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Review

Current Status, Challenges and Future Perspectives of Operation Optimization, Power Prediction and Virtual Synchronous Generator of Microgrids: A Comprehensive Review

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Abstract

With the increasing prominence of the energy crisis and environmental problems, microgrid technology has received widespread attention as an important technical means to improve the stability and reliability of new energy access. Focusing on the latest development of microgrid operation control technology, this paper combs and summarizes the related research at home and abroad, including the key technologies of microgrid optimization operation, power prediction and virtual synchronous active support control technology, and points out their advantages and limitations. First, this review describes the concept and structure of microgrids, including components such as distributed power sources, energy storage devices, energy conversion devices and loads. Then, the microgrid optimization operation technologies are analyzed in detail, including energy management optimization algorithms for efficient use of energy and cost reduction. Focusing on microgrid power forecasting techniques, including wind energy and PV power forecasting and load forecasting, the contributions and impacts of different power forecasting methods are summarized. Furthermore, the inverter control strategies and the stability mechanism of the virtual synchronous generator (VSG) active support control technology are investigated. Finally, synthesizing domestic and international microgrid development experience, this review summarizes the current state-of-the-art technologies, analyzes the advantages and limitations of these key technologies (including optimization scheduling, power prediction and VSG-based active support control) and highlights the necessity of their continuous improvement to provide a solid foundation for promoting the widespread application and sustainable development of microgrid technology.

Keywords: microgrid; operation optimization; power prediction; virtual synchronous generator

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1. Introduction

In recent years, the rapid economic development is accompanied by the increasing demand for energy, and the world is gradually facing problems such as the shortage of conventional fossil fuels and environmental pollution. With advances in small generators, energy storage devices and power electronics and the gradual rise in fuel costs, building large, centralized power plants in many cities is not an optimal solution. Therefore, the microgrid is replacing centralized power generation as a new power system [1]. The microgrid has a high penetration rate of renewable energy, in particular wind and solar, which accounts for 91% of the global renewable energy generation capacity [2,3].

With the continuous improvement of the comprehensive utilization of renewable energy technology, wind power and photovoltaic (PV) power generation, as emerging energies in many countries, play an important role in the strategic energy structure, promoting the rapid development of the industry. Since 2000, the installed capacity of wind power and photovoltaic in the world and China have shown a doubling growth [4,5]. The global cumulative and new installed wind power capacity from 2015–2024 is shown in Figure 1 [6], and the global cumulative and new installed solar PV capacity from 2015–2024 is shown in Figure 2 [7]. Data from the Global Wind Energy Council's (GWEC) Global Wind Power Development Report 2024 show that between 2015 and 2024, the cumulative installed capacity of global wind power increased from 433 GW to 1167 GW, with a compound annual growth rate of 11.12%. In 2024, the global new installed wind power capacity reached 155 GW, while China's cumulative installed wind power capacity exceeded 500 GW, and its cumulative installed solar PV capacity reached 886 GW. China's wind power capacity accounted for over 50% of the global cumulative total, and its solar PV capacity represented 44.54% of the global cumulative installed capacity. Clean energy is projected to exceed 85% of the global energy mix by 2050.

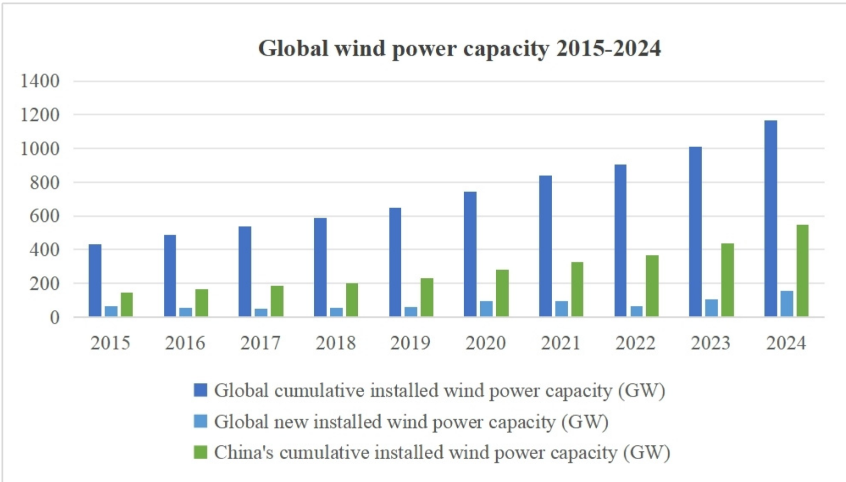


Figure 1. Global cumulative and new installed wind power capacity from 2015–2024.

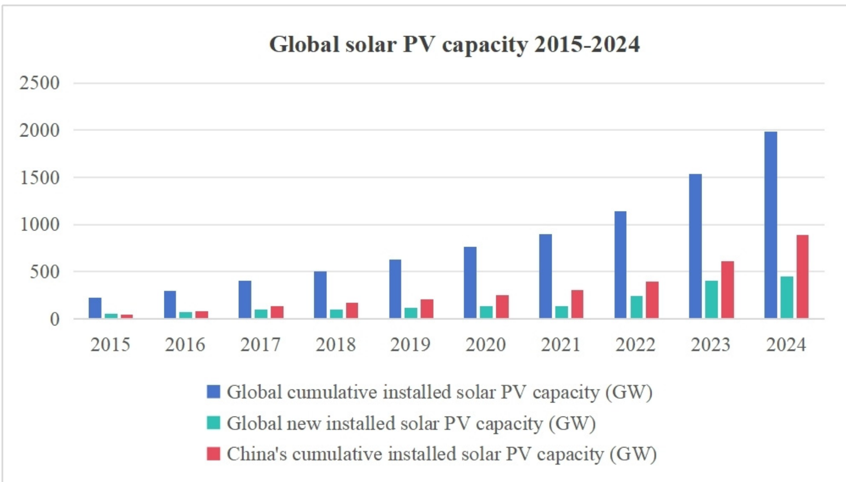


Figure 2. Global cumulative and new installed solar PV capacity from 2015–2024.

The inherent flexibility of the power system can accommodate a certain amount of intermittent renewable energy, but as it enters the medium to high or extremely high ratios, the system will face multiple challenges in different time scales, such as stability control, operation and planning. With the large-scale application of renewable energy, the penetration rate is increasing, and the continuous development of intelligent technology and the construction of a new type of power system are accelerating. In order to ensure the stable and reliable operation of renewable energy grid-connected power generation, microgrids have become an important solution to the problem of the power systems in some countries. Among them, the current status and development trends of microgrid operation optimization technology, the research progress and trends of microgrid power prediction technology, virtual synchronous control technology and other key technologies have attracted significant attention from academia and the industry and have played a key role in promoting the innovation of microgrid technology [8–10]. In recent years, many countries, such as the United States, China, Japan and Europe, have carried out the research of microgrid technology and made important progress, successfully addressing theoretical problems related to microgrid operation, protection, economy and so on [11–13].

The renewable energy microgrid is an important construction object to promote the green development of new power systems. With the increasing application of intermittent renewable energy sources in the new-generation microgrids, the share of renewable energy in energy supply is gradually increasing. This decarbonization transition from fossil fuels to renewable energy not only reduces the controllability of microgrid power output but also introduces uncertainty. Both wind and solar power renewable energies have inherent characteristics such as randomness, intermittency and volatility. In addition, wind power has anti-peaking characteristics. Load demand can also exhibit stochastic behavior, and load demand and renewable generation usually have different peak and valley characteristics. These uncertainties lead to certain difficulties in the stable operation and optimal dispatch of the microgrid after the renewable energy is connected [14]. Therefore, the most central problems of microgrids are the optimized scheduling and power quality control of the distributed power sources, the distributed energy storage, the loads and the grid [15]. The optimal scheduling of microgrids is beneficial to improve the consumption capacity of distributed energy, such as wind power and solar PV power, in the distribution grid, increase the utilization rate of renewable energy and reduce the losses and operating costs of the distribution grid. The source-load-storage multi-type, flexible resources are fully coordinated and interactive in the microgrid-source, load, and storage are no longer an independent operation, but are combined through the power grid framework to realize the interaction of the coupled system. The participation of different types of flexible resources greatly enhances the interaction capabilities among the source-side renewable energy, energy storage system and users in the process of microgrid optimization. Shifting load demand from peak to trough of electricity consumption improves the consumption of the distributed power supply, while the flexible resources on the energy storage side are fully utilized. By absorbing excess renewable generation and releasing electricity at peak times, shifting renewable energy output is realized on a time scale. In addition, the accuracy of wind power, solar PV power, and load power prediction in microgrids constrains the optimal dispatch of the microgrid and affects the full utilization of renewable energy. Therefore, accurate power prediction is an important research direction for renewable energy microgrid energy management systems (EMSs) [16]. Therefore, this paper introduces and summarizes the latest theoretical results of the operation optimization strategy and the power prediction of microgrids in detail.

The microgrid can operate either in grid-connected mode or independently (islanded mode). Regardless of the operating mode, the system requires appropriate control strategies to ensure the reliability and stability of the power supply, and hierarchical control is widely used in power systems [17,18]. The hierarchical control structure of the microgrid is shown in Figure 3. Optimal scheduling calculations of the microgrid occur at the upper decision-making layer (third layer), which regulates the power flow direction of the microgrid and the power grid, solves the optimal scheduling problem to calculate the power of each distributed source and sends it to the second layer control to ensure the stability and economy of microgrid operation. The second layer control regulates the output voltage amplitude and frequency of the inverter through the control signals sent from the given values of the first layer control of the distributed power supply and realizes the balance of the power and stabilization of the main grid system. The signal collected by the first layer control is the local signal of the controller, which generally refers to the power, current and voltage control of the converter [19].

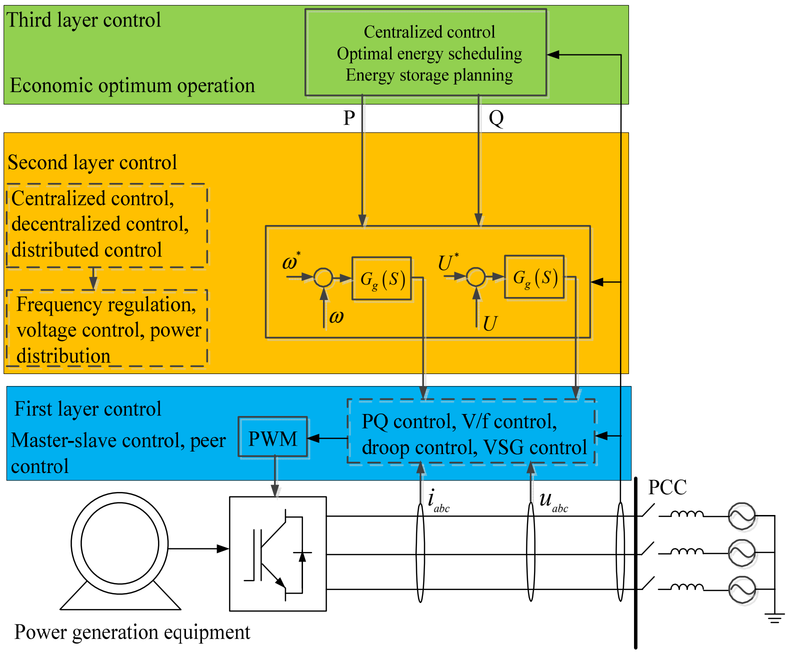


Figure 3. Hierarchical control structure of the microgrid.

Therefore, in renewable energy microgrids, the control technology of inverters is particularly important, as it serves as the medium for connecting distributed generation to the grid and determines the static and dynamic response performance and stability of the microgrid system. The main functions of the inverter are to realize microgrid connection and disconnection, active and reactive power decoupling, terminal voltage stabilization and regulation of the power balance between power supply and load. Currently, the mainstream control strategies for microgrid inverters include the following: PQ control, V/f control, droop control and virtual synchronous generator (VSG) control [20].

