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Review

Power Generation Scheduling for a Hydro-Wind-Solar Hybrid System: A Systematic Survey and Prospect

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Abstract: In the past two decades, clean energy such as hydro, wind, and solar power has achieved significant development under the "green recovery" global goal, and it may become the key method for countries to realize a low-carbon energy system. Here, the development of renewable energy power generation, the typical hydro-wind-photovoltaic complementary practical project, is summarized, and some key problems in complementary systems such as the description and prediction of the power generation law in large-scale stations, risk management, and coordinated operation are analyzed. In terms of these problems, this paper systematically summarizes the research methods and characteristics of a hydro-wind-solar hybrid system and expounds upon the technical realization process from the prediction and description of wind and solar power station cluster output, the risks brought about by large-scale renewable energy grid-connected operation, and the long-term and short-term coordination modeling and resolution thoughts on the hydro-wind-solar hybrid system in cluster mode. Finally, based on the aforementioned analysis, the existing research gaps are discussed from the standpoints of generation forecast, risk management, and cluster scheduling, and the future work outlook is presented accordingly. A hybrid system that combines hydro, wind, and solar energy is emerging as a way to make up for each other's shortcomings and will be a fruitful area of study in the future.

Keywords: hydro-wind-solar system; energy complementary; optimal scheduling; risk management

1. Introduction

Over the past few decades, the demand for electricity has grown rapidly because of the rapid growth of the global economy and population. The traditional power supply is dominated by non-renewable fossil energy (e.g., coal and oil), whose accelerated consumption has caused serious pollution problems. The energy crisis and environmental pollution have received widespread attention from countries around the world. Therefore, the need to develop clean and renewable energy is becoming more and more urgent [1,2]. Efforts are accelerating globally to develop renewable energy and its associated technologies, which are now recognized as a strategic sector [3,4]. Governments all over the world have adopted new regulations and policies encouraging the employment of renewable energy technologies [5,6].

In 2020, the installed capacity of renewable energy even surpassed that of 2019 against the backdrop of the coronavirus pandemic and the global economic slowdown. This undoubtedly shows that the transformation and upgrading from the traditional energy structure to renewable energy is the general trend. Figure 1 below shows that in the past decade, the total installed capacity of wind, solar, hydro, etc. renewable energy in the world has shown an upward trend year by year, and the growth rate is stable and improving. In the future, as the proportion of renewable energy in the global energy consumption market gradually increases, the strategic position will become more prominent, which will have a profound impact on the global energy supply system and consumption pattern. The future energy supply pattern will also undergo fundamental changes.

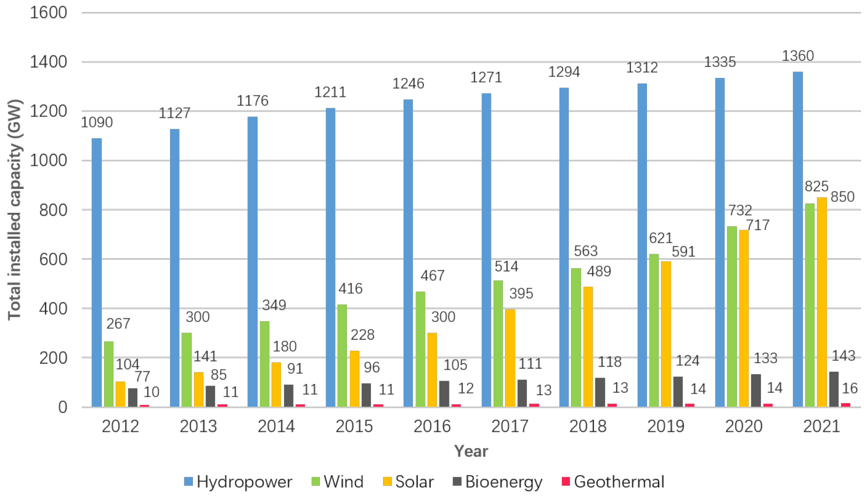

Figure 1. Global renewable energy installation (classification).

As power grids have moved from single-energy generation to today's multi-energy mix generation, the study of dispatch optimization has moved from deterministic to uncertain optimization, linear to nonlinear problems, and from highly conservative static characteristics to dynamic planning. Solar photovoltaic and wind energy resources led various researchers to pursue several methodologies for unit sizing and the optimization of hybrid energy systems based on photovoltaic and wind resources [7–9].

In 1983, Almeida et al. developed a simple multi-variable weather model which includes the solar radiation, wind speed, and rainfall. The power generation system gives the association with the battery storage facility to smoothen the time distribution mismatch between renewable energy generation and the load [10]. The use of wind, solar, and pumped hydro storage for powering an island in Boston Harbor was planned in 1985 for public education and recreational use [11]. In recent years, Wang et al. [12] proposed a short-term optimal operation hydro-thermal-wind model based on the principles of complementing hydro and wind power to reduce carbon dioxide emissions. The results showed that the hybrid system can significantly reduce wind power curtailments by using a hydro-wind complement and the hydropower peak-shaving capability. Concerning the water flow delay, Gupta et al. [13] proposed the use of reservoir-filling coefficients based on the adjustable storage capacity for load distribution of cascade hydropower stations, which provided a new idea for hydro-PV-wind short-term optimal operation. However, the former lacks the description method of the hybrid system net load and rarely involves the role allocation of hydropower stations, and the latter did not analyze the role that the hybrid system should play in the power grid. The existing research pays limited attention to the complementary role allocation and synchronous peak shaving of cascade hydropower stations.

