

Analysis of Planning, Configuration, and Operational Control of Wind–Solar–Storage Hybrid Power Generation Systems in Smart Grids

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Abstract. Under the two-carbon goals of carbon peaking and carbon neutrality, the installed capacities of wind and photovoltaic (PV) power generation have been increasing at a high rate. The proportion of renewable energy is now relatively high, so we have experienced problems with unstable power generation, a lack of regulation facilities, and increased requirements for frequency and voltage stability. To address the above problems, Wind-Solar-Storage (WSS) hybrid power generation systems have added energy storage devices for peak-shaving, valley-filling and output-smoothing; as a result, grid-integration issues have been reduced and the adaptability of renewable energy has improved. This paper presents the smart grid integration architecture, provides necessary enabling technologies for power forecasting, grid-forming control and storage management, and introduces three types of optimisation methods along with their strengths and weaknesses: deterministic, heuristic and artificial intelligence (AI)-based approaches. The current problems in research are an inadequate model for source-load uncertainty, a lack of grid-forming support, and poor interpretability of AI methods. In the future, research will be conducted on the integration of model-driven and data-driven methods, multi-timescale coordinated optimisation, and the strengthening of system resilience in the face of severe weather.

Keywords: Wind–solar–storage hybrid systems, Smart grid, Optimal dispatch, Energy storage management, Grid-forming control

1. Introduction

In accordance with the national objectives of carbon peaking and carbon neutrality, wind and photovoltaic (PV) power generation in China have been developing at a high speed. By the end of 2024, China's new PV capacity will reach 278 GW and account for about 60% of the world's new installations; cumulatively, the globe will have added as much as 1,136 GW of wind power, with China leading at 521 GW [1]. Wind and PV power generation are highly dependent on weather conditions, and are thus variable, stochastic and intermittent. With the increase in the proportion of renewable energy, power balance has become more difficult to achieve, and voltage stability and renewable energy accommodation are under greater pressure [1, 2].

Wind-solar-storage (WSS) hybrid power generation systems have been widely considered to be feasible solutions to the above problems. Energy storage devices control the flow of electricity by charging and discharging, absorbing excess power when renewable energy generation is high and releasing it when there is a power shortage; they provide peak-shaving, valley-filling, output-smoothing, and frequency-regulation ancillary services. Wind power, solar power and energy storage systems can be combined to reduce the fluctuations of individual renewable energy sources and address problems in grid connection [1, 3-5]. A representative WSS system includes wind farms, PV stations, energy storage stations and an energy management system (EMS); the EMS acts as the operating "brain" to coordinate power dispatch [4]. This paper provides all-encompassing analysis of the system architecture, planning approach, control strategy and future problems in WSS systems, and aims to offer a systematic technical reference for the integrated development of WSS systems in the context of smart grids.

2. System architecture and key technologies

2.1. Integration architecture of wind-solar-storage systems in smart grids

A WSS hybrid system generally uses a "source-network-load-storage" integrated structure. Wind turbines and PV arrays are generally connected to AC or DC buses via power converters, and various topologies, such as centralized grid-connected systems and AC-DC hybrid microgrids, can be constructed. A bidirectional power converter is used to enable two-way power flow of the energy storage system, and an EMS is employed for data collection, status observation and optimised power dispatch [4, 6]. Wind turbines in this structure may be doubly-fed induction generators (DFIGs) or permanent magnet synchronous generators (PMSGs), and MPPT devices are added to the PV array to maximise power generation efficiency. A typical structure of an energy storage subsystem includes high-power-density devices (such as supercapacitors) and high-energy-density devices (such as lithium-ion batteries), and both are used simultaneously. All the units are connected to a common bus via AC/DC converters to form an AC-DC hybrid microgrid structure, and the mature technological advantages of AC grids and the high-efficiency transmission characteristics of DC networks are utilized [6].