PQ control is a common strategy for grid-connected inverter operation, also known as constant power control, which ensures that the output active and reactive power of the inverter are constant and consistent with the given value. Due to the particularity of its control, it can realize decoupling between the output active and reactive power [21]. However, PQ control cannot be used as the main control method in islanded mode because it cannot provide voltage and frequency support to the grid. Therefore, in a microgrid with master–slave control, the distributed power supply, which is the master control unit when grid-connected, is controlled by PQ, and the load changes are followed by the master control unit. When the microgrid changes from grid-connected to islanded, the master control unit changes from PQ mode to V/f control. V/f control is a common strategy for off-grid operation of inverters, also known as constant voltage and constant frequency control. This control ensures that the output voltage and frequency of the inverter are constant, its output power is determined by the load and the external characteristics can be equated to a voltage source [22]. Because it can provide voltage and frequency support, it is very suited for islanded operation, but it requires a sufficient amount of energy to meet load demand, so the capacity of the distributed power supply is relatively large, and it usually requires a backup power supply. Droop control can adjust the output voltage, frequency and power of the inverter, similar to the principle of a traditional synchronous generator; it mainly includes Q-V, P-f regulation of forward control and P-V, Q-f regulation of reverse control. Due to the established linear relationships between active power and frequency (P-f) and between reactive power and voltage (Q-V), the droop control can realize the power equalization without communication. However, droop control does not provide inertia and damping to the system. Virtual synchronous generator (VSG) technology simulates the power and voltage control algorithms of a conventional synchronous generator and introduces inertia and damping characteristics, which can slow down the oscillation of frequency and power and improve the anti-interference performance of microgrids. Currently, there are two main VSG-controlled inverters, voltage type virtual synchronous generator and current type virtual synchronous generator [23]. VSG technology is a new generation of new energy power generation technology that turns new energy from passive regulation to active support. It is an effective way to enable new energy power generation to have the ability to support the power grid with inertia support, primary frequency regulation and active voltage regulation. It is the exploration and practice of solving the problems faced by the double-high power system [24,25]. Therefore, this paper provides a detailed introduction and summary of the latest theoretical results of VSG active support control technology.

Microgrids have been widely used in industrial parks, islands and remote areas due to their flexible and efficient characteristics. Many countries in the world have established their own microgrid demonstration projects.

The United States has made important achievements in microgrid development and is in a leading position in microgrid demonstration projects, technical concepts and key technologies; the policy environment and market mechanisms and research institutions and industrial chains. The United States has the largest number of microgrid demonstration projects in the world, which cover a variety of application scenarios and capacities from a few kilowatts to several megawatts. Among them, some large-scale microgrid projects include the Smart Microgrid Demonstration Project and the Solar City Demonstration Project. At the same time, the United States government and various state governments have given attention to and supported the development and application of microgrids by introducing a series of policies and regulations, such as solar investment tax credits, energy liberalization and power market reform. These policies provide a favorable policy environment and market mechanism for the development and application of microgrids. In addition, the United States has numerous research institutions and industrial chains, such as the National Renewable Energy Laboratory, the Solar Energy Research Institute and the Microgrid Industry Association, which provide important support and guarantees for the research and practice of microgrids [26].

Europe is one of the regions in the world where microgrid development is relatively active. In Europe, intelligent control and integrated management are used to improve the operating efficiency and reliability of microgrids. At present, the European Union has produced some research results in the areas of distributed power modeling and island interconnection. The Demotec microgrid structure of the Solar Energy Technology Institute at Kassel University in Germany and the Cyclades Islands of the Aegean Sea in Greece are typical representatives of microgrid demonstration projects [27].

In recent years, the number of microgrid demonstration projects in Japan has increased year by year to more than 100, covering a variety of application scenarios, such as urban, rural and island. The capacity of these demonstration projects ranges from tens of kilowatts to hundreds of megawatts. The combination of decentralized control and centralized management is used to control and manage the microgrid in Japan, which improves its operational efficiency and reliability. In addition, Japan has promoted some new technologies and applications, such as virtual power plants and the energy internet, which have very promising development prospects [28–30].

In order to improve the structure of the power grid, increase the efficiency of new energy generation and promote the implementation of the dual-carbon strategy, China has also invested a lot of money and energy in the field of microgrids, with the strong support of governmental departments, and has built a variety of microgrid demonstration projects for different environments. For example, small offline microgrids for towns and residential school scenarios have been constructed in Qinghai Province to improve the economy and reliability of the grid. A grid-connected microgrid project for industrial parks has been constructed in Nanjing, Jiangsu Province, to provide a reliable power supply for the parks. Through the implementation of microgrid demonstration projects, some experiences and results have been obtained. With the growing maturity of microgrid technology, it has become an important part of the smart grid and energy internet.

As an important interface between renewable energy and large-grid, the microgrid is an effective way to solve the problem of new energy consumption and improve the overall energy efficiency of the system, and it is also an important direction of future power grid research and development. A microgrid has more efficient, flexible and reliable operation control, which can ensure the stable, efficient and low-carbon operation of the smart grid. A microgrid has broad application prospects in the future energy field. Therefore, it is necessary to carry out more in-depth research on the new power system for microgrids to meet the needs of future smart grids. This paper introduces the latest theoretical results of microgrid key technologies, such as operation optimization strategy, power prediction and VSG active support control technology, and aims to show the current application status of operation optimization strategy, power prediction and VSG active support control technology in microgrid systems, so as to strengthen the connection between theoretical work and industry applications, expand the horizon of future research and provide some references for microgrid-related research.

However, a comprehensive review simultaneously addressing operation optimization, power prediction and virtual synchronous generator (VSG) technologies, particularly their latest advancements and interdisciplinary synergies, is lacking. To bridge this gap, this review aims to (1) Systematically synthesize recent breakthroughs in microgrid operation optimization strategies; (2) Critically evaluate state-of-the-art power forecasting methodologies for renewable sources and loads and (3) Analyze emerging VSG control paradigms for active grid support. The graphic paper is represented in Figure 4. The subsequent structure of this paper is as follows: Section 2 examines optimization strategies for microgrid operations and classifies the energy management algorithms of microgrid and their applications. Section 3 assesses power prediction techniques, comparing statistical, machine learning and hybrid models for wind/PV generation and load forecasting. Section 4 explores VSG control technologies, focusing on stability mechanisms and adaptive control innovations. Finally, conclusions are presented in Section 5.

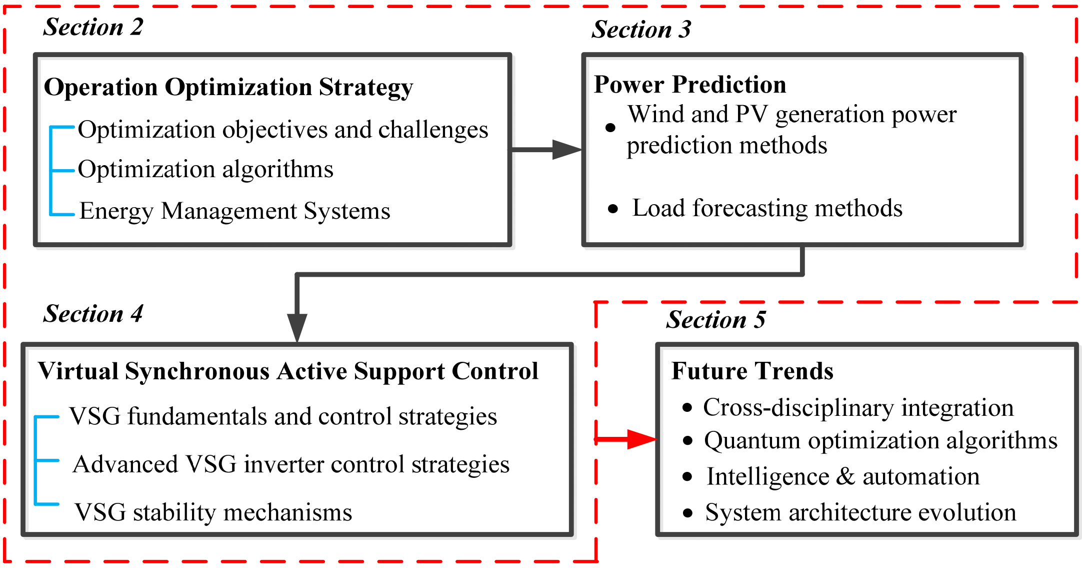


Figure 4. Graphical representation in the review in this paper.

2. Research Status of Operation Optimization Strategy of Microgrids

2.1. Optimization Objectives and Challenges

Different from the traditional big-grid dispatching, a large number of renewable energy sources are connected to the microgrid system. The inherent strong fluctuations and uncertainty of renewable energy output make the constraints, objective functions and dispatching strategies of energy management and the optimal dispatching of microgrids diverse and complex, and the energy management and optimal dispatching of microgrids become more complex. The process of energy management and optimal dispatching is to forecast the renewable energy output power and load power according to a large number of historical data, combine various constraints, environmental information, market rules and other factors to formulate the energy management and optimal dispatching production plan for the microgrid and make real-time adjustments and corrections to realize the optimal dispatching of safety, economy and environmental protection of the microgrid in the actual operation process. The microgrid has various types of power sources, different control methods and variable and complex operation modes, so the stable control of the microgrid itself and the energy management research of distributed power sources and energy storage systems are important. With the continuous development of control technology, the use of advanced control strategies and energy management techniques to improve the performance of the microgrid has become a major trend [31]. The microgrid energy management system (EMS) is an advanced energy management method that integrates monitoring, operation and dispatching. It can optimize and coordinate the operation of energy storage and distributed power sources, so as to achieve efficient and stable operation of the power system and give full play to the advantages of new energy [32]. The energy optimization management of the microgrid can coordinate the multi-side demand of source–load–storage, improve the utilization efficiency of intermittent energy and reduce carbon emissions and operating costs, so as to improve the comprehensive economic benefits of the microgrid but also reduce the negative impact on system stability. It is key to achieving efficient and stable operation of the microgrid [33–35].

The microgrid structure includes renewable energy sources such as wind power and PV power generation, energy storage systems, power dispatching systems, EMS, SCADA (Supervisory Control and Data Acquisition) systems and gas turbines, where the energy storage systems and gas turbines are mainly used to balance the intermittency and volatility of renewable power generation, as shown in Figure 5. The maximum power point tracking (MPPT) control is used for wind power and PV power generation. Gas turbines, as backup power sources, often use power control to regulate their output power. The energy storage system and the bidirectional converter system adopt voltage closed-loop control to maintain the constant DC bus voltage by regulating the power direction and size, absorbing the residual energy in the microgrid. Additionally, a battery management system (BMS) is equipped to monitor the battery pack state of charge (SOC). In the EMS, the net load power is the difference between the user load and the renewable energy output power, which can be obtained in real time by measuring the outlet voltage and current of the battery energy storage system and the generator system. On this basis, with the goal of improving power generation economy and limiting the fluctuation of the battery SOC, the gas turbines output power is determined according to the net load power and the real-time measured battery SOC to realize the dynamic distribution of the net load between the battery storage system and the generator system [36].

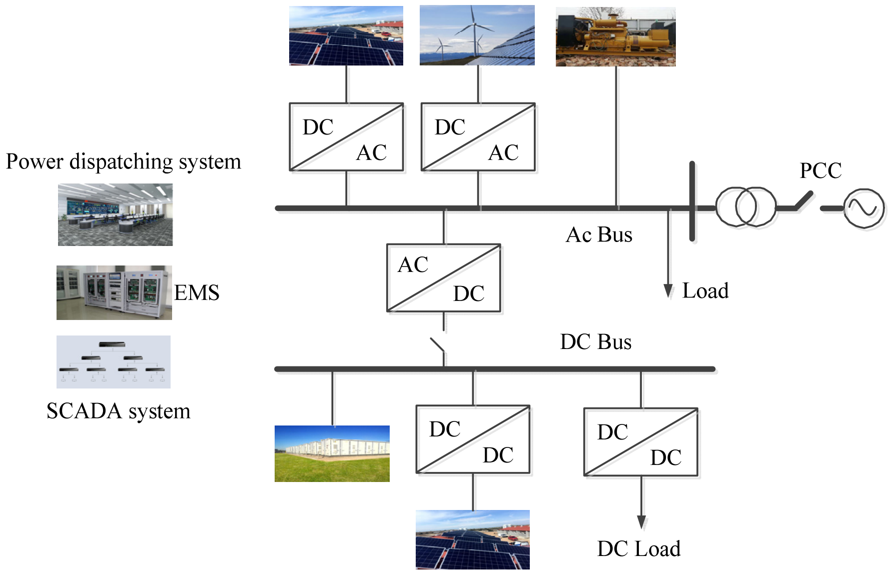


Figure 5. AC/DC hybrid microgrid component structure.

2.2. Classification and Review of Optimization Algorithms

Through the analysis of the optimal operation of the microgrid, it can be learned that the optimal operation of microgrids usually involves multiple objectives, such as operating costs, pollutant gas emissions, profits and other factors [37–39]. If the optimal operation of the microgrid ignores the impact on the environment and only considers the operating profit or operating cost, it will certainly lead to the massive emission of pollutants. However, compared with the consideration of cost and profit, if the objective function only considers the pollutant emission of the microgrid, the model is simpler. Therefore, when establishing the operation model of the microgrid, it is necessary to consider the operation cost and the treatment cost [40–42]. Multi-objective optimization of the microgrid is the key to solving the dispatching problem, and the establishment of a multi-objective optimization model is an important research direction for the long-term healthy operation of microgrids.