Many feasibility studies have been proposed with various approaches to signify hydro-wind-solar systems, such as a real-time case study to analyze the overall efficiency [14], different storage options for hydro-wind-solar systems [15], analysis of pumped hydro storage as daily and seasonal energy storage [16], and the technical feasibility of pumped hydro storage for an island in Hong Kong with a developed operating strategy [17].

Various studies performed reliability analysis for hydro-wind-solar systems, such as through an optimization model considering system stability as the main objective [18], maximization of solar and wind outputs using pumped hydro storage [19], robust scheduling optimization in a multi-energy hybrid system to analyze the influence of uncertainty in solar and wind power [20], and assessment reliability based on the loss of load and the expected energy not provided [21].

Several energy management strategies are proposed in the literature as well for effective hybrid renewable energy system operation, such as that of Soliman, Alahmadi et al. [22,23], who provided a high-order sliding mode control method and fuzzy logic control to manage and control the energy inside a DC microgrid consisting of multiple energy sources, a power control scheme to reduce the revenue losses and improve the generation profile [24], a power management algorithm implemented to ensure smooth output power [25], and integration of a hydropower station to analyze the ramp rate and grid energy exchange [26].

The economic significance of hydro-wind-solar systems, such as the effect of grid and CO_2 costs on hydro-wind-solar systems [27], the role of the storage cost in hybrid renewable energy systems [28], and the execution of existing hydropower as a substitute for diesel generators [29], are analyzed in the literature. Several hydro-wind-solar system studies accomplished techno-economic analysis with different approaches, such as renewable energy electrification considering seasonal variations [30], bi-objective optimization with different loads [31], scenario based techno-economic analysis [32], and flexible plant modeling considering various conditions [33].

New energy power generation needs to consider the coordination of wind and solar energy. Strengthening energy storage and multi-energy complementarity is an effective means to coordinate the operation of a power grid [34]. However, the energy storage system is limited by factors such as safety, service life, and investment. Thus, it is difficult to support the demand for large-scale new energy consumption. Due to the significant randomness and volatility of new energy sources such as wind energy and solar energy, after large-scale new energy power generation is connected to a power system, the controllability of the supply side of the system is reduced, and the power system presents strong randomness in both supply and demand [35,36]. This bilateral randomness will not only have an impact on the security and stability of the power system, but it will also cause non-optimal exploitation of the primary resources (i.e., wind and insolation) [37,38], and the problem of new energy consumption is prominent [39,40]. As a power source that can flexibly adjust the output of generator sets [41,42], hydropower plays a good supporting role in the integration of renewable energy power generation in a grid [43,44], and with many of the above examples using pumped hydro storage for energy management, PHS is a useful method for storing a lot of electricity, but it has a high initial capital cost and needs good terrain. A flexible, dependable, and efficient distribution and transmission system is required, given the rising trend of employing intermittent energy sources [45]. Large-scale hydro-wind-solar hybrid systems could make important contributions to the global transition to low-carbon energy systems [46].

When reviewing the development of optimal scheduling of pumped hydro storage, wind power, and solar PV systems for a grid-connected system, for exploring the possibilities and opportunities to scrutinize the sequential progress of optimal scheduling in hydro-wind-solar hybrid systems, the literature have been reviewed thoroughly. In order to turn up the potentiality and exploration of possibilities in the near future as well as in the future, a study based on the seven points mentioned below comprehensive analysis can be outlined as follows:

1. The prediction of power generation is very important for the operation of hydro-wind-solar hybrid systems. Wind and solar power generation is random and difficult to predict accurately. The common methods of wind and solar power generation and their advantages and disadvantages are summarized, and the general direction of future forecasting technology is pointed out.

2. According to the error between the forecast and the actual power generation value, the risk brought by the error is considered. To ensure the balance of the entire energy system and avoid a large amount of wasted resources, risk management is essential.

3. After the preliminary work is completed, it is necessary to consider the unit combination according to the relationship between the load and the predicted value. Be-

cause hydro-wind-solar hybrid systems are more complicated than a general single power station, it is necessary to determine the type of power plant that generates electricity and the proportion of the power plants involved.

4. Energy complementarity is a feature of hydro-wind-solar hybrid systems. According to the season, climate, and other factors, a reasonable water level control rule and a general long-term power generation plan should be formulated by using the regulated power storage capacity of hydropower.

5. In the face of changing loads and real-time weather conditions, optimization methods are used to determine flexible short-term scheduling plans.

