated AC/DC communications. In addition, evaluations of control, architecture, and performance, as well as hardware and software, are conducted using various converters and a static synchronous compensator (STATCOM) to assess performance [171]. The expansion of energy resources and their addition to traditional distribution is becoming more complex. In the power part, the writers described the resistance to introducing microgrids and how adopting microgrids would reduce energy loss. The software used for microgrid homework is capable of performing three primary functions. Simulation, sensitive analysis, and optimization can be utilized to achieve optimal operation [172]. The energy industry will be profoundly affected by big data technologies. Through the application of cross-domain data, a big data platform facilitates the production, development, monitoring, and exploitation of smart energy resources. A web-based decision support system for multi-source data to assist in the design of energy management plans was developed. The implementation of DSS results in a considerable decrease in energy consumption, a reduction in CO2 emissions, and a 10% increase in energy production from renewable energy sources. The conclusion is that the outcome is always determined by the present condition and future goals [173]. Given the current state of the environment and economy, utilizing hybrid energy sources is essential. Domestic consumption of heat and electricity is growing. Real-coded genetic algorithms are utilized to attain optimal operational costs in smart homes. Consideration was given to the thermal and electrical loop that includes a boiler, a battery energy storage system, and an electric vehicle in addition to a conventional load. Numerous tests and observations revealed that a micro combined heat and power system's electric load plays a significant impact in lowering total energy costs [13].

The authors compared various EV-charging methods. Two-way power flow enables users to sell excess energy back to the grid. During the study, it was determined that flexible billing mechanisms were advantageous for both customers and utilities and had a substantial positive effect on the economy [174]. Renewable energy resources (RERs) and energy storage systems (ESSs) are extremely beneficial for nations with a severe shortage of electrical energy. The study offers methods for Home-to-Grid energy management (H2G). It provides the following:

- Methods for improving energy performance.
- Lower energy costs.
- Reduced uncertainty through the integration of PV and ESS while considering user preferences.

The GA algorithm was applied to optimize its scheduling and energy management, yielding considerable results [14]. Table 5 shows the optimization methods used in the smart grid system.

Table 5. Optimization methods used in literature.

Techniques	Optimization Methods	Functions and Key Objectives
Deterministic Techniques	MILP [11,110]	MILP is used for optimization, and it is easily operatable on CPLEX Solver, which is used in unmanned aerial vehicles (UAVs) to simulate their movement ways.
	Dynamic Programming Algorithms (DP) [175]	It is used to solve optimization issues, robot control, navigation systems, and dependability design.
	MINLP [11,71]	Mixed-integer non-linear programming (MINLP) is a strategy to solve the optimization problems involving continuous, discrete, and complex variables.
Metaheuristics Techniques	Particle swarm optimization (PSO) [16,18,28,29,68,151,176]	PSO is an algorithm to address optimization issues like power management and it can be utilized for graphical effects.
	Genetic algorithms (GA) [12–14,19,55,175]	The genetic algorithms are used to find a comprehensive architectural solution and are also used for image processing, learning of robot behavior, and distributed applications for data collection.
	Artificial Fish Swarm [68]	Artificial Fish Swarms have frequently handled issues, image processing, data clustering, robotics, wireless sensor networks, power systems, financial forecasting, and medical diagnosis, as well as great precision. There are some other applications like neural network studies, color leveling, data segmentation, etc.
Artificial Intelligence Techniques	Artificial Neural Network [50,105,125,139]	There are a lot of applications of deep neural networks like handwriting recognition, picture compression, and stock exchange prediction.
	Fuzzy Logic [147,151]	This is very useful in spaceflight of the automobile industry, enhancement of transmission system's performance, and traffic control.
Special Techniques	Elephant Herding Optimization [22]	This is a natural-phenomenon-inspired optimization algorithm that depends on the herding behavior of elephants.
	Pontryagin's Minimum Principle [23]	This is a principle that is utilized in optimal control theory to find the optimal control over a system by having the constraints on states and input in mind.

9. Future Scope and Challenges

The integration of energy storage systems, electric vehicles, and artificial intelligence can offer promising opportunities for microgrid energy management. These include multi-objective optimization, efficient V2G integration, predictive EV load forecasting, grid-aware EV routing, and EV-integrated microgrid management. Advanced energy storage systems, distributed management, AI-driven control, and hybrid design are some of the microgrid applications for these advanced technologies. The future of AI-powered microgrid management and control includes deep reinforcement learning for optimal decision making, machine learning for anomaly detection and fault diagnosis, federated learning for distributed microgrid intelligence, explainable AI for microgrid transparency, and AI-based predictive control. Microgrids require strong cybersecurity frameworks, secure data collecting, storage, and access control, as well as blockchain-based security solutions, to provide cybersecurity and data privacy. Additionally, standardization and interoperability are crucial for open-source platforms and standardized data formats encouraging research and development.

Similarly, in future prospective buildings, energy management systems can be connected with grid-interactive buildings to provide coordinated control of loads and renewable energy sources. Community dynamics and user behavior modelling are examples of human-centric techniques. Microgrid technologies' lifecycle assessments analyze their effects on the environment and point out areas where sustainability can be improved. Adaptive control techniques, interoperability standards, resilience measurements, and policy frameworks for microgrid integration are some examples of regulatory and policy considerations. Through these initiatives, sustainable energy management techniques will be promoted, and the overall stability and security of the energy infrastructure will be improved.