At present, the research on optimal operation algorithms for microgrids mainly includes the following aspects: rule-based control strategies, model-based control strategies, cooperative control strategies, optimal control algorithms and artificial intelligence-based and heuristic algorithm control strategies [43]. Rule-based control strategy is developed according to experience and rules, which meet the basic microgrid requirements but lack flexibility and adaptability. Zhang et al. proposed a multi-timescale energy management strategy based on rule-based, which considers different timescales and proposes a real-time scheduling energy management strategy that can achieve the economic optimum for economic scheduling and ensure the stability of the system, but the strategy is less adaptable to complex nonlinear systems [44]. The control strategy based on model prediction models and predicts the output units and loads of the microgrid by establishing a microgrid model, and uses the model to optimize control, which can improve the operation efficiency and performance of the microgrid. Li et al. proposed a control strategy for microgrid EMSs based on model predictive control, to achieve dynamic optimization and dispatching control by modeling and predicting the load of the microgrid [45]. The control strategy based on cooperative control realizes the cooperation between the components of the microgrid through cooperative control to improve the efficiency and performance of the microgrid. Yue et al. proposed establishing a distributed energy unit control scheme based on a multi-agent system. Each distributed energy unit is controlled by a primary unit control agent, while a secondary distributed cooperative control agent manages the second level, so as to realize the cooperative control and optimization of distributed energy. However, this method is highly dependent on information and communication technology [46].

Under the dual pressures of energy and environment, the requirements for the economy and energy-saving and emission reduction performance of microgrid generation are constantly increasing. Using optimal control theory to optimize the energy distribution has gradually become a research hotspot in the field of new energy technology in recent years. The optimal control algorithm is simple to program and can quickly obtain the optimal solution in the offline. Control strategies based on the optimal control algorithm use certain parameters of the microgrid as independent variables and find the optimal solution of the generalized function under the constraints of the allowable control range. There are two main operation optimization strategies based on optimal control theory: Dynamic Programming (DP), proposed by American scholar Bellman, and Pontryagin's Minimum Principle (PMP), proposed by Soviet scholar Pontryagin. The DP and the PMP methods are analytical in nature and are effective in solving variational problems with closed set constraints on control.

In DP, Khalid et al. built a battery simulation model to optimize the charging and discharging cycling process of the battery through a DP algorithm to achieve the lowest operating cost with known load and generation capacity [47]. However, the DP strategy easily leads to dimensional catastrophe due to its huge and complex operations. In order to solve this problem, Venayagamoorthy et al. proposed a neural network-based adaptive DP algorithm model based on the output power of the distributed power of the microgrid system and the forecasted data of load demand; the evaluation function in the DP is processed by using the J-function estimator of the feed-forward neural network, which reduces the computational complexity in the optimization process [48]. Regarding the problem that the DP strategy has difficulty handling large-dimensional data, Das et al. established an islanded microgrid model based on Markov decision-making and proposed an approximate DP to achieve energy optimization with minimum operating cost [49]. Cheng combined DP with fuzzy control to solve the supply–demand imbalance problem in microgrids due to the instability of the clean energy [50]. The energy management algorithm based on DP is complex, and the power generation of clean energy and the power consumption of loads need to be known in advance, so it is less applicable in real-time controls. The optimal control algorithm based on the PMP is mainly used to solve continuous or discontinuous nonlinear problems. It can take a parameter of the island microgrid model as a variable and obtain an optimal solution by constantly adjusting the costate variable. However, it is an offline algorithm overly relying on artificial experience, leading to difficulties in covariate selection [51,52].

For the shortcomings of traditional optimization algorithms in solving the multi-objective optimization process, researchers at home and abroad have continuously explored, improved and proposed various intelligent optimization algorithms [53,54]. The control strategy of the heuristic algorithms is to imitate the algorithm summarized by the law of nature and give the feasible solution according to the example problem. Torkan et al. applied a multi-objective genetic algorithm to deal with the uncertainty of load and renewable energy to achieve the minimum cost and minimum greenhouse gas emissions [55]. In order to select the optimal size of the microgrid components, Li et al. proposed a genetic algorithm to find the minimum microgrid cost [56]. In addition, many researchers have used Simulated Annealing (SA) to solve multi-objective optimization problems. Hafez et al. used SA optimization tools to solve the battery scheduling optimization problem for residential microgrids [57]. The particle swarm optimization (PSO) algorithm is also a widely used algorithm. Wang et al. established an economic power dispatch model for multiple microgrids by comprehensively considering many factors, such as generation cost, discharge cost, power purchase cost, power sales revenue and environmental cost and solved the economic power dispatch model by using the PSO algorithm [58]. Sharmistha et al. used the Grey Wolf Optimizer (GWO) algorithm in order to minimize the energy cost of the microgrid and make better use of renewable energy sources [59]. Wang et al. developed an operational optimization model and optimized it using the Moth Flame Optimization algorithm in order to obtain the minimum operational cost [60]. Pesaran et al. proposed a hybrid PSO algorithm to enhance particle diversity by combining the crossover and mutation operators of genetic algorithms with the original particle swarm algorithm [61]. Ref. [62] adopted a newly developed crow search algorithm (CSA) to optimize the energy management of the microgrid to reduce the generation cost and pollutant emissions. The CSA mimics the memory of crows and the strategies of hiding and chasing food. For the energy management of the microgrid, several practical complexities are considered, such as valve-point load effects, joint economic emission scheduling using the price penalty factor method and modeling of renewable energy and energy storage systems. The obtained results are then compared with many different soft computing techniques, such as genetic algorithms and PSO, to demonstrate the effectiveness of the proposed algorithm. Ref. [63] employed the Self-Adaptive Comprehensive Differential Evolution (SACDE) algorithm for solving the Economic Load Dispatch (ELD) and Combined Economic Emission Dispatch (CEED) problems to achieve optimal power usage in isolated microgrids. This method has strategically superior effectiveness compared to the price penalty factor technique. Ref. [64] presented an improved Lévy optimization algorithm for energy management of a renewable solar/wind microgrid. The microgrid has multiple diesel generators and is suitable for off-grid remote communities. The main objective is to solve an economic emission scheduling problem with a price penalty factor to minimize the energy cost and emission level. The enhanced heuristic Lévy optimization algorithm is used to improve the searchability of the optimal solution compared to traditional arithmetic algorithms. The Lévy optimization algorithm is used for the management of the microgrid and compared with other heuristic optimization algorithms. Results show that the Lévy algorithm achieves significant cost savings compared to other algorithms, such as arithmetic algorithms and the crow search algorithm (CSA), hybrid improved grey wolf optimizer (HIGWO), internal search algorithm (ISA), cuckoo search algorithm (CS), particle swarm optimization (PSO) and ant colony optimization (ACO).

Some scholars have combined multiple heuristics to greatly improve the adaptability and feasibility of the algorithms. The Hybrid Improved Grey Wolf Optimizer (HMGWO) proposed in ref. [65] was used for economic dispatch and emission dispatch of the microgrid. According to the wolf hunting strategy, the population-based sine cosine algorithm strategy is combined with the crow's position update method to form a robust hybrid algorithm. The proposed economic emission scheduling method was compared with the existing price penalty factor method (PPF) and fractional programming (FP) method to solve the joint economic emission scheduling problem on three dynamic test systems, and a better optimization scheme between power generation cost and pollutant emission was found. A new heuristic algorithm called the Arithmetic Optimization Algorithm (AOA) was proposed in ref. [66], which exploited the distributional behavior of the main arithmetic operators (multiplication, division, subtraction and addition) in mathematics in order to perform the optimization process over a wide search space. The performance of the AOA was examined through 29 benchmark functions and several real-world engineering design problems, and the performance, convergence behavior and computational complexity of the proposed AOA were analyzed in different scenarios. The AOA method is used to find the best solution, which sometimes gets stuck in a local optimum during the search process [67,68]. This leads to longer search times to find the optimal solution. In addition, it requires a more comprehensive evaluation when the optimal solution is distributed over a wider range of possibilities. In ref. [69], an augmented algorithm combining the Lévy optimization algorithm and the AOA was proposed to improve the efficiency of the AOA and successfully applied to different engineering problems. The proposed method enhances the AOA's exploration and exploitation capabilities and is used to optimize the operation of a renewable energy microgrid with multiple diesel generators. Ref. [70] proposed an intelligent energy management system (SEMS) based on artificial intelligence-embedded FPGA, which used two multi-objective optimization algorithms, Gorilla Army Optimization Algorithm (GTO) and Reptile Search Algorithm (RSA), to solve the optimization problem. The proposed Smart Energy Management System (SEMS) included two levels of control to achieve optimal management and operation of the isolated microgrid. The first layer used FPGA as the central controller, and the second layer was based on the optimized operation and management of the isolated microgrid to formulate a coordinated operation strategy to optimize the coordinated use of backup power. Ref. [71] developed a hybrid algorithm using the crow search algorithm and JAYA to conduct the combined economic emission dispatch (CEED) for four power systems with and without renewable energy source participation, respectively. Both the price penalty factor (PPF) and fractional programming (FP) methods were used to solve the CEED of all four test systems, and they were analyzed with the goal of minimizing the emission of harmful and toxic gases into the atmosphere.

2.3. Energy Management Systems and Case Studies

New energy, as the main distributed power source to access the grid, has many defects, such as high volatility and instability. The main role of energy management is to ensure the economic operation of the system under the premise of safety and reliability of the microgrid. Solving the problems of intermittency, voltage and frequency fluctuations of distributed power sources is the key to realizing the coordinated management of electric energy and maintaining a dynamic balance [72]. With the rapid development of the microgrid, the EMS faces greater challenges [73]. Although the capacity of the microgrid is not as high as that of the big grid, its EMS is equally complex and requires the integration of several factors, such as variations in natural conditions, charge/discharge control logic, load fluctuations, operating costs and pollution emission costs. [74]. Meanwhile, the SOC of the battery is an important operating condition parameter, and exceeding the SOC limit will affect the long-term operation of the microgrid. The EMS is needed to help the microgrid integrate battery SOC and achieve desirable fuel economy and pollution emission levels. Due to the stochastic nature of the environment, the efficient operation of the microgrid EMS depends to a large extent on the real-time performance of the control algorithm [75–77].

The EMS objectives of the microgrid mainly include the following aspects: minimizing the operating cost, generation cost, voltage deviation and pollutant emission and maximizing the comprehensive benefit. Jung et al. and Vaka et al. minimized the operating cost of the microgrid by optimizing the energy management strategy from the perspective of considering the operating life and the capacity of the energy storage system [78,79]. Fouladfar et al. proposed a multi-objective EMS based on demand response and dynamic pricing. In addition to reducing the market clearing price and increasing the producer profit, it also focuses on reducing the emission level of generating units, and the improvement effect is good [80]. Li et al. developed a mathematical model of an islanded microgrid based on an island with the NSGA-II algorithm, which fully considered the power balance constraints of the microgrid and the operating power of storage batteries and diesel generators to optimize the operation of the micropower [81]. Yong et al. established a model of the lowest power generation cost and the least pollutant emission in the microgrid and balanced and compromised the two goals by using different control strategies to optimize the objective function in the grid-connected microgrid project [82].

Alanazi et al. used variable step size and fixed step size methods to search the optimal value of the microgrid multi-objective function to achieve the minimum voltage deviation and minimum carbon dioxide emissions [83]. Shuai et al. designed a reinforcement learning strategy optimization model framework in order to accurately predict renewable energy generation and realize online dispatch. The Monte Carlo method is used to make the learning model obtain the best decision, so as to achieve the purpose of economic and reliable operation of the microgrid [84]. Ali et al. proposed a novel reinforcement learning approach that utilized a distributed approach to teach the medium to interact with a single microgrid environment and used a global agent to search for a system cost-optimal solution for the microgrid group. However, this type of strategy requires continuous reinforcement learning upfront and a large amount of training data, which may become computationally expensive or less efficient in finding the least-cost solution [85].

The operation optimization strategy of the microgrid is undergoing a remarkable transformation, evolving from its previous single-objective, static-model framework into a more complex and advanced multi-objective, collaborative, dynamic, self-adaptive operation mode. With the continuous advancement of technology and the increasing demand on power systems, the future direction of development will require breaking through the bottlenecks in efficiency and robustness of existing algorithms. In order to achieve this goal, it is necessary to combine emerging technologies, such as artificial intelligence, big data analysis and the Internet of Things (IoT), to build a comprehensive "source–network–charge–storage" intelligent collaborative system. Such a system will be able to achieve efficient allocation and optimal management of resources, so as to provide solid technical support and guarantee the construction and development of new power systems.