6. Challenges are faced by renewable energy hybrid system generation.

7. Near-future actions and assessment are explained.

The optimal scheduling problem of the hydro-wind-solar system should fully consider important factors such as the operation mode of the power system, the optimal scheduling objective, the optimal scheduling strategy, and the operation constraints. The optimal scheduling problem of a water-solar system should fully consider important factors such as the operation mode of the power system, the optimal scheduling objective, the optimal scheduling strategy, and the operation constraints. First, optimal scheduling of power systems is not limited to day-ahead scheduling unit commitment (UC), security-constrained unit commitment (SCUC), intraday scheduling, real-time economic dispatch (ED), or security-constrained economic dispatch (SCED) and also covers various fields such as power flow calculation, operation optimization, and the power market. Therefore, optimal scheduling is large-scale and complex work. Although the research in each branch area has commonalities, the objective functions, constraints, and problems to be solved in each branch area are quite different. Secondly, the operation of clean energy based on hydropower and wind power is still in the exploratory stage at the practical level. Facing a series of problems, such as the description and prediction of power generation law in large-scale stations, risk management and coordinate operation were analyzed. Theoretical and technological breakthroughs are urgently needed.

Numerous literature reviews on renewable energy generation dispatch have been conducted but not specifically for hydro-wind-solar systems. This study aims to present a systematic summary of the research methods and characteristics of a hydro-wind-solar hybrid system. This might serve as a guide for researchers looking into the most recent hydro, wind, and solar power generation technology, the direction of hydro-wind-solar hybrid system research, and the viability of large-scale hydro-wind-solar hybrid systems. To this end, this paper analyzes the development of clean energy. Section 2 briefly analyzes the characteristics of typical practical projects. Section 3 summarizes the key issues of hydro-wind-solar hybrid system optimal scheduling. Section 4 sorts out the research status of hydro-wind-solar renewable energy generation scheduling optimization. Section 5 analyzes the important future development direction of hydro-wind-solar hybrid systems.

2. Hydro-Wind-Solar Energy System and Practical Engineering

As many economies look to reduce their reliance on highly polluting fossil fuels during the energy transition, the penetration of clean energy has increased significantly [47–49], with 28% of the world's electricity coming from renewable sources in 2018, 96% of which came from hydro, wind, and solar technology. Renewables are expected to collectively increase their share to provide 49% of global electricity generation by 2050. In 2020, the newly installed capacity of renewable energy in Asia reached 167.61 GW, and the total installed capacity reached 1286.31 GW, ranking first in the installed capacity of renewable energy in the past 10 years, and it is the fastest growing region in the world. The total installed capacity in Europe ranks second in the world with 600.50 GW at the end of 2020. North America ranks third in the world in terms of total installed capacity, being at 421.70 GW at the end of 2020 (Figure 2). In 2021, China's newly installed renewable energy capacity was 134 million kW, accounting for 76.1% of the country's newly installed power generation capacity. Renewable energy power generation has grown steadily, reaching

2.48 trillion kW and accounting for 29.8% of the total electricity consumption of the whole society. Figure 3 shows the highest potential countries for onshore wind and utility-scale PV capacity by capacity factor tranches [50]. Table 1 shows recent results on an integrated basis for hydro, wind, and solar power up to 2020. New progress has been made in clean energy consumption.

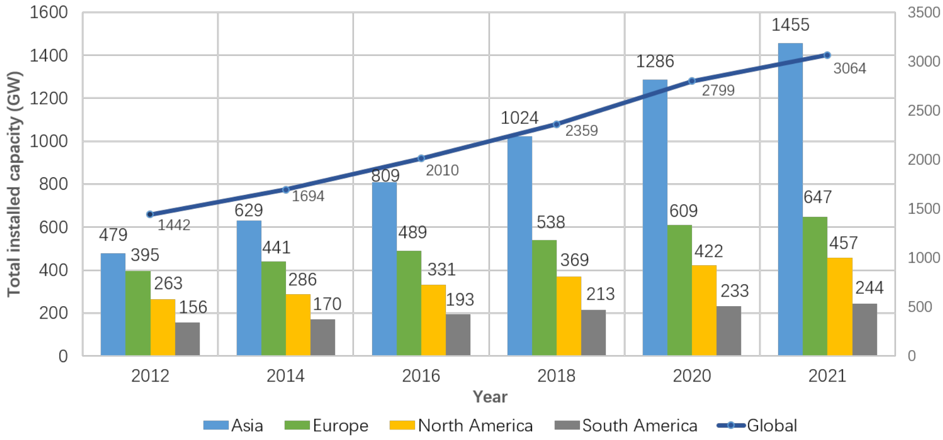

Figure 2. Changes in the total installed capacity of renewable energy by continent from 2012 to 2021.

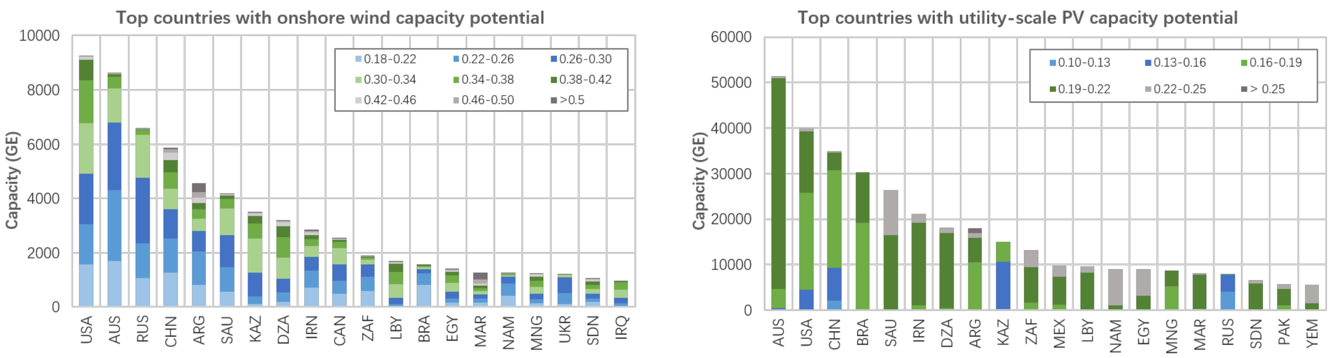

Figure 3. Highest onshore wind (**left chart**) and utility-scale PV (**right chart**) capacity potential countries and the CF tranche breakdown.