Interoperability, cybersecurity risks, regulatory barriers, funding and cost issues, limited scalability, standardization issues, policy uncertainty, grid connection issues, community engagement, technology obsolescence, environmental impact assessments, grid resilience requirements, complex permitting processes, low awareness and education, energy market integration, ageing infrastructure, land use and zoning, reliability and maintenance, public perception, and limitations to energy storage are just a few of the challenges that microgrids must overcome to be integrated. While cybersecurity threats involve cybersecurity vulnerabilities, interoperability issues involve the smooth integration of various microgrid components and technologies. The specific qualities of microgrids may not be sufficiently addressed by regulatory restrictions, impeding their widespread implementation. Regions with limited financial resources face issues due to costs and budget limits. Energy storage solutions, such as batteries, can be expensive to install and maintain, with limited capacity. Efficiency charging patterns in microgrids can be unpredictable, and integration with microgrid management system requires sophisticated algorithms and data analysis. The widespread adoption of EVs in microgrids is hindered by the high initial infrastructure costs and enhances the need for clever pricing strategies. AI algorithms require accurate and high-quality data for accurate predictions and optimal energy management decisions.

10. Conclusions

The researchers have managed to track down numerous technological anomalies in the microgrid system that impede its seamless functionality and plunge its efficiency. The energy management system, especially DSM, is optimized using demand response strategies. Hybrid DR schemes should be comprehensively perused in the literature to present a tangible solution for the existing technological issues. One major obstacle hindering the smooth operation of the smart grid is uncertainty encompassing renewable energy resources. In the modern era, AI techniques are extremely beneficial in rendering smooth technological operations and diminishing uncertainty regarding renewables and energy demands. Different optimization techniques, such as metaheuristic techniques, are incorporated in the literature that offer dynamic solutions. The techniques based on machine learning are more resourceful and robust for many applications. So, ML-based techniques are highly recommended for future work. In the energy management system, the energy storage mechanisms are integrated into the system for numerous purposes. Batteries are preferred as a primary storage source compared to mechanical energy storage. The system with cybersecurity is indispensable to assure the safe and hazard-proof operation of the power system.

Recently, microgrids are becoming increasingly popular in addressing the widely prevalent issues concerning the production and distribution of electrical power. In this paper, comparative analysis has been conducted to investigate the various optimal approaches for the efficient functionality of microgrids in tandem with figuring out how to optimize demand-side load management.

The results of the comprehensive analysis point out numerous areas for improvement in the existing microgrid systems that bring about inefficient energy management due to the recurrent utilization of outdated techniques. Furthermore, the paper examines the potential of DR and DMS techniques and observes the role of utility-side management (USM), generation-side management (GSM), and demand-side management (DSM) to smarten up the overall energy management (EM) system.

The study reveals that DR management can be further divided into two distinctive responses; the first is incentive-based demand response (IBDR) and the other is the price-based demand response (PBDR) that further integrates factors like energy demand reduction, load side control, and time of use, which ultimately provide an understanding of the demand response management strategies. The review paper further signifies using an energy storage system (ESS) to optimize the consumption of electrical power and, subsequently, presents a solution of using the combination of EESs and RESs for considerable cost reduction and to handle fluctuation in the system effectively. The paper also incorporates the growing importance of electric vehicles (EVs), which would help subside carbon emissions and, as a result, would reduce the greenhouse effect. Hybrid electric vehicles are the most advanced versions of electric vehicles available today and are deemed to be the most integral part of the intelligent transportation system (ITS).

Moreover, the study emphasizes that technologically amplifying AI-based equipment bodes well for secured and reliable electrical power transmission. The AI systems under discussion include machine learning, natural language processing (NLP), robotics, and machine vision. They act as vital components to effectively handle the uncertainties in load management and process the data in microgrid management. The insidiously spreading threat of cyber-attacks is also discussed in this paper, which needs to be pre-empted through optimized AI-based security modules. The methods discussed in the paper significantly reduce the possibility of false data injection (FDI) in the communication systems of the microgrids. It can also be observed that the values of real-time pricing, time of use, and critical peak pricing can be falsified through illegitimate intervention, and consequently, could cause major problems for both the suppliers and the users.

Author Contributions: Conceptualization, M.R.K. and Z.M.H.; methodology, M.S.B.; software, F.H.M.; validation, M.S.B., M.R.K. and Z.M.H.; formal analysis, F.H.M.; investigation, Z.M.H.; resources, M.S.B.; data curation, Z.M.H.; writing—original draft preparation, M.R.K.; writing—review and editing, K.S.S.A.; visualization, F.M.A.; supervision, K.S.S.A.; project administration, K.S.S.A.; funding acquisition, F.M.A. and K.S.S.A. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Department of Education of Guangxi Autonomous Region under grant number 2023KY0826.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The corresponding author can provide access to the data on request, which was analyzed for this research.

Acknowledgments: The authors are highly grateful to their affiliated universities, institutes and the Office of Research Innovation and Commercialization (ORIC), The Islamia University of Bahawalpur, Pakistan (Project No. 3900/ORIC/IUB/2021), for providing the state-of-the-art platform required for research facilities.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric Vehicle
ESS	Energy Storage System
AI	Artificial Intelligence
V2G	Vehicle to Grid
AMI	Advanced Metering Infrastructure
ANN	Artificial neural network
PSO	Particle swarm optimization
WDO	Wind Driven Optimization
LSTM	Long Short-Term Memory
SVM	Support Vector Machine

KNN	K-Nearest Neighbor
GP	Gaussian Process
PCA	Principal Component Analysis
GMM	Gaussian Mixture Model
MTGS	Micro Gas Turbine Generation System
ICT	Information and Communication Technology
DRP	Demand Response Program
BESS	Battery Energy Storage System
CHP	Combined Heat and Power
DR	Demand Response
HOMER	Hybrid Optimization of Multiple Electric Renewables
MIP	Mixed-Integer programming

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