3. Research Status of Microgrid Power Prediction

The power output of wind power and PV in microgrids is affected by natural conditions and has large fluctuations and randomness, while the load in microgrids also has the disadvantage of large fluctuations. These lead to large errors in the power prediction of source–load–storage. Therefore, improving the accuracy of wind–PV power prediction and load prediction in the microgrid, and combining with the energy storage system for complementary power generation to optimize the economic and environmental benefits of the microgrid is of great significance to its reliable and economic operation [86,87].

3.1. Research Status of Wind and PV Generation Power Prediction Methods

The wind and PV power prediction methods are divided into physical methods and statistical methods according to the different principles of prediction models. Statistical methods are the most widely used and can be further divided into the time-series method, (e.g., Auto Regressive Integrated Moving Average—ARIMA), machine learning, the deep learning method and the artificial neural network method. Researchers have studied wind power for a long time, and specialized wind power generation prediction systems have been established in Denmark, Germany, the United Kingdom and China, as shown in Table 1. Table 2 shows the classification of solar PV generation methods.

Table 1. Power prediction method of wind power generation.

Prediction Model	Core Technology/Algorithm	Prediction Horizon	Key Strengths/ Focus Area	Typical Input Data	Reference
Prediktor	Physical modeling (NWP + wake modeling)	Short-Medium	Physical accuracy, terrain effects	NWP, terrain data	Louka et al. [88]
WPPT	AR models, transfer functions (Statistical)	Short-Term	Computational efficiency, simplicity	Historical power, simple meteo	Cutler et al. [89]
Zephry	Mesoscale modeling (Phys) + Kalman filter (Stat)	Short-Term	Hybrid approach, data assimilation	NWP, SCADA data	Smith et al. [90]
Previento	CFD modeling (Phys) + Statistical post-proc	Short-Term	High spatial resolution, local effects	Detailed NWP, site specifics	Giebel et al. [91]
Sipreolico	Multi-scale meteo + ML + Data assimilation	Multi-scale	Multi-scale integration, optimization	Multi-source meteo, power data	Lobo et al. [92]
AWPPS	Fuzzy neural network (AI)	Short-Term	Handling uncertainty, non-linearity	Historical power, meteo data	Wang et al. [93]
LocalPred-RegioPred	Phys model + ML correction + Cross-scale	Multi-scale	Regional adaptation, error correction	NWP, regional power, ML features	Banakar et al. [94]
WEPROG-MSEPS	Deep integration phys models + Stat learning	Short-Medium	Robustness, hybrid performance	High-res NWP, historical stats	Pope et al. [95]
AWPT	Fuzzy neural network (AI)	Short-Term	Pattern recognition, adaptability	Historical power, meteo data	De Giorgi et al. [96]
GH-FORECASTER	Adaptive regression (Stat/AI)	Short-Term	Adaptability to changing conditions	Real-time data streams	Pirjan et al. [97]
ANEMOS	Hybrid model	All, esp. Extreme	Extreme weather forecasting	NWP, ensemble forecasts	Kariniotakis et al. [98]
WPP	Physical + statistical method	Short-Medium	General purpose, flexibility	NWP, historical data	Zhang et al. [99]
WPFS	B/S structure, cross-platform	Up to 144 h (Medium)	Practical deployment, long horizon	NWP, operational constraints	Aggarwal et al. [100]
NSF3100	BP-ANN (AI) + Refined techniques	Short-Term	Statistical learning, data refinement	Historical power, processed meteo	Wang et al. [101]

Table 2. Power prediction classification of solar PV generation.

Classification Angle	Predictive Classification	Core Methodology/ Algorithm Examples	Key Characteristics/Applications	Reference
Methodological approach	Physical method	Sky imagery, irradiance modeling, PV cell physics	Based on first principles, good for clear sky	Roberts et al. [102]
	Statistical method	ARIMA, Regression (linear, nonlinear)	Simpler, relies on historical patterns	Shan et al. [103]
	AI/Deep learning method	ANN (BP, RNN, LSTM, GRU), SVM, Ensemble Methods (RF, GBDT)	Handles non-linearity, complex patterns, big data	Wai et al. [104]
	Hybrid method	e.g., Phys + Stat, Phys + AI, AI ensemble	Combines strengths, aims for robustness and accuracy	Voyant et al. [105]
Forecasting horizon	Ultra short-term prediction	Minutes to 6 h	Grid balancing, real-time dispatch	Wang et al. [106]
	Short-term prediction	6 h to 72 h	Unit commitment, market bidding	Yao et al. [107]
	Medium-term prediction	3 days to 2 weeks	Maintenance planning, resource assessment	Wang et al. [108]
	Long-term prediction	Weeks to years	Investment planning, policy making	Liu et al. [109]
Forecast output type	Point forecast	Single expected value	Most common, simple	Van der Meer et al. [110]
	Probabilistic forecast	CDF, quantiles	Quantifies uncertainty, risk-aware decisions	Sanjari et al. [111]
	Interval forecast	Prediction intervals (e.g., PIs)	Provides range of likely values	Kodaira et al. [112]

The physical method of power prediction is a method that expresses the contribution of various physical factors and wind–PV power through mathematical formulas. For example, the Prediktor system (widely used in Spain, Ireland, etc.), and the LocalPred-RegioPred tool (developed in Madrid, Spain) can predict wind power output.

Firstly, according to the wind speed, temperature, wind direction and pressure and other meteorological data obtained by Numerical Weather Prediction (NWP), a calculation method similar to the Wind Atlas Analysis and Application Program (WASP) is used to convert meteorological data into wind speed and wind direction at the height of the wind turbine hub, and then the corresponding output power is calculated according to the corresponding curve [88]. It is difficult to speculate the detailed weather conditions around the wind farm from the weather forecast, which makes the physical prediction method difficult to implement and causes large errors. Another common method is the statistical method, which runs calculations based on power and weather factors, finds the patterns and then obtains the regression model. In addition, there is a hybrid of the physical and statistical prediction methods. However, the physical method is not suitable for short-term prediction because it has the disadvantage of a large amount of calculation and a slow update speed [94].

The statistical method finds the functional relationship between weather factors and wind power through mathematical methods. It mainly inputs the historical data of wind power generation and its influencing factors, etc., and establishes the mapping model between the original data and the predicted data through the time series method, regression analysis, Bayesian statistics, Markov chain, etc., so as to obtain more accurate power prediction results [113]. Time series methods directly use historical data to establish black box models. The commonly used sequence methods include the following. (1) The ARMA prediction model, which uses the fitting of historical data to predict future data and is generally used in stationary series. Ref. [114] compared several forecasting methods for average hourly wind speed data using time-series analysis. (2) The wind power prediction model based on spatial correlation. Because the wind speed and wind power of the wind farm are not evenly distributed in space, but there is some correlation in space and time, the geographic and weather characteristics of the wind farm, wind speed and wind power can be predicted by modeling the spatial correlation at different known locations.

The common machine learning methods include the random forest algorithm, linear regression, naive Bayes algorithm, K-means algorithm, etc. Ref. [115] proposed a hybrid model for short-term prediction of wind and light consisting of variational modal decomposition (VMD), the K-means clustering algorithm, and the long-short-term memory (LSTM) network. The VMD was utilized to decompose the original wind power sequence into a certain number of sub-layers with different frequencies, and the K-means was utilized to decompose the data into approximate fluctuation layers according to the fluctuation level to achieve the power prediction. In order to evaluate the fitting ability of the proposed model, seven different models were compared on multiple scales in four wind turbine families, including the back-propagation neural network method, the Elman neural network method, the LSTM method, the VMD-BP method, the VMD-Elman method, the VMD-LSTM method, and the VMD-K-means-LSTM method. In order to solve the problem of inaccurate prediction due to the obvious fluctuation of wind power generation caused by weather changes, ref. [116] proposed a prediction model using an improved time series deep residual network, which combined the multilayer residual network and the tandem residual learning method of DenseNet and had high prediction accuracy and parameter efficiency. Ref. [117] proposed a combined forecasting method based on day-ahead numerical weather prediction (NWP) positioning technology for ultra-short-term wind power prediction (WPP). Firstly, the NWP information and time window were used to approximately locate the time point with low prediction accuracy of rolling WPP, and then a hybrid method combining the neural network and continuous method was proposed to predict future wind power output. In [118], a model combining VMD, a Convolutional Long Short-Term Memory network (ConvLSTM) and error analysis was used for short-term wind power prediction. The VMD algorithm was used to decompose the wind power signal into a set of different frequency components, and the convolution operation was embedded into the LSTM network to obtain the preliminary prediction results. The LSTM was used to model the error sequence trend of the preliminary prediction results. The prediction error sequence was integrated with the preliminary results to obtain the final prediction result. The results show that the proposed model has the highest prediction performance for hard-to-capture wind power generation sequences. In terms of power prediction, the machine learning method has a more obvious improvement in accuracy compared with the traditional statistical method. The common machine learning single model can complete the prediction of generation power well, but it requires a large amount of data compared with the traditional statistical method [119–121].

In recent years, deep learning has become more and more accurate in dealing with problems in various fields, and it also has relatively high accuracy in wind power prediction. With the development of deep learning, LSTMs, Bi-LSTMs, gated recurrent units (GRUs), artificial neural networks (ANNs) and other methods in deep learning algorithms have also been introduced into renewable energy generation power prediction [108]. These methods effectively mine spatiotemporal correlations between outputs and inputs and have advanced significantly for complex time series. However, in the process of model training, setting too long a time-series length may affect its stability [122–125].

Ref. [126] proposed two wind power prediction models, the K-means-LSTM network model for wind power spot prediction and a nonparametric kernel density estimation (KDE) model with bandwidth optimization for wind power probability interval prediction density estimation. The LSTM established correlations between the before and after data, and the K-Means clustering method composed different clusters of wind power impact factors to generate a new LSTM sub-prediction model. The bandwidth optimization of the nonparametric KDE was achieved using the mean integral squared error criterion. Ref. [127] introduced a deep learning approach to achieve a more accurate wind–solar towers (WST) power output prediction model. In order to predict the output power of the system, several machine learning models were evaluated based on quality metrics, a set of features and regression models were built using this data. Further, the prediction accuracy was improved by incorporating nonlinearity using second order polynomial regression. In addition, the data was trained and tested using deep neural networks to improve the performance of the power prediction. The fuzzy C-mean algorithm is often used to optimize other machine learning algorithm models for power prediction and the PSO is used to optimize the extreme learning machine. In view of the intermittency, randomness and fluctuation of PV power systems due to complex weather conditions, ref. [128] proposed short-term forecasting using an LSTM, which was based on the time scale of global horizontal irradiancy one hour in advance and one day in advance. In order to improve the prediction accuracy of cloudy weather, the clear sky index was introduced as input data in the LSTM model, and K-means was used to classify the weather types into cloudy weather and mixed (partly cloudy) weather during data processing. A neural network model was built to compare the accuracy of different methods. The traditional statistical method in power prediction can output more accurate prediction results to a certain extent, but it has a larger potential for error in power generation prediction results for the influence of stronger volatility of weather and other factors [129]. Ref. [130] proposed a PV power generation prediction algorithm based on an LSTM neural network. By combining statistical knowledge of historical solar irradiance data with publicly available weather forecast types for the city, a comprehensive weather forecast was created for the target PV plant location, enabling more reliable PV generation forecasts. The K-means algorithm was used to categorize the historical irradiance data into dynamic-type sky groups that change hourly during the same season. The performance limitations of using fixed-type sky categories were alleviated by converting them into dynamic and numerical irradiance predictions using historical irradiance data. The results showed that the proposed integrated weather prediction embedded statistical features from historical weather data, significantly improving accuracy. In addition, the superiority of the LSTM neural network with the proposed features was verified by comparing machine learning, including a recurrent neural network, generalized regression neural network, and extreme learning machine.