Table 1. Installed capacity of hydro, wind, and solar power on an integrated basis by countries up to 2020.

Base or Project	Area	River Basin	Wind Power (MW)	PV (MW)
Xinjiang New Energy Base	Xinjiang, China	Burqin River	23,610	12,260
Qinghai Haixi New Energy Base	Qinghai, China	Upper Yellow River	8430	16,010
Yunnan Hydro-Wind-Solar Comprehensive Development Base	Sichuan, China	Upper Jinsha River	4260	1910
Guizhou Hydro-Wind-Solar Comprehensive Development Base	Guizhou, China	Yalong River	5800	10,570
Sichuan Hydro-Wind-Solar Comprehensive Development Base	Yunnan, China	Lower Jinsha River	8810	3930
Southeastern Tibet Hydro-Wind-Solar Comprehensive Development Base	Tibet, China	Lower Brahmaputra River, Upper Salween River, Upper Lancang River	200	6000
Aşağı Kaleköy Santrali	Turkey	Aşağı Kaleköy	-	80
Multi-Energie-Kraftwerk Sperenberg	Kassel, Germany	-	45 wind turbines	10
PHS-Integrated Hybrid PV-Wind Power System	Brack, Libya	Pumped Hydroelectric Storage	>5	>1

The hydro-wind-solar hybrid power generation system can be roughly divided into two categories: one is the integration of multiple energy forms in the grid, forming a rich energy supply structure system, such as the EU Future Internet for Smart Energy Project [51], EU Islands Project [52], Germany's E-Energy Project [53], California's electric grid [54], Libya's PHS-integrated hybrid PV-wind power system [55], and China's Sichuan, Hubei, Yunnan, Guizhou, and other places having large-scale installed capacity for three types of power supplies, while the second is the hydro, wind, solar, and clean energy bases for cascade utilization of river basins, such as the China Longyangxia Hydro-Solar Hybrid Project [56,57], the Yalong River Basin Hydro-Wind-Solar Hybrid Project [58], the Hongshui River Basin Hydro-Wind-Solar Hybrid Project [59], the Wujiang River Basin Hydro-Wind-Solar Hybrid Project [60], and the Jinsha River Basin Hydro-Wind-Solar Hybrid Project [61].

Taking the Yalong River Clean Energy Base as an example, The Yalong River Basin is rich in wind and solar energy resources within 60 km between the two sides of the Yalong River Basin. The water, wind, and solar resources are multi-complementary, and hydro, wind, and solar power are seasonally complementary, while wind and solar energy can form intraday complementarity during the day and night. With a total installed capacity of 80 million kW, the base will become one of the largest green and clean energy bases in the world, equivalent to four times the size of the Three Gorges Hydropower Station. After the completion of comprehensive development, it can contribute 220 billion kW·h of clean electricity per year, which is equivalent to saving about 120 million tons of raw coal consumption and reducing carbon dioxide emissions by about 230 million tons.

However, the problem of integrated hydro-wind-solar consumption dominated by the river basin has been prominent for a long time. Solar energy and wind energy have intermittent and uncertain characteristics, and hydropower has characteristics such as wet seasons and dry seasons, which affect the stability and power quality of the system. How to effectively coordinate the power generation plan of large-scale hydropower, controllable power supply, and uncontrollable wind and solar power stations, overcome the difficulties of prediction, control, and dispatch, and ensure the safe and reliable operation of the system have become the main challenges for China Southern Power Grid in implementing a water-solar multi-energy hybrid system. The solution to this problem is crucial for expanding the scale of clean energy and the quality and utilization efficiency of new energy power generation in the later stages.

3. Key Issues in Optimal Scheduling of Hydro-Wind-Solar Hybrid Systems

In order to establish a hydro-wind-solar hybrid system (Figure 4), the control of multiple power sources and the coordination and real-time scheduling between multiple power sources must be solved. This section summarizes the key issues of scheduling optimization of a hydro-wind-solar hybrid system. The realization of a multi-energy complementary system first needs to pay attention to the form in which dozens or even hundreds of wind and solar power plants participate in power generation scheduling, how to predict and describe their power generation laws, and the risks brought about by their uncertainties, in addition to to paying attention to the coordinated operation of hydropower stations and large-scale wind power stations on multiple time scales.