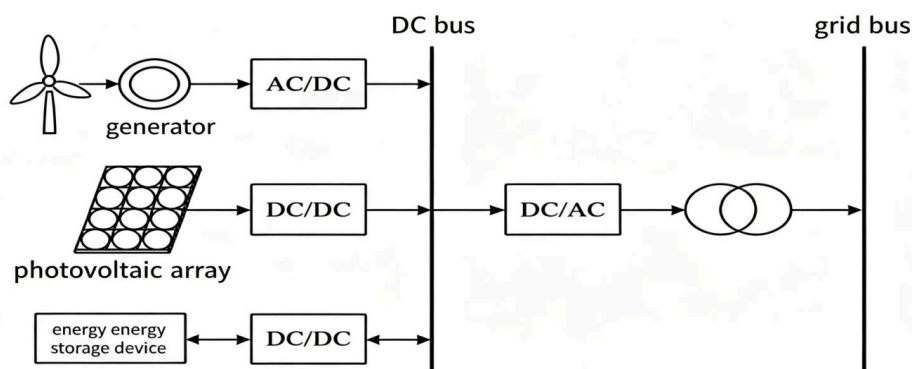


Figure 1. Typical structure of a wind-solar-storage hybrid power system

2.2. Key enabling technologies

Technologies that combine numerical weather prediction (NWP) and spatiotemporal coupling models have been applied to power forecasting to reduce the forecasting error from 12% to less than

5% [3]. Precise power forecasts are required to optimise the dispatch plan of the system, so many methods for forecasting have been used to date, including physical models, statistical learning techniques, deep learning methods, etc. Traditional inverters in the grid-forming control area operate in grid-following mode and use grid voltage and frequency signals as references; on the other hand, grid-forming control can autonomously set voltage and frequency references to actively support grid stability [7]. Grid-forming control technology can offer inertia and damping support to the grid in a way that is similar to that provided by traditional synchronous generators, and is thus one of the key technologies for future power systems with a high proportion of renewable energy. For Energy Storage Management, a hybrid storage system of lithium-ion batteries and supercapacitors can be employed to meet both high-power-density and high-energy-density requirements simultaneously. A hierarchical State-of-Charge (SOC) control strategy can extend the service life of storage [3]. The Storage operating range in hierarchical SOC management is divided into a prohibited area, a buffer area and a priority area; power-type storage is used for high-frequency fluctuation regulation and maintains the SOC in the range of 40%-60%, while energy-type storage is employed for low-frequency fluctuation management and keeps the SOC in the range of 20%-80%. The zonal management mode has expanded the regulation scope and extended the life of storage services [3]. A comparison of the above energy storage technologies is shown in Table 1.

Table 1. Comparison of common energy storage technologies

Energy storage type	Power density (W/kg)	Response time	Cycle life (times)	Application scenarios
Lithium-ion battery	500–2000	ms–s	3000–5000	Power smoothing, frequency regulation, peak shaving
Supercapacitor	5000–10000	μs–ms	500,000–1,000,000	High-frequency power fluctuation suppression, primary frequency regulation
Pumped hydro storage	Very low	min	tens of thousands	Daily energy shifting, large-scale storage
Lead-acid battery	100–300	ms–s	500–1000	Backup power, small off-grid systems

Data Source: [7]

3. Planning and optimization methods

3.1. Capacity configuration and siting

The Scale of WSS systems will directly affect their economics and stability. Based on previous research, most studies have found that the additional benefit per unit increase in storage deployment relative to installed wind and PV capacity is decreasing. The optimal configuration ratio is jointly determined by several factors, such as resource characteristics, load profiles, electricity pricing mechanisms, and control objectives, and no single universal ratio can be established [8]. Capacity planning needs to consider all the spatiotemporal complements of wind and solar resources, load demand features, as well as investment costs and operating revenues for the energy storage system. Capacity configuration problems are generally formulated as multi-objective optimisation problems, and the objective functions usually include minimising the annualised total economic costs, maximising the utilisation of renewable energy, and increasing the reliability of power supply [8, 9].

3.2. Comparison of optimization methods

The three general types of frequently used optimisation methods are deterministic optimisation, heuristic algorithms and AI-based optimisation, as shown in Table 2. The categories and their corresponding application effects are as follows.

Deterministic Optimisation Methods are those that find the optimal solution by means of mathematical programming techniques based on accurate mathematical models and deterministic input parameters. Among them, Mixed-Integer Linear Programming (MILP) is a typical algorithm that converts the original problem into a standard form suitable for solving by commercial solvers via piecewise linearisation of nonlinear constraints [8]. Zhang and his colleagues applied MILP to a study on the short-term optimal dispatch of cascaded hydropower stations, used piecewise linearisation to handle single-variable hydraulic nonlinear constraints, and introduced quadrilateral grid discretization and SOS2 constraint modelling to address binary electrical nonlinear constraints. Therefore, the peak-to-valley differential was reduced by 56%-69% compared with that of the successive approximation dynamic programming algorithm, and the computation efficiency improved by 38%-45% [10]. The strengths of MILP are relatively high accuracy and guaranteed feasibility; however, it has a limited ability to address the uncertainty in wind and PV power generation, and the computational cost increases exponentially with an increase in the number of variables [8].