Ref. [131] proposed a hybrid deep learning model combining a time-series decomposition algorithm and a GRU network. The time-series decomposition algorithm consists of two parts: (1) the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and (2) Wavelet Packet Decomposition (WPD). The Normalized Wind Speed Time Series (WSTS) was processed by CEEMDAN to obtain pure fixed frequency components and residual signals. The WPD algorithm performed second-order decomposition on the first component of the original WSTS containing complex high-frequency signals. Finally, a GRU network was established for all relevant components of the signal, and the predicted wind speed was obtained by stacking the predictions of each component. An efficient deep learning-based wind power prediction model was proposed to address the uncertainty of wind power generation that makes it difficult to integrate into energy systems [132]. The proposed model was divided into two stages. In the first stage, the past wind power signal was decomposed using Wavelet Packet Transform (WPT). In addition to disaggregated signals and lagged wind power, multiple external inputs such as calendar variables and NWP were used as inputs to forecast wind power. In the second stage, a new prediction model, the Efficient Deep Convolutional Neural Network (EDCNN), was used to predict wind power. The demand-side management scheme was developed based on the predicted wind power, day-ahead demand and price, and the performance of the proposed forecasting model was evaluated on the big data of wind farms in the U.S. Figure 6 shows the structures of the GRU and BiGRU networks.

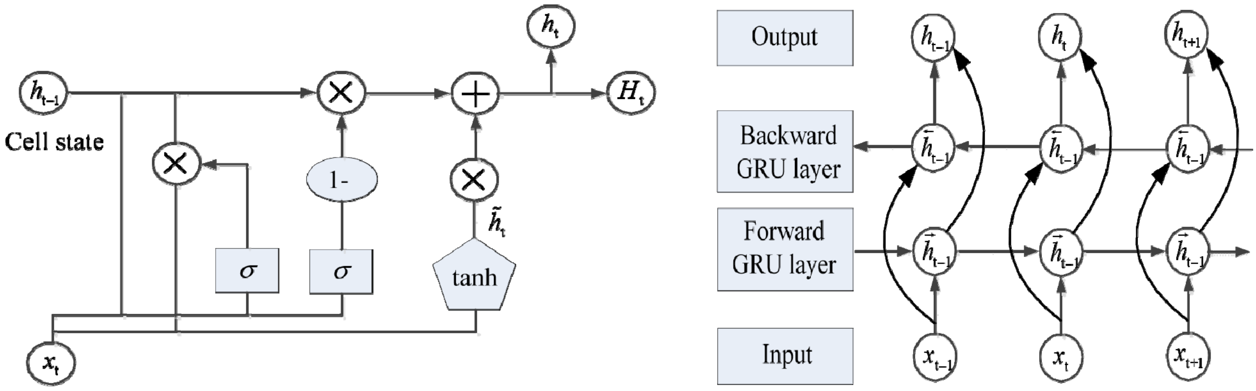


Figure 6. Structures of the GRU and BiGRU networks [132].

The deep learning model combining a nonlinear auto-regressive neural network, a convolutional neural network, and an LSTM recurrent network prediction was used to further improve the prediction accuracy [133–135]. Figure 7 shows the architecture of the GRU network for PV power forecasting.

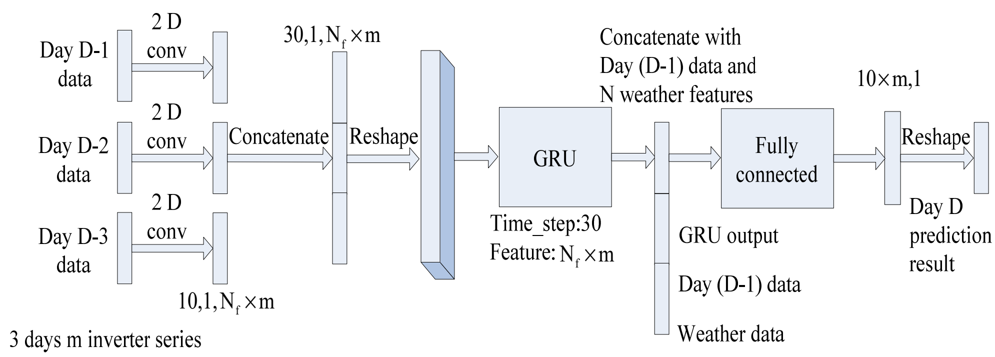


Figure 7. Architecture of the GRU network for PV power forecasting [134].

The artificial neural network approach combines artificial intelligence and neural network approaches for wind power prediction [136]. For the uncertainty and intermittency of wind power, a short-term wind power prediction model based on a Small-World BP Neural Network (SWBP) was constructed [137]. The input features of the SWBP were selected by the improved mutual information method. The selection criterion establishes the relationship between many input and output variables associated with wind power prediction by eliminating redundancy. Compared with the BP neural network and radial basis function neural network algorithm, this method effectively improves the prediction accuracy. Ref. [138] proposed a combined wind power prediction method based on Artificial

Neural Networks (ANNs) and Support Vector Regression (SVR) algorithms. The wind power combination forecasting model was formed by the weighted average of each single forecasting algorithm, which improved the prediction accuracy of the model. However, the combined prediction algorithm based on the weighted average did not reflect the overall weighting effect of the prediction errors of individual samples in the sample set. Ref. [139] proposed a prediction method based on a sequential forward feature selection algorithm for wind–solar hybrid power generation, which combined two different objective functions with an artificial neural network method. For the diversity and dynamics of training samples, caused by the intermittency and volatility of wind and PV power, a variety of hybrid prediction models were proposed by using data mining methods composed of grey relational analysis, K-means clustering and a bagging neural network (NN) to solve complex control problems in wind and PV power systems and optimize the control of the microgrid [140–143].

According to the wind power ramp events in the economic operation and risk management of smart grids, ref. [144] proposed a hybrid prediction model based on a semi-supervised Generative Adversarial Network (GAN) to solve the problem of short-term wind power output and ramp events prediction. In the proposed model, the original time series of wind energy data was decomposed into several sub-sequences characterized by intrinsic mode functions (IMFs) with different frequencies, and the data was expanded using semi-supervised regression with label learning to extract nonlinear and dynamic behaviors from each IMF. The unlabeled virtual samples were obtained using the GAN to generate a model for capturing the data distribution characteristics of wind power outputs, while the semi-supervised regression layer was used to redesign the discriminant model to perform the point prediction of wind power. After two GAN models, a min–max game was formed to improve the quality of sample generation and reduce the prediction error. Ref. [145] quantified the prediction uncertainty caused by the intermittent and fluctuating characteristics of wind energy through wind power interval prediction. For the two most critical objectives in interval prediction, effective coverage and short interval length, a new interval prediction method was proposed, which combined the Conformal Quartile Regression algorithm with Time Convolution Networks (TCNs) without using any distributional assumptions. Compared to conventional RNN-based methods, the adopted TCN architecture avoided iterative propagation and gradient vanishing and could process very long sequences in a parallel fashion. According to the instability and volatility of load sequences, ref. [146] proposed a dynamic decomposition–reconstruction integration method by combining reconstruction and secondary decomposition techniques. The decomposition-integrated prediction framework was improved by introducing a dynamic classification and filtering-based decomposition reconstruction process and given criteria for determining the components that needed to be decomposed again. The model leveraged decomposition, complexity analysis, reconstruction, secondary decomposition and hyperparameter-optimized neural networks, demonstrating superiority in prediction accuracy, stability, correlation, overall performance and statistical tests. The short-term load prediction results provided effective support for the safe operation of the electric power system and rational scheduling.

In addition, extreme Gradient Boosting [147], Light Gradient Boosting Machine [148], Adaptive Boosting [149] and other tree integration algorithms, as representatives of artificial intelligence technology in wind and PV power prediction, have achieved good application results. The wind and PV power prediction technology has been widely studied throughout the world. The artificial neural network method, as an intelligent feature extraction method, uses a self-learning artificial intelligence method to help the management of mathematical models, and its research has practical application prospects [150–152].

3.2. Research Status of Microgrid Load Forecasting Methods

According to the scheduling needs of the power system dispatching department, the microgrid load forecasting is divided into short-term and medium-long-term, according to the forecasting time scale. According to the predictive modeling method, it is divided into a traditional statistical model and an AI-driven model.

Short-term load forecasting methods for microgrids mainly include traditional statistical methods and machine learning methods. Traditional statistical methods mainly include the Autoregressive Integrated Moving Average (ARIMA) model, Suppot Vector Machine (SVM), etc. [153]. These kinds of methods have simple principles and modeling and consider the time-series relationship of data but have limited prediction ability for nonlinear load data with relatively high complexity. Machine learning algorithms can effectively deal with nonlinear problems. Traditional machine learning methods mainly include Artificial Neural Network (ANN), Support Vector Regression (SVR) [154], random forest (RF), wavelet neural network [155], deep residual network [156], etc., but these methods are based on strongly correlated input. These methods can better reflect the nonlinear relationship between the data, but their common problem is the lack of consideration of the time correlation of time series data. Ref. [157] proposed a medium-short-term load forecasting, using a hybrid model of the Multilayer Feedforward Neural Network (MFFNN) and the Grasshopper Optimization Algorithm (GOA), which can be used to predict the load at different times and on different days of the month. The MFFNN processed the input layer and output layer, weather factors such as temperature were used as the input of MFFNN and, finally, the appropriate number of hidden layers was selected. The main steps included feeding data into the network, training the model and finally implementing the prediction process. The results show that the temperature has a clear influence on the predicted load in the proposed model. In addition, there are differences between the maximum and minimum loads in winter and summer. A regression model was introduced to determine the relationship between the dependent variable (load) and the independent variables affecting the load (such as temperature). Combined with load forecasting, ref. [158] developed a new power flow management algorithm for islanding power systems, which can simultaneously achieve more stable conventional unit operation and reduce the demand peak values. The forecasting module was based on the feedforward artificial neural network and can forecast short-time day-ahead load. Then, the predicted load curve of the previous day is used as the input of the pattern recognition algorithm to classify it according to the shape (pattern) of its load curve. Subsequently, if the classification result is a clear night peak pattern, the hourly trajectory of the diesel generator operation can be estimated, and the charging set point of the battery energy storage system can be derived. The SVM is a supervised learning method that always finds the global optimal solution and performs well on smaller datasets. However, when the data set becomes larger, it is prone to overfitting problems. Although the SVM can solve nonlinear problems well, the convergence speed of the SVM is slow due to the increase in computational complexity, and the relaxation variables and kernel parameters need to be set manually [159]. Ref. [160] proposed a multi-task learning model based on the Least Square Support Vector Machine (LSSVM), which realized the simultaneous output of electricity, heat, cold and gas load forecasting tasks.

The continuous development of deep learning has brought more choices for microgrid load forecasting. Different types of deep learning models are applied in the field of load forecasting [161,162]. It mainly includes convolutional neural networks (CNNs), recurrent neural networks (RNNs), LSTMs [163], deep belief networks (DBNs), etc.

Ref. [164] used CNNs to automatically extract features from input data and consider the correlation between different times of the day and different days of the week, which achieved good results compared to traditional machine learning methods, but the method only performs well on small data, and when the data fluctuates greatly, a single CNN model is unable to make good predictions. In ref. [165], the Multiple Time Series (MTS) was generated by combining macro and micro information of continuous time series and discrete time series to improve the performance of short-term load forecasting. The MTS included four information sequences: short-term, periodic, long-short-term, and trans-long-short-term. The MTS was used to build a short-term load forecasting system using a recurrent neural network (RNN) model that could learn sequential information between continuous and discrete sequences. Ref. [166] proposed a variant of the RNN based on the LSTM, which effectively solved the gradient explosion defect of recurrent neural networks by adding forgetting units. As an optimization of the LSTM network, GRU simplifies the internal unit structure of the LSTM, achieves similar prediction accuracy as the LSTM and has the advantages of fewer training parameters and high speed. The Bi-directional Long Short-Term Memory (Bi-LSTM) network can extract time series features from both the front and back directions and has better representation of continuous time series, and the multiplexing of weight parameters makes it less demanding on data [167]. The above network model can fully reflect the long-term historical process in the input time series data, but it cannot extract the effective information between the discontinuous data, so it cannot deeply explore the potential relationship between the data. Ref. [168] constructed an iterative multi-step load forecasting method by incorporating an extreme learning machine and dynamic neural network to mine features. The features of the two were learned and fused to output the predicted value for the current time step. Subsequently, the prediction was iteratively made into the future based on the predicted value and historical data. Ref. [169] proposed a hybrid attention LSTM network based on an encoder–decoder framework to better capture dynamic temporal features in an interpretable form.