3.1. Prediction and Description of Wind and Solar Power Generation

Affected by the natural environment, climatic conditions, and geographical space, wind speed and light intensity have great variability and uncontrollability in time series, resulting in strong volatility, intermittent, and uncertainty in the time and space distribution of wind power and photovoltaic power generation [62–66]. How to accurately predict and describe the output law of wind and solar power plants is one of the core issues in promoting new energy consumption and speeding up the development and operation of multi-energy complementary, involving the identification of power generation-influencing factors [67–70]. There are many factors that affect the output power of wind and solar power generation systems. If each influence is considered, then this will increase the complexity and difficulty of prediction. It is necessary to accurately analyze the factors that are closely related to the output power and find the corresponding relationship to construct a mathematical index so as to provide a premise for the prediction of wind and solar power generation. Accurate renewable power generation forecasting is very important for the scheduling optimization of hydro-wind-solar hybrid systems. The problems of medium- and long-term forecasts and uncertainty are currently intractable. How to reasonably select and improve the corresponding forecasting methods for different loads to ensure energy output efficiency is still an issue worthy of in-depth discussion.

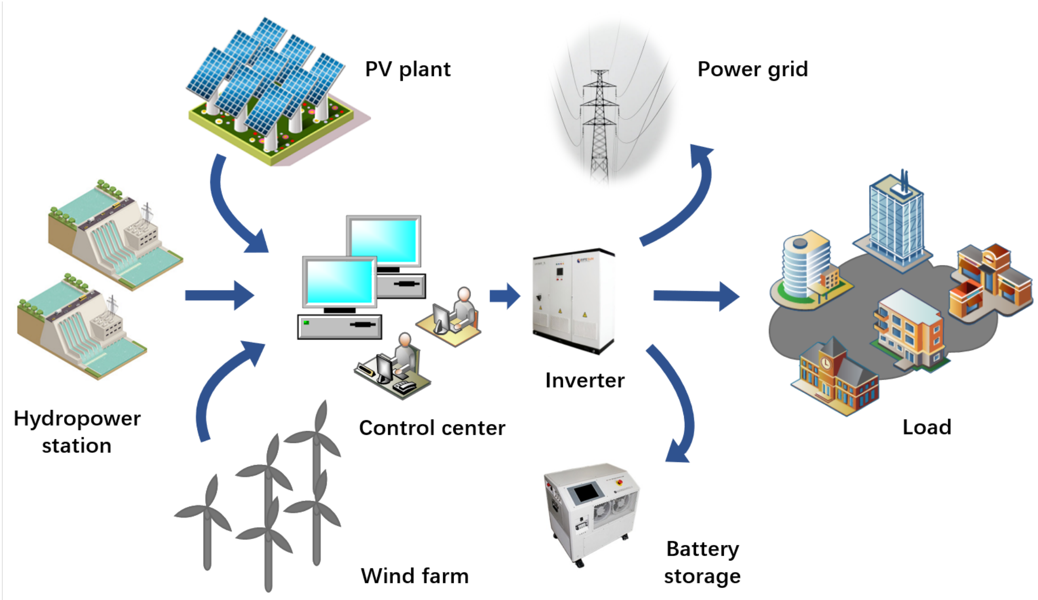

Figure 4. Schematic of a hybrid wind-PV-hydro power generation system.

3.2. Risk Management of Hydro-Wind-Solar Hybrid Systems

Due to the uncertainty of wind and solar power generation, large-scale direct grid connection of new energy will disrupt the balance of a power system and cause a serious impact on the power grid. Quantifying the uncertainty of the output of water, wind, and photovoltaic power generation can allow one to directly analyze the characteristics of power generation or study the error law of the predicted output [71]. Uncertainty is very important in the operation of a hybrid energy system, and the uncertainty of a hybrid energy system is basically considered in the usual research [35,72], but the risks brought by uncertainty are mostly ignored. Hydro-wind-solar hybrid systems often face risks such as load curtailment, no water for power generation at the end of the dry season, power curtailment, output shortages, and spilled water [73–76].

The power balance of the power system is the basis for stable operation of the power grid. However, the starting, stopping, and changing of power sources and loads, as well as the interruption of transmission lines, can lead to power imbalances in the grid. When the power grid is unbalanced, the voltage and frequency fluctuate, which may cause the grid frequency and node voltage to exceed the limit and even cause serious accidents such as grid oscillation and disconnection. When power is redundant, generation shedding is a proven method for controlling the power system and returning to stable operation [77]. In a power system with high penetration rates of wind power and photovoltaic power, wind and photovoltaic shedding are gradually applied to maintain the power balance of the power system. In a power system with high penetration rates of wind power and photovoltaic power, both are also gradually applied to maintain the power balance of the power system. When the power is insufficient, because the short-term power boosting capacity of the synchronous generator is limited, the load shedding method is often used to balance the power [78,79]. However, generation shedding is not conducive to the restoration of the power grid, and the reconnection of generators to the grid may also cause shocks. Load shedding has economic and reliability problems, and increasing the reserve capacity of synchronous generators can reduce load shedding. However, its cost is high, especially in a power system with a high proportion of new energy. The installed capacity of synchronous generators has difficulty meeting the demand for a reserve. Accordingly, it is of great practical significance to ensure the effective management and control of risks while maximizing the benefits by using new energy to connect to the grid and adjust in a random environment.