Heuristic algorithms are a type of algorithm based on intuition or empirical rules that can find a good-enough feasible solution at a relatively low computational cost, but they do not guarantee the optimal solution. Representative heuristic algorithms are Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) [11]. PSO simulates the foraging behaviour of bird flocks, and each particle continuously updates its velocity and position according to its own best-found position and the global best position of the swarm to gradually converge to an optimal solution. GA simulates the process of natural selection through selection, crossover and mutation, and conducts a global search of the solution space. GA can reduce the fuel consumption and emissions of a hybrid-electric vehicle energy-management optimisation by about 14% and 12%, respectively [11]. Tan and others used heuristic algorithms for techno-economic optimisation of a wind-solar-biogas-storage AC-DC hybrid rural microgrid and reduced the system's operating costs significantly [12]. Heuristic algorithms are generally good at handling complex, non-linear and non-convex constraints and are more adaptable; however, they may also be subject to local optima, sensitive to the selection of parameters, and exhibit different results in multiple runs [11, 12].

Recently, with the application of deep reinforcement learning (DRL), artificial intelligence-based optimisation techniques have shown excellent results in the optimal dispatch of WSS systems. DRL is a combination of deep learning for perception and reinforcement learning for decision-making; thus, an agent learns an optimal state-to-action mapping strategy by interacting with an environment through trial and error. The agent observes the state variables of the WSS system, such as wind speed, solar irradiance and SOC, outputs control actions, such as storage charge-discharge power, and is trained to minimise operating costs as the reward function [7]. Based on the above studies, the DRL-based dispatch strategy has reduced operating costs by up to 5% compared with the traditional method [7]. In addition, an improved algorithm based on proximal policy optimisation (PPO) in a bilevel planning framework for hydro-wind-solar-storage systems has reduced the total cost by about 7.8% compared with the previous method and is suitable for complex system optimisation [13]. The strengths of AI-based optimisation include online learning, strong adaptability and real-

time response to environmental changes; its weaknesses are high training costs, poor interpretability and a need for large amounts of high-quality training data [7, 13].

Table 2. Comparison of the three categories of optimisation methods

Method Category	Representative Algorithm	Advantages	Limitations	Applicable Scenarios
Deterministic Optimization	Mixed-Integer Linear Programming (MILP)	Precise solution, guaranteed feasibility	Poor handling of uncertainty; exponential computational cost	Day-ahead scheduling; capacity planning (known scenarios)
Heuristic Algorithms	Particle Swarm Optimization (PSO); Genetic Algorithm (GA)	Highly adaptable; handles nonlinear and non-convex constraints	Prone to local optima; parameter-sensitive; results may vary across runs	Medium-to-long-term planning; multi-objective optimization
AI Optimization	Deep Reinforcement Learning (DRL)	Online learning; strong adaptability; real-time control capability	High training cost; poor interpretability; requires large datasets	Real-time energy management; dynamic dispatch

4. Operational control strategies and future challenges

4.1. Energy management and multi-timescale control

Most Energy Management Systems (EMS) are divided into multiple time scales. At the ultra-short-term level, the objective is power balancing, and a high-speed response of the energy storage system to rapid fluctuations in wind and PV generation is required. At the short-term level, the aim is economic optimisation and cost reduction under the load demand. At the medium- to long-term level, equipment life management will be used to avoid damage caused by overcharging or over-discharging of the storage system [3]. The Zhangbei National Wind-Solar-Storage-Transmission Demonstration Station has a three-level control system and keeps the power-fluctuation rate at 15 minutes or less within 7% [3]. This station is the world's first all-encompassing demonstration project for the paradigm of wind-solar-storage joint generation technology, integrating wind power, PV generation, chemical energy storage and intelligent power transmission. The operation has successfully provided a reference for the engineering practice of WSS systems. A rule-based energy-saving strategy for a residential microgrid reduced grid power consumption by 28% and overall costs by 22% in hardware experiments, demonstrating the effectiveness of a hierarchical control system [14].