In ref. [170], the DBN based on the restricted Boltzmann machine was used to extract the features of data, and multi-task learning was combined to realize the comprehensive energy load forecasting of electricity, heat and gas. Ref. [171] proposed a new hybrid ensemble deep learning method for low-voltage load side forecasting. In order to improve the regression ability of the DBN, a series of integrated learning methods, such as bagging and boosting variants, was introduced. In addition, the different transformation technique was used to ensure the stationarity of the load time series of the bagging and boosting methods. Based on the idea of integrated learning, a new hybrid integration algorithm was proposed by combining multiple independent integration methods. Considering the diversity of various ensemble algorithms, an effective k-nearest neighbor classification method was used to adaptively determine the weight of the sub-models. On this basis, using the inherent re-sample idea of bagging and boosting, a probabilistic prediction method based on hybrid ensemble deep learning (HEDL) was proposed. The above comprehensive energy multivariate load forecasting literature adopts different methods for forecasting, and most of them also consider the complex dynamic characteristics between energy sources, but do not fully mine the important information of more dimensions in the data.

With the diversification of training data types and the improvement of load forecasting accuracy requirements of the power grid, combined forecasting models have emerged to overcome the shortcomings of a single model in load forecasting accuracy [172]. Ref. [173] explored using a gated convolutional network and GRU network to solve a day-ahead multi-step load forecasting problem. By introducing a linear gated unit, the defect of convolutional neural networks having difficulty addressing time-series prediction was remedied. The recursive strategy was used for prediction, which greatly depended on the prediction results of the previous order. In the process of transmission, it is easy to cause the superposition of the prediction errors of the previous order, which leads to the decline in the prediction accuracy of the model. Ref. [174] proposed a hybrid network model by combining the attention mechanism. Compared with the unfused attention model, the proposed method is more accurate for real-time prediction and shows better adaptability in peak consumption situations. Ref. [175] adopted a Seq2Seq method in Encoder–Decoder architecture to enhance the load timing feature mining capability, and the CNN was added to extract the coupling feature information in the integrated energy system, which further helped Seq2Seq to achieve the accurate prediction of system load. Ref. [176] used the Copula method to analyze the nonlinear correlation between loads, screened the larger correlation factor features as the input features of the prediction model and constructed a bidirectional long- and short-term memory network to predict the electricity, heat and cold loads. Ref. [177] constructed three load CGRU-feature mining networks, established high-dimensional abstract features and cooperated with enhanced multi-task learning with homoskedastic uncertainty to output short-term prediction results for electricity, heat and cold loads. Ref. [178] proposed a load forecasting method based on nonlinear relationship extraction by training two convolutional neural networks individually to extract nonlinear load features and nonlinear load–temperature features, respectively, and the extracted features were fed to the SVR model for one hour ahead of load forecasting. Experimental results show that the method exhibits excellent prediction performance compared to LSTM, CNN and SVR methods.

With the continuous development of data decomposition algorithms, in order to reduce the influence of volatility and nonlinearity in the load sequence and further improve the accuracy of short-term load forecasting, a combined forecasting method that combines data decomposition algorithms with the existing forecasting models has been widely used in the field of load forecasting. The classical signal decomposition algorithms mainly include Wavelet Decomposition (WD), Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD). These combined prediction methods firstly decompose the original load sequence into multiple components with different characteristics by means of data decomposition algorithms and then build a prediction model for each component and reconstruct the prediction results of each component to obtain the final prediction value. Ref. [179] proposed a probabilistic load forecasting model based on wavelet transform. Before using quantile regression forest and random forest to establish a probabilistic forecasting model, the wavelet decomposition was used to preprocess a load time series, which effectively improved the forecasting accuracy. However, the decomposition effect of the WD is related to the selection of the wavelet basis and the amount of decomposition, lacking adaptability. The EMD method absorbs the advantage of multi-resolution of the wavelet transform and, at the same time, overcomes the difficulty of selecting the wavelet basis and determining the decomposition scale in the wavelet transform. So, it is more suitable for nonlinear and nonsmooth signal analysis and is an adaptive signal decomposition method. A hybrid method for STLF in the microgrid was proposed, which integrated the EMD, the PSO and an adaptive network based the fuzzy inference system [180]. Ref. [181] proposed an STLF method combining the EMD, the Bi-LSTM and the attentional mechanism, where the load sequence was decomposed into several Intrinsic Mode Functions (IMFs) by EMD, and, subsequently, an attentional mechanism-based Bi-LSTM neural network was applied to each of the extracted IMFs in order to predict the variation trends of these IMFs. However, the EMD needed to solve the problems of modal aliasing and endpoint effects. Ref. [182] used the VMD algorithm to decompose the original data and eliminate the noise present in the data, which helped the LSTM improve the accuracy of the STLF. Compared with the WD and EMD algorithms, the VMD is more adaptive and has the ability to overcome modal aliasing, so it has been widely used in the field of load forecasting. However, the VMD method lacks evaluation criteria to guide the parameter setting, and the parameters are often given empirically, which leads to unsatisfactory decomposition results.

Power prediction is a necessary precondition to ensure the balance of power supply and demand in the microgrid. Only with effective generation of power prediction and system consumption can load prediction be used as the condition of power dispatching at the same time. High-precision power prediction can ensure the correctness of power dispatch, reduce supply deviation and improve the operational stability and safety of the power system. In the prediction time, the current new energy power prediction main research focuses on ultra-short-term (same day) and short-term (next day) power prediction. And less research and results are oriented towards the future 3–10 days duration prediction. If the future is predicted for a longer time, the time resolution of the weather forecast is lower, the weather forecast model may have drift and the accuracy of the weather forecast will decrease day by day. Due to this constraint, when the traditional method is facing the future 3–10 days, the power prediction effect will be significantly reduced compared with the ultra-short-term and short-term. Therefore, medium-term power prediction is one of the urgent problems to be solved in microgrids, and its research has far-reaching significance and practical engineering value. Through the close integration of AI technology and the IoT, microgrid power prediction is shifting from a "passive response" to an "active sensing–decision-making" mode, which has become a key technology pivot for the intelligence of new power systems.

4. Research Status of Virtual Synchronous Active Support Control Technology

4.1. VSG Fundamentals and Control Strategies

When the power electronic interface circuit adopts droop control or other control methods, it has the characteristics of fast response and low inertia. With the emergence of a large number of distributed power supplies connected to the power system through the power electronic interface circuit, and the rotating reserve capacity in the system is reduced, which reduces the operation stability of the power system. In order to solve this problem, the inverter has the external characteristics of a synchronous generator by adopting the appropriate algorithm, which is the virtual synchronous control of the inverter. Virtual synchronous generator (VSG) technology facilitates the transition of renewable energy generation from passive regulation to active grid support. It not only enables inertia support, primary frequency regulation and active voltage regulation capabilities but also addresses challenges in power systems with high renewable penetration and power electronics ("double-high" systems).

VSG includes current mode and voltage mode. In the development of VSG, the early control scheme was current type. The concept of Static Synchronous Generator (SSC) was first proposed by the IEEE Task Force in 1997 [183]. On this basis, Johan Morren, Sjoerd W. H and other scholars from Delft University of Technology in the Netherlands proposed the idea of using a distributed power supply to participate in system voltage and frequency regulation and creatively proposed the principle of simulating synchronous generator primary frequency modulation characteristics and moment of inertia in 2005 [184], when, VSG's research was still in early stages. In 2007, Beck H. P of the Technical University of Lausktal in Germany took the lead in proposing the VISMA (Virtual Synchronous Machine) scheme, which enabled the inverter to have the same moment of inertia and damping characteristics as the synchronous generator [185]. The European VSYNC project was jointly launched by several scientific research institutions such as Devteco University of Technology and the Netherlands Energy Research Center, focusing on improving the overall stability of microgrid systems through inverter control and energy storage devices, and the concept of VSG was first proposed in the same year [186]. The above schemes are current-type VSG controls, and the whole system can be equivalent to the current source. Although these schemes can improve the dynamic performance of the system by simulating the characteristics of synchronous generators to a certain extent, due to the limitations of the current source itself, they cannot be applied to the off-grid mode of microgrids.

In order to solve the shortcomings of current-type VSG control and ensure that reliable voltage and frequency can be provided in off-grid mode, voltage-type VSG control has received extensive attention. In 2009, Professor Qingchang Zhong of Loughborough University proposed the concept of voltage VSG control technology with Synchronverter. By simulating the second-order electromagnetic model of synchronous generators, the distributed power script was equivalent to the electrical and mechanical characteristics, as well as the frequency and voltage regulation characteristics of SG [187]. In 2012, Salvatore D'Arco of the Norwegian Academy of Industrial Sciences and Jon Are Suul of the Norwegian University of Science and Technology proposed the VSM (Virtual Synchronous Machine) scheme. By adding an output voltage control loop (voltage and current double closed-loop control) to the power control loop in the VSG control, the output performance of the system was improved, and the design of various parameters of the control link was analyzed [188]. Since the European VSYNC Engineering Center first proposed virtual synchronous control technology in 2008, relevant technical theories have been continuously supplemented and developed [189,190].

4.2. Advanced VSG Inverter Control Strategies

The inverter control strategy based on virtual synchronous generator (VSG) technology can fully simulate the operating characteristics of a synchronous generator and provide inertial damping support for the system in the dynamic process while realizing the functions of primary frequency modulation and primary voltage regulation. Virtual synchronous generator (VSG) control is different from traditional microgrid inverter control. By simulating the mechanical and electrical characteristics of a synchronous generator, VSG can not only achieve a droop effect similar to droop control but also have further inertia and damping characteristics, so that the transient process of the microgrid inverter becomes slow, providing voltage and frequency support for the system. Finally, the anti-interference ability of the system is improved [191]. The circuit structure of the inverter based on VSG technology is shown in Figure 8.

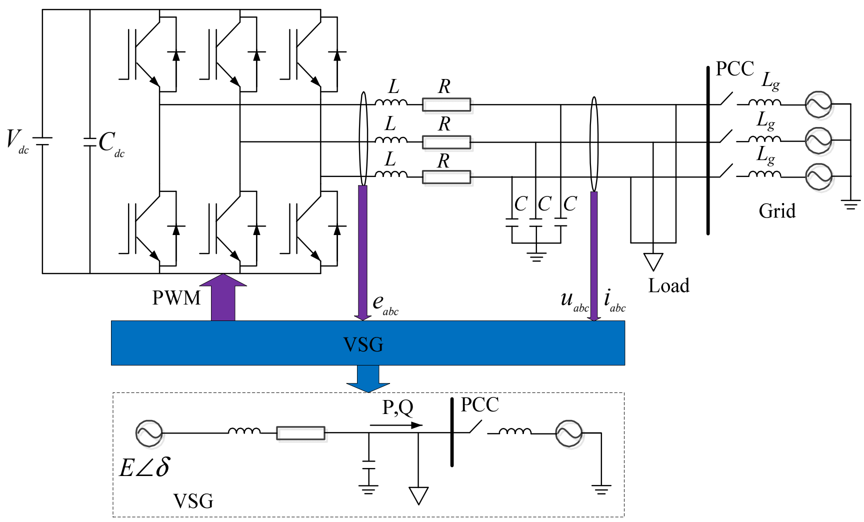


Figure 8. Circuit structure of the inverter based on VSG technology [191].

The traditional virtual synchronous generator adopts fixed parameters, which cannot reflect the advantages of flexible parameter regulation. Some scholars proposed a VSG control method with adaptive parameter adjustment to reduce the duration of the transient process. When the system is disturbed, according to the rate of change of the rotor angular speed or the difference between the angular speed and the rated value of the virtual synchronous generator, the moment of inertia is changed adaptively. For large disturbances, greater inertia is used, and for small disturbances, less inertia is used, so that the system quickly enters a stable state. The concept of inertial midpoint was proposed, and according to this concept, the parameter design of the inverter in the multistage parallel system of virtual synchronous generators was guided, so as to optimize the frequency response of the entire isolated network system and improve the operation stability of the isolated network system [192]. An adaptive inertia control method was proposed to enable virtual synchronous generators to have different amounts of inertia under different working conditions, so as to improve the frequency regulation process of microgrids in reference [193]. The inertial response of the PMSM wind turbine control system and hybrid energy storage system controlled by a virtual synchronous generator were analyzed respectively, which expanded the application prospect of virtual synchronous generator control [194]. Ref. [195] derived the closed-loop characteristic equation of a VSG power loop, establishing relationships between dynamic performance and designing parameters (inertia coefficient and damping coefficient). Ref. [196] designed and proposed a rotational inertia adaptive control strategy based on VSG control and studied the dynamic response of VSG through parameters such as peak time and overshoot. By studying the change law of angular frequency, the adaptive adjustment scheme of moment of inertia is designed. Through the real-time change of moment of inertia, the control effect is obviously improved, the overshoot of the system is reduced and the adjustment time is shortened.