3.3. Optimal Dispatching of Hydro-Wind-Solar Hybrid Systems

The power station of the water-solar hybrid system has a large scale, and the power generation scheduling of large-scale power station groups faces both technical problems, such as unified management and maintenance of massive operation information, as well as basic theoretical problems, such as the accuracy of large-scale system optimization modeling and calculation efficiency. However, with a single power station as the control point, the interactions of direct dispatching of instructions will greatly affect the power generation dispatching model's construction and solution efficiency, and it is difficult to accurately control the power generation law, which also brings great uncertainty to the power generation planning and dispatching operation of a power grid. In this case, cluster scheduling of power stations is an effective way to reduce the number of directly dispatched power stations [80], but how to determine the appropriate number of clusters and the power stations they contain is the main problem faced by this method. The specific cluster division method is closely related to the actual engineering characteristics, such as power supply composition, and the installed capacity, as well as the power generation characteristics, so practical and effective methods are needed.

The key to the complementary operation of hydro and wind power lies in that the reservoir has the regulation and storage capacity and hydropower has strong regulation properties [81,82]. The power transmission characteristics of hydropower at "non-peak regulation" and "anti-peak regulation" will increase the difficulty of peak regulation and trough consumption pressure in a power grid. Therefore, how to rationally utilize the storage capacity of a reservoir will be directly related to the long-term operation effect and efficiency of a complementary system [83]. In this operation mode, not only should the uncertainty of the flow be considered but also the short-term flexibility adjustment needs and long-term power consumption needs of wind and solar power. Reconstructing the long-term operation mode of the main stream cascade-controlled reservoir group and the water level control rules of the key nodes before and at the end of the flood season is another key problem in the complementary operation of water and wind power. The essence is a stochastic optimization problem of large-scale multi-type power station groups under the conditions of long, medium, and short multi-time scale coupling, runoff, and wind and solar power generation with multiple uncertainties. Compared with the scheduling rule optimization of a single-type hydropower system, this is more complex and difficult. It is necessary to explore innovative ideas and solutions in model construction.

When the proportion of new energy installed reaches a certain degree, the influence of power fluctuations increases significantly in the power grid load trough and peak periods, which increases the demand for flexible adjustment of day-ahead and real-time dispatching. This aggravates the difficulty of power balance in the whole cycle and the pressure of power grid peak shaving and frequency modulation [84], which can easily cause the problem of system stability [85]. From the perspective of short-term operation, the problem of hydro-wind-solar complementarity and coordination is prominent. On the one hand, the complementarity between hybrid energy sources cannot be ignored [86]. It is necessary to consider the uncertainty of wind and solar power generation to accurately describe the flexibility adjustment requirements of the system [87] (i.e., how much adjustable capacity is needed to stabilize the fluctuation of new energy output). The flexibility index and its characterization method need to be studied. On the other hand, it is necessary to study the day-ahead joint dispatch model and real-time coordinated control strategy of large-scale new energy and adjustable hydropower stations, considering the target requirements of system flexibility, new energy consumption, etc. to realize the efficient solution of the model and determine day-ahead and real-time start-stop methods and the output plans of a complementary system and its units.

Essentially, multi-energy coupling makes the operation of hydro-wind-solar hybrid systems more complicated and increases the complexity of decision making during system operation, such as the increase in the dimension of decision variables, multiple constraints on optimization problems, and possible non-convex nonlinearity. In the scheduling of hydro-wind-solar hybrid systems especially, the analysis and finding solutions to the problem will become more difficult. The design of an energy scheduling framework under multi-energy technology, the physical constraint modeling of multi-energy scheduling, the establishment of a multi-energy elastic demand characteristic model, and the solution of non-convex nonlinear energy scheduling optimization problems have become challenges for the operation research of hydro-wind-solar hybrid systems.

4. The Research Status of Power Generation Scheduling Optimization for Hydro, Wind, and Solar Renewable Energy

As mentioned above, prediction and description, risk management, multi-time scale scheduling, and other problems need to be considered in the power generation of a hydro-wind-solar hybrid system. Figure 5 gives an overview of the current research situation. Table 2 lists the main research methods in the prediction and description of wind and solar power generation, the risk management of a hydro-wind-solar hybrid system, and the scheduling optimization of a hydro-wind-solar system. This section will introduce the research status of power generation in a hydro-wind-solar complementary system.