4.2. Frequency stability and accommodation bottlenecks

A sudden drop in wind and PV power generation may cause a frequency excursion of the system. According to the data at the demonstration station, the largest frequency deviation is ± 0.55 Hz [7]. Storage participation in primary frequency regulation can reduce the response time from 1 second to 300 milliseconds [3]. Curtailment rates for wind and solar power also need to be lowered further, and some projects have already reached a rate of less than 3% [7]. At the foundation of frequency stability is the problem of reduced system inertia due to fluctuations in renewable energy generation; thus, traditional frequency-regulation resources have shown a slow response speed. Energy storage systems can respond in the order of milliseconds, so they are suitable for addressing this problem; to

strengthen the frequency stability of the system, appropriate planning of storage capacity and a coordinated control strategy need to be developed [7, 8, 10-14].

4.3. Deep integration of artificial intelligence and resilience enhancement

Deep reinforcement learning has been applied to optimise the charging and discharging strategy of energy storage and reduced costs by about 5 per cent compared with traditional methods [7]. AI algorithms can be used to optimise the energy system of a microgrid and thus reduce the levelised cost of electricity (LCOE). For example, using genetic algorithms, artificial bee colony algorithms and ant colony algorithms to optimise a microgrid with PV, wind, biomass and storage resources has reduced the LCOE to a minimum of \$0.037/kWh, which is a 67% reduction compared with the reference cost [15]. In the future, more research will be conducted on how to apply AI and digital twin technology to build a resilient WSS system in the face of extreme weather events [4]. Digital Twin technology creates a real-time virtual model of the physical environment and, based on this model, observes and predicts changes in the system to support optimisation decisions. In addition, in the event of extended overcast conditions, weak winds or a typhoon, the actual reduction in wind and PV power may be more severe than anticipated. Increasing the survivability and rapid recovery capability of systems in the face of extreme conditions, that is, system resilience, is also a focus of research in the future [16].

5. Conclusion

This paper will systematically introduce the architecture, planning method and operating control strategy of wind-solar-storage (WSS) hybrid power generation systems under smart grid conditions. Based on the analysis of the system integration architecture and key enabling technologies, optimisation algorithms, multi-timescale energy management, etc., some good results have been obtained. First, the source-network-load-storage integrated architecture offers a stable foundation for the WSS system. To regulate power flexibly and enhance grid compatibility, wind turbines, photovoltaic arrays, a hybrid battery-supercapacitor storage unit, a bidirectional converter and a central energy management system are employed. Grid-forming control technology can provide synthetic inertia and voltage regulation by inverter-based resources to strengthen grid support in high-penetration renewable energy systems. Second, hierarchical State-of-Charge management and multi-timescale dispatch coordination are required improvements to the utilisation of energy storage. By dividing the storage operating range into independent functional areas for power-type and energy-type equipment, improved regulation accuracy and an extended service life of the equipment will be achieved, thereby reducing long-term operating costs. Third, in terms of optimisation methods, deterministic approaches such as mixed-integer linear programming are most suitable for day-ahead scheduling under known conditions, and heuristic algorithms, such as particle swarm optimisation and genetic algorithms, can be used to solve non-linear, multi-constrained problems. Deep reinforcement learning is suitable for real-time adaptive control and can reduce operating costs by about 5% compared with the former method in actual operation. Fourthly, there are still some current problems in three areas: accurate joint modelling of generation-side and demand-side uncertainty; scalable grid-forming support for large-scale renewable energy integration; and improved interpretability and generalizability of AI-driven dispatch algorithms. To address the above deficiencies, the physics-based model will be integrated with data-driven methods more closely. In the future, multi-timescale coordinated optimisation frameworks will be developed to integrate ultra-short-term power balancing with medium- and long-term economic and reliability

goals. Given that the old forecasting models will fail during a severe weather event, we need to strengthen the stability of the system. With the continuous progress of digital twin technology and satellite-assisted communication facilities, high-fidelity real-time observation and predictive control of distributed Wireless Sensor Networks (WSNs) have become more feasible. In short, the WSS hybrid system offers a way to achieve a clean, flexible and high-reliability new-type power system.

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