The real-time measured network frequency was used as the frequency reference value of VSG, and the constant power control of VSG was realized under a grid-connected steady state. A virtual synchronous generator control method for suppressing harmonic current and power frequency fault inrush current under non-ideal large power grid conditions was proposed, and the proposed method was verified [197]. Ref. [198] proposed an enhanced VSG control method to address the problem of active power oscillation and improper distribution of transient active power in VSG control. Based on state space analysis, it achieved oscillation damping and proper transient active power sharing by adjusting virtual stator reactance. Ref. [199] proposed a mode-switching control method that would change the VSG mode when the power grid failed. However, differential detection was used, which can lead to a lot of noise and additional system instability. At the same time, with the mode switching control method, if the VSG does not have an equilibrium point, it may oscillate at the boundary. Ref. [200] proposed an improved virtual synchro control method based on Lyapunov energy function for direct power control under the condition of power grid voltage imbalance to solve the power fluctuation problem when the power grid voltage was unbalanced. Ref. [201] explored the influence and configuration of inertia and damping on energy storage and used linear optimization control to adjust power frequency fluctuations, so as to enable the microgrid system to have secondary frequency modulation capability and optimize power output. The proposed control scheme for the cascaded H-bridge-based BESS in grid-connected mode is shown in Figure 9.

Ref. [202] studied the application of VSG technology in different scenarios, such as wind power, photovoltaic and energy storage, and each scenario had grid-connected and networking operating conditions. For VSGs with dual-mode operation, it is necessary to ensure that the charged state SOC of the energy storage unit is within the safe range during both charging and discharging. Once the SOC of the energy storage unit exceeds the safety range due to the power fluctuation of the distributed power supply on the DC side of the VSG or the participation of the VSG in the primary frequency modulation, it is necessary to stop discharging or charging. Ref. [203] clarified the energy conversion method of inertia and energy storage and used equivalent calculation to configure energy storage but ignored the constraint of state of charge (SOC) of energy storage. When the battery has a low SOC, its output power changes greatly, and it cannot meet the adjustment requirements of the microgrid. The overall control diagram of the VSG is shown in Figure 10.

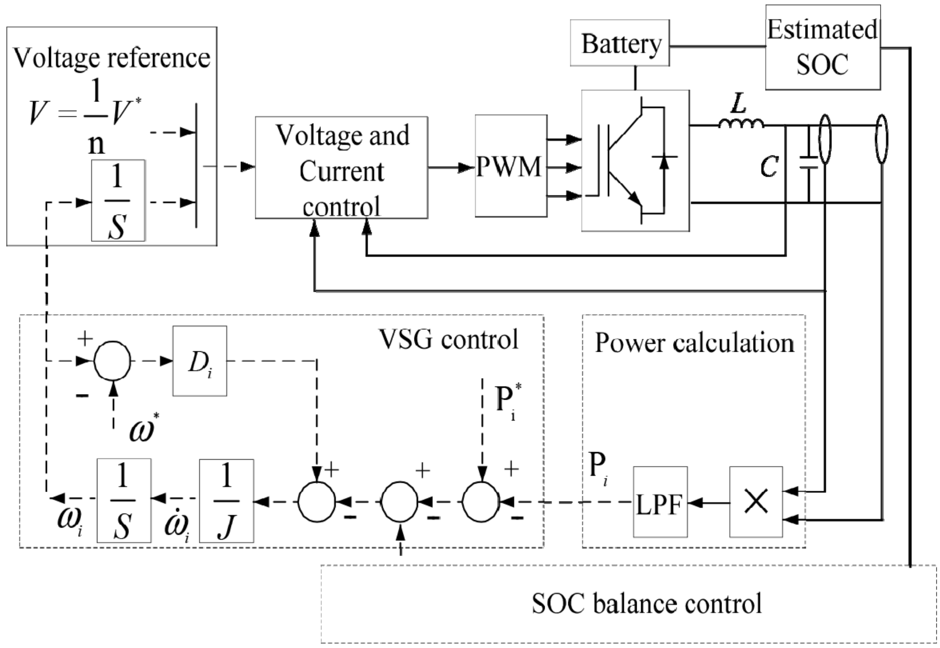


Figure 9. Proposed control scheme for the cascaded H-bridge-based BESS in grid-connected mode [201].

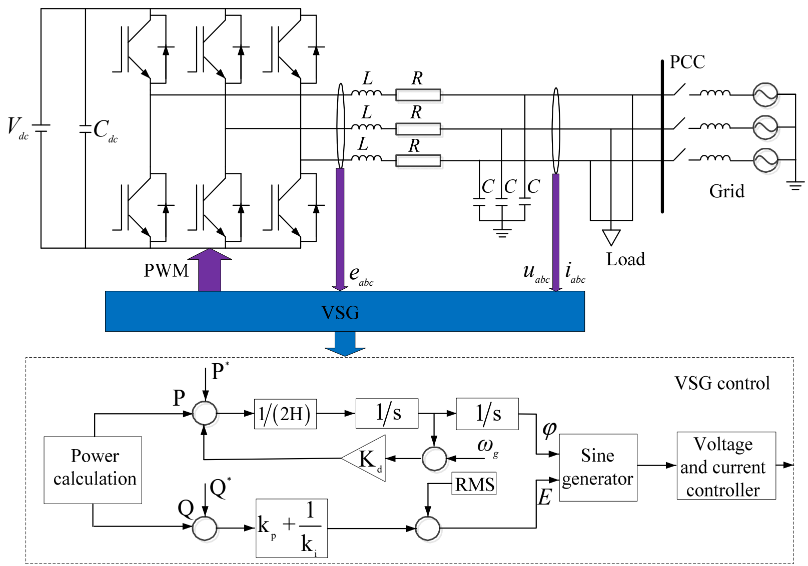


Figure 10. Overall control diagram of VSG [203].

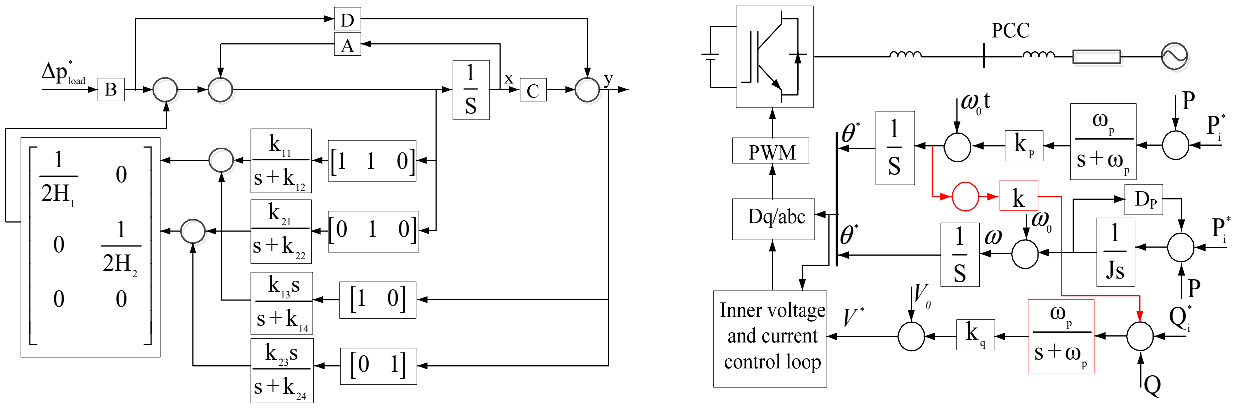
The parallel operation of multiple VSGs is one of the hot topics in the research of high-proportion renewable energy power systems, and the core challenge is to solve the problems of stability reduction, model accuracy deficiency and multi-machine cooperative control [204]. In order to solve the stability problem caused by the high proportion of renewable energy connected to the power system, Wang X et al. studied the parallel system of a grid-constructing multi-machine VSG inverter and grid-following PQ inverter. By establishing Thevenin and Norton equivalent impedance models, and based on global admittance stability criteria, the influence of control parameters and line impedance on system stability was analyzed. They found parallel coupling could improve PQ inverter stability but potentially destabilize VSG inverters. The study provided a new theoretical support for the stability analysis of multi-inverter parallel systems [205]. Long proposed a power-frequency admittance model considering power coupling to solve the problem of insufficient model accuracy caused by power coupling in multi-VSG grid-connected systems. The model modified the second admittance by considering the power coupling, which significantly improved the accuracy of the model under the condition of high line impedance in the medium- and low-voltage microgrid. In addition, the conductivity matrix model of the multi-VSG system was extended to analyze the effects of line impedance and reactive power loop coefficients on system stability. Simulation results showed the proposed model's error was significantly lower than traditional models under strong power coupling [206]. Lin et al. proposed a multi-VSG mutual damping control strategy based on a model predictive control and consistency algorithm. The system power oscillation was effectively suppressed by distributed calculation of the power increment and information exchange. This study not only proved the stability of the controller through the Lyapunov theory but also introduced the gain adjustment function to improve the robustness in non-ideal communication environments. Simulations demonstrated significant advantages in dynamic response optimization and economic dispatch [207].

4.3. VSG Stability Mechanisms

The stability problem is one of the basic problems in power system analysis, which mainly includes power angle stability, voltage stability and frequency stability. The proposal and application of VSG technology is to solve the problem that large-scale new energy enters the power grid through power electronic equipment and affects the stability of the power grid. According to the magnitude of the disturbance, it can be divided into static stability and transient stability.

In terms of static stability, ref. [208] studied the stability of DC microgrids under the high permeability of high-voltage power electronic convertors and proposed three active damping solutions. The stability of the system under different compensation schemes is evaluated by small signal analysis. In addition, the reconstructed source impedance and modified voltage tracking dynamic performance of the voltage source inverter interface under different compensation schemes are derived. The dynamic coupling between active damping and voltage tracking controllers is evaluated by sensitivity and robustness analysis. The problem of secondary control of voltage and frequency in isolated island microgrids is transformed into the problem of first-order system tracking synchronization using feedback linearization technology [209]. The stability of VSGs was proved by using the eigenvalue method of small signal modeling, and key parameters such as inertia coefficient, excitation coefficient, sag coefficient and virtual impedance were analyzed by eigenvalue and sensitivity [210]. Ref. [211] used the impedance method to establish impedance models of the VSG, power grid and load, respectively, and gave the Nyquist stability criterion. The influence of each impedance on system stability was reflected from the separate frequency response of load and source impedance, and the cause of instability of a digitally controlled voltage source inverter operating as a microgrid was explained through experiments. The state space method was used to analyze the stability of small signals in power electronic systems. After linearizing the study variables at the operating point, the state space equation was formed, and the stability of the system was judged by the eigenvalue of the state matrix. Compared with the impedance method, the state–space method simplifies the system model by linearizing the system equation and can study the degree of influence of different parameters of the system on system stability and the interaction between different parts of the system [212]. Ref. [213] modeled each dynamic element of the VSG to form a state–space model, and then the eigenvalue and singular value decomposition (SVD) analysis were used to evaluate the impact of the network model and virtual impedance on the dynamics of the VSG.

Ref. [214] focused on the small-signal modeling and parameter design of the VSG power loop, pointing out that in order to avoid serious distortion of VSG output voltage, the bandwidth of the power loop should be much less than twice the bandwidth of the line frequency. On this basis, the linear frequency average small-signal model of the VSG was derived, which was used for system analysis and parameter design. The coupling effect between active loop and reactive loop was analyzed from the point of view of system stability. Ref. [215] pointed out that when dynamic changes of inverters and circuits are considered, system stability is constrained by virtual inertia and damping parameters. Ref. [216] studied a VSG implementation based on a voltage source converter (VSC), including a virtual impedance and an outer loop frequency droop controller. The linearized small-signal model, including the converter and its network-side filter, the control system and a network-side equivalent circuit, was established and verified by time-domain simulation of the nonlinear system model. However, there are 19 state variables in this model, and it is difficult to extend it to parallel or even multi-machine models because of too many variables considered. A full analytical model of the VSG's small-signal output impedance in the dq coordinate system was established, considering the dynamics of sag control and virtual inertia [217,218]. The small-signal models of power level, external power control loop and internal voltage and current controller were derived. The full analytical model's accuracy was then verified using SABER simulation measurements. Based on the generalized Nyquist criterion (GNC), the impedance model was used to analyze the stability of a VSG in grid-connected mode, and the information required for system stability was analyzed. However, this method can only be applied to systems with access to stable AC points, otherwise the operating points will no longer be constant. Ref. [219] proposed an additional damping strategy to suppress power oscillations. After analyzing the relationship between the output power and angular acceleration, an acceleration control damping strategy with disturbance compensation was designed. The block diagram of small-signal model for a paralleled VSG system is shown in Figure 11a. The stability of the method was studied by small-signal analysis. A small-signal model of an inverter based on sag control and VSG control was established, and the dynamic response of time was compared. An adaptive time constant control strategy based on improved sag control was proposed, which improved the response characteristics of output frequency and active power when the power command changes in grid-connected mode and can provide sufficient inertia characteristics [220]. Ref. [221] studied the synchronization stability of virtual synchronous generators under power grid faults. Qualitative analysis was carried out based on a linearization model, and quantitative analysis was combined with a nonlinear model to reveal the internal mechanism of a low-pass filter to improve synchronization stability in a reactive power control loop. Figure 11b shows the block diagram for enhancing VSG transient stability with a low-pass filter. Ref. [222] proposed a hybrid harmonic suppression scheme consisting of a local voltage harmonic control loop and an adaptive grid current control loop, aiming at the problem that local nonlinear load and network distortion will affect the power quality of virtual synchronous generators. Small-signal modeling is used to study the stability of the system and its robustness to parametric perturbations. Refs. [223,224] provided the small-signal models of grid-connected mode and island mode and analyzed the stability of the system by analyzing the eigenvalues of the small-signal models and their parameter sensitivity.