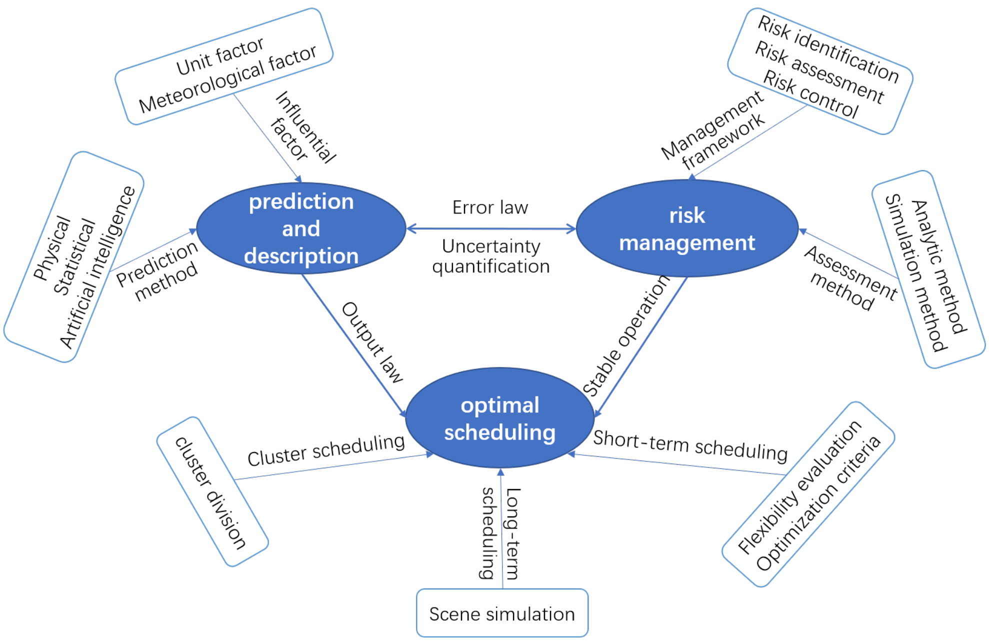

Figure 5. General overview of research status.

Table 2. Research status of optimal scheduling for hydro-wind-solar renewable energy complementary system.

Research Contents		Important Methods and Indicators	
Prediction and description of photovoltaic-wind power generation	Generation impact factor identification	Unit factor, meteorological factor	/
	Prediction approach selection	Physical	Physical output model [88,89]
		Statistical	Time series method [90], fuzzy prediction [91]
		Artificial intelligence	Backpropagation [92], radial basis function [93]
Risk management of hydro-wind-photovoltaic complementary systems	Uncertainty quantitative analysis	Uncertain optimization	Robust optimization [94], stochastic optimization [95], polyhedral set
	Assessment method	Analytic method	Fault tree analysis [96], state space method, network method
		Simulation method	Monte Carlo method [97], state selection method, Latin hypercube sampling [98]
		Other methods	Risk-averse decision making [99], stochastic optimization method
Optimal scheduling of hydro-wind-photovoltaic complementary operation	Cluster scheduling	Cluster division	Index of cluster structure strength: correlation degree within the cluster, correlation degree between clusters, cluster internal connectivity, cluster scale, modularity Index of cluster autonomy: active and reactive power regulation capability, voltage sensitivity, supply and demand matching degree Multi-objective optimization
	Long-term scheduling	Scenario simulation	Discretization of continuous probability distribution, auto-regressive moving average model
		Scenario reduction	Method of forward selection, clustering algorithm
	Short-term scheduling	Flexibility evaluation	Source side: gradeability, boot time, response time, optimal start-stop time, output steady state Load side: net load ramp rate Flexibility of power system
		Optimization criteria	Clean energy consumption criterion: minimum curtailed electricity, energy maximization Benefit criterion: minimum operating cost, maximizing generation profit, minimum network loss, maximum environmental benefit Stability criterion: minimum output fluctuation, minimum voltage deviation, load follow

4.1. Research Status of Wind and Solar Power Generation Forecasting and Description

The prediction methods of wind and solar power generation can be divided into physical methods, statistical prediction methods, and artificial intelligence methods according to principle (Figure 6). The former comprehensively considers the surrounding terrain information, related physical information, and system power curve data of the wind and solar power generation system. Then, it takes the meteorological forecast data as important input, uses physical equations for prediction, and establishes a mapping prediction model of the wind and solar power generation, wind speed, and light intensity [100–104]. The output model of the photovoltaic system based on the physical model can be described as follows [88]:

$$p_{PV} = \eta S_{PV} I(1 - 0.005(T_{\text{out}} + 25)) \quad (1)$$

When the photovoltaic panel area S_{PV} (m^2) and energy efficiency η are constant, the photovoltaic output p_{PV} (kW) is mainly determined by the solar radiation intensity I

(kW/m^2) and the outdoor ambient temperature T_{out} (°C) at that time. For wind turbines, the physics-based output model can be described as follows[89]:

$$p_{WT} = \begin{cases} 0, v_h \leqslant v_{ci}, v_h \geqslant v_{co} \\ c_1 + c_2 v_h + c_3 v_h^2, v_{ci} \leqslant v_h \leqslant v_r \\ p_r, v_r \leqslant v_h \leqslant v_{co} \end{cases} \tag{2}$$

where v_{ci} and v_{co} are the cut-in and cut-out wind speeds, respectively, v_r is the rated wind speed, p_r is the rated power, and the wind turbine output p_{WT} is mainly affected by the current wind speed.

Compared with the physical method, the statistical prediction method correlates the historical operation data of wind power and photovoltaic power stations with historical meteorological data and conducts statistical analysis of their correlation, based on which the mapping relationship between wind and photovoltaic generation power and the meteorological data is established [105–108]. Common examples include traditional statistical methods represented by time series methods, modern statistical forecasting methods represented by artificial neural networks, and fuzzy forecasting methods. The time series method uses a set of basic data of wind and solar power generation to form a digital sequence in chronological order, which is processed by mathematical statistical methods to realize the forecasting of future wind and solar output, such as the autoregressive integrated moving average (ARIMA) [90]. The time series of wind and solar power generation has a seasonal change trend, and a seasonal difference transformation can be applied to it.