(**a**) (**b**)

Figure 11. Block diagram of small-signal model for paralleled VSG system to enhance the VSG transient stability with low-pass filter (**a**) Block diagram of small-signal model (**b**) Configuration of a three-phase grid-connected VSG [219,221].

In terms of transient stability, ref. [225] used the phase portrait method to conduct an in-depth analysis of the transient stability of power synchronous controlled voltage source converters. The results showed that, following a transient disturbance, synchronization with the grid can be maintained as long as an equilibrium point exists. The critical clearance angle of a power synchronous control voltage source converter, that is, the power angle of unstable equilibrium point after fault, is identified when there is no equilibrium point in the power network fault. Ref. [226] proposed a method to improve the transient stability of the power grid of multiple virtual synchronous generators (VSGs) by controlling the oscillation of the electromagnet relative to the inertia center frequency of the power grid in the case of a short circuit. The proposed method can prevent the increase of the relative irreversible distance angle of the multi-virtual synchronous generator, which was the main factor preventing the multi-virtual synchronous generator from reaching the instability point, and its stability was verified by the Lyapunov function. The PSO algorithm was introduced to optimize and adjust the VSG unit parameters, and a scheme of alternating the moment of inertia value was applied to the dynamic voltage control system of a microgrid to rapidly suppress oscillations and improve transient stability after large disturbances [227]. In this scheme, the moment of inertia of the VSG is switched by the angular frequency of the VSG relative to the equilibrium point and its rate of change. Ref. [228] studied the transient rotor angle stability of parallel SG-VSG systems through comparative analysis. It showed that differences between parallel units affect transient stability, particularly during faults. A control method to improve the transient stability of shunt SG-VSG systems was proposed. On this basis, the nonlinear model of isolated island microgrids was established by using the Lyapunov method, and the attractive domain of parallel systems was quantified.

Ref. [229] designed a simple energy function to study the transient stability of VSGs and then proposed a Bang-Bang control strategy using the power angle relationship to improve the transient stability, but it is difficult to implement. Ref. [230] studied the transient stability of grid-connected voltage source converters under large signal interference. The dynamic performance and transient stability of four typical control schemes—power synchronization control, basic droop control, low-pass filter droop control and VSG control—were compared. The results show that transient stability and basic droop control can maintain stable operation as long as the equilibrium point exists, because they have a non-inertial transient response. However, the low-pass filter droop control and the virtual synchronous generator control are unstable even in the presence of an equilibrium point due to the lack of damping in their inertial transient responses. Through a phase portrait, the stability mechanism was clearly explained, and the quantitative effects of controller gain and virtual inertia were analyzed. The system stability of a static synchronous compensator (STATCOM) using a virtual synchronous generator was deeply analyzed [231]. The synchronizer and vector control performance were compared using different mathematical tools, such as eigenvalue analysis, numerical simulation and the Lyapunov theory. Finally, the feasibility of using synchronizer control strategy was verified on an IEEE 39-bus system. The results show that the synchronizer brings the advantage of artificially increasing system inertia, which is an important problem in modern power systems. The virtual synchronous generator was essentially a nonlinear system, and nonlinear control design was needed to maintain the stable operation of the synchronous generator when the power grid failed. Ref. [232] proposed an adaptive method to solve this problem, which can realize the full power injection of the power grid under unbalanced conditions, and analyzed the stability of the system through the Lyapunov function. In this method, the supplementary internal nonlinear controller was used as the external subsystem, and the power angle and inverter voltage were adjusted step by step using the on-line reverse updating law. The transient angular stability of VSGs was studied by the Lyapunov direct method. The influence of reactive control loop on transient angular stability was analyzed, and then the voltage change was considered using the Lyapunov direct method. The effects of different parameters on the transient angular stability were studied. Finally, a control method was proposed to improve the stability margin of VSGs by adjusting the reference active power.

Due to its excellent characteristics and the gradual maturity of distributed power technology, VSG technology will become the core technology of power structure transformation and smart microgrid construction in the future. Although there have been a large number of studies on the small-signal and large-signal stability of VSG, and there are a large number of studies on the parameter optimization design and parameter adaptive of VSG systems, most of the research results are based on the simplified model of a single machine connecting to an infinite power grid or island parallel, which can be regarded as a long-distance transmission model because it ignores the parameters of some transmission lines. This is inconsistent with the actual situation of the current user-side energy storage facilities connected to the grid, so it is of great significance to study the multi-machine VSG system with transmission line parameters. At the same time, because it is difficult to guide the system parameter design with the Lyapunov method, it is necessary to consider a new large-signal stability analysis method.

Although VSG technology can significantly improve the stability of the power grid and the ability to connect renewable energy to the grid, it still faces many economic and technical challenges in practical applications. VSGs have high initial investment costs and require high performance inverters and DSP controllers, which are more expensive than traditional synchronous machines [233]. The VSG itself does not store energy and requires a battery (BESS) or supercapacitor (SC) to provide actual power support. The VSG needs to simulate the inertia, damping and other characteristics of synchronous generators but under different grid conditions (such as microgrid, large grid, high proportion of new energy access), and parameters need to be dynamically adjusted, otherwise it may lead to oscillation or instability [234]. At the same time, it is necessary to realize the functions of frequency modulation (P-f), voltage regulation (Q-V) and harmonic suppression simultaneously, and the control strategy is complex. In the case of power grid faults (such as a short circuit or voltage drop), the VSG needs to quickly switch control mode to avoid going off grid [235]. At high grid impedance, such as remote microgrids, VSGs can cause resonance or voltage instability. When multiple VSG systems are connected in parallel, a mismatch of control parameters may lead to power oscillation or circulating current problems. A high proportion of new energy grids have low inertia, and the virtual inertia of the VSG may aggravate the frequency fluctuation if it is improperly designed. VSG technology has great potential in improving power grid stability, but it still needs to solve key problems such as high control complexity, energy storage dependence and high cost. In the future, through algorithm optimization, hybrid energy storage and policy support, VSGs are expected to become one of the core technologies of the smart grid.

5. Conclusions and Future Perspectives

5.1. Conclusions

Microgrids enhance grid reliability and flexibility while enabling effective renewable energy utilization. This paper summarizes recent microgrid research progress, focusing on operation optimization strategies, power prediction methods and the latest advances in VSG active support control technology. Key conclusions are drawn as follows:

(1) Operation Optimization Strategies: Energy Management Systems (EMSs) leveraging heuristic algorithms (e.g., PSO, GWO), multi-objective optimization and AI-driven strategies significantly enhance economic efficiency and renewable energy utilization. Challenges remain in handling high-dimensional computations and real-time adaptability in complex scenarios.

(2) Power Prediction Methods: Hybrid models integrating decomposition techniques (e.g., VMD, CEEMDAN) with deep learning (e.g., LSTM, GRU) improve the accuracy of wind/PV and load forecasting. Medium-term (3–10 days) prediction remains underdeveloped due to meteorological uncertainty and data resolution limitations.

(3) VSG Control Technology: Voltage-type VSG technologies emulate synchronous generator characteristics, providing inertia support and frequency regulation. Stability mechanisms (e.g., impedance modeling, Lyapunov-based analysis) are established for grid-connected/islanded modes, yet multi-VSG coordination and transient stability require further validation.

These findings underscore the maturity of core microgrid technologies while highlighting persistent gaps in scalability, real-time performance, and cross-domain integration. This review aims to provide insights for enhancing economic, reliable, safe and stable microgrid operation, promoting further research and application

5.2. Future Perspectives

To address unresolved challenges and propel microgrid technology toward industrial deployment, future research should prioritize the following:

(1) Quantum Optimization for EMSs: Address computational bottlenecks in large-scale, high-dimensional microgrid optimization using quantum algorithms (e.g., leveraging superposition and entanglement [236]). This can reduce optimization time from minutes to seconds, enabling real-time EMSs for 24 h scheduling. Cross-energy coupling optimization (electricity, hydrogen, heat) across multiple timescales is also crucial.

Advanced Power Prediction: Enhance prediction accuracy via multi-modal deep learning and spatiotemporal graph neural networks, integrating diverse data sources (satellite, radar, local sensors). Develop physical-information fusion systems using digital twins updated with real-time data [237]. Implement ultra-low-latency edge forecasting by integrating LSTM cores into dedicated weather chips (<50 ms) [238].

Next-Generation VSG Hardware: Utilize superconducting materials for near-zero-loss, ultra-fast response VSGs (100× speed increase) [239]. Employ wide-bandgap materials

(SiC, GaN) for high-frequency switching (>10 kHz), reducing losses by 50% and enabling wider impedance bandwidth control.

Distributed VSG Coordination: Develop intelligent, self-organized VSG cluster control strategies for synchronous frequency regulation, reducing reliance on centralized systems and aligning with distributed microgrid trends.

(2) There is an urgent need to deepen research in the field of automation and intelligence of microgrid systems. Advanced technologies such as AI, IoT and big data analytics are deeply integrated with microgrid technology to build a comprehensive "source–grid–load–storage" intelligent synergistic system. Intelligent microgrid systems have the ability to automatically identify load demand, make accurate power predictions and optimize dispatch. Through independent management and automatic control, efficient and low-carbon energy utilization is achieved. Through the close integration of AI technology and the IoT, the microgrid is shifting from a "passive response" to an "active sensing-decision-making" mode.

(3) There is an urgent need to strengthen the in-depth research of multi-level hybrid microgrid technology, so as to promote the transformation process of regional multistage distribution systems of microgrids and realize the evolution of microgrids in the large-capacity and regional hybrid direction. At the same time, it is essential to deepen the research on application technology and integration technology, in order to promote the development of microgrids in the direction of integration. VSG technology faces a number of challenges, including high control complexity, dependence on energy storage systems and relatively high cost. These problems have become obstacles to the further development and wide application of VSG technology. However, with the continuous progress and innovation of technology, through the continuous optimization of algorithms, the in-depth application of hybrid energy storage technology and strong support from the policy level, VSG technology is expected to overcome these challenges in the future. Once these problems are properly solved, VSG technology will most likely become one of the core technologies in the field of smart grids, providing strong technical support for the stable operation of smart grids and the efficient use of energy.

(4) There is an urgent need to strengthen the research on energy storage technology. As a core component of microgrids, energy storage systems play a crucial role in optimizing energy structure, improving energy efficiency and ensuring the stability of the energy supply. With the continuous expansion of the scale of microgrids, the energy regulation function of energy storage systems in time series has become the key to solving the inherent randomness and volatility of renewable energy and maintaining the stable operation of microgrids. The VSG itself does not have the function of energy storage and must be combined with battery energy storage systems or energy storage devices such as supercapacitors to provide actual power support. By effectively integrating VSGs with these storage devices, power distribution can be optimized to improve the stability and efficiency of the entire system. Therefore, the combination of energy storage systems and VSG technology is the key to promoting the development of more intelligent and efficient microgrids.

In the process of rapid development of distributed generation technology, the microgrid has emerged to provide a boost to the operation of the power system. In the future, the microgrid will continue to face the challenges of technological innovation and marketing. The microgrid is a nonlinear complex system. In order to further improve the microgrid, it is necessary to flexibly apply more advanced intelligent energy management systems, power prediction technology and VSG active support control technology to further enhance the efficiency and flexibility of the microgrid, thereby promoting the development of the microgrid towards intelligence and holistic integration. Overall, with the continuous improvement of microgrid technology and the refinement of the system, the microgrid has broad prospects and will make significant contributions to sustainable energy supply and environmental protection.

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