A seasonal difference operator $\nabla_S = 1 - B^S$ is introduced, where $\nabla_s^D = \left(1 - B^S\right)^D$ with S as the period. Then, the seasonal ARIMA model is

$$\varphi(B)\phi(B^s)\nabla^d\nabla_s^D y_t = \theta(B)\Theta(B^s)a_t \tag{3}$$

where $\varphi(B)$ is a p-order autoregressive process, $\phi(B^s)$ is a p-order autoregressive model, $\theta(B)$ describes a Q-order moving average process, $\Theta(B^s)$ is a q-order moving average model to explain periodic factors, B is a hysteresis operator, and a_t represents an uncorrelated stationary process with a mean value of zero.

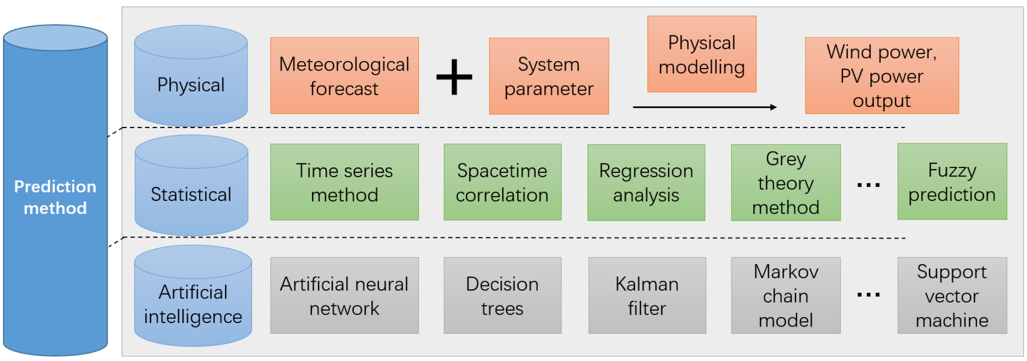

Figure 6. Prediction method classification of wind and PV power output.

In addition to autoregressive models, there are also studies based on the Markov chain model, Kalman filter (KF) model, data mining, wavelet transform, etc. for power generation prediction. The authors of [109] first assumed that a short-term change in wind speed is a stationary process and has Markov properties. By discretizing the historical state and calculating the state transition matrix, the future wind speed state is predicted according to the Markov property, and the predicted value of the wind speed is estimated according to the empirical wind speed distribution. Kalman filtering can be regarded as an autoregressive data processing method and does not require a stationarity assumption, so it is very effective for new energy power generation forecasting. Since 1985, wind power forecasting based on a Kalman filter has been studied [110]. The authors of [111] provided more accurate wind speed forecasts for both onshore and offshore wind data by combining the ARIMA and KF techniques to obtain wind data on hills, offshore, and in other regions. The research results in this area are very important for a system to build a multi-energy complementary theory and method system. It is still necessary to combine the engineering characteristics of hydro-wind-solar hybrid systems of different scales and different compositions as well as the application requirements of actual dispatching scenarios and learn from the existing achievements at home and abroad to carry out adaptability research and constantly refine and summarize the results.

Artificial intelligence prediction (such as through neural networks, a biological intelligence algorithm, etc.) is a hot topic in hydro-wind-solar power prediction [112,113]. Among these methods, the artificial neural network (ANN) has been widely used in the field of prediction in recent years [114–116] (see Equation (4) for its mathematical expression). The ANN is one of the most mature artificial intelligence algorithms at present. It is a large-scale distributed processing system that simulates the information processing mechanism of the human brain and has a remarkable effect on solving complex nonlinear problems [117]. ANNs mainly include the backpropagation (BP) neural network, radial basis function (RBF) neural network, and so on. The BP neural network is the most widely used neural network at present. It has high self-learning and self-adaptive abilities, but the selection of feature inputs and the composition of the sample space often lack consistency. The essence of artificial neural network prediction is to use mathematical analysis to establish a mathematical model and simulate the characteristics of animal neural networks, as well as train it repeatedly through distributed parallel information processing operations, continuously adjust the connection mode and weight of each node in the artificial neural network, and finally achieve the purpose of predicting and processing information:

$$\hat{y}(x_t) = \int (x_t; \omega) \tag{4}$$

where $\hat{y}(x_t)$ is the output variable or the predicted object. In deterministic prediction, it is estimated as the expected value of the prediction, and it can also be in the form of probabilistic prediction results, such as quantiles. Meanwhile, x_t is the input variable, and ω is the parameter in the neural network, mainly including weight and bias.

In addition, other neural network methods are also used in power prediction. For example, in [118], a generative adversarial network (GAN) was applied to the scene generation of wind and solar power generation for the first time, where it could better simulate the probability characteristics of day-ahead wind and solar power. However, its main structure is two-dimensional convolution, which may make it difficult to fully characterize the time series characteristics and key output events of wind and solar power, and thus it cannot be directly used to simulate the monthly wind power with more high-dimensional and complex time series characteristics. Ghoushchi et al. predicted a wind power plant's power output using weather and power plant parameters and employed an extended fuzzy wavelet neural network (FWNN), achieving higher precision for short-term wind power forecasting [119].

4.2. The Research Status of Hydro-Wind-Solar Hybrid System Risk Management

Risk is a comprehensive measure of the probability and severity of uncertain operating scenarios. For quantitative analysis of uncertainty, through the uncertainty set, we can use the method of describing the uncertain factors in the robust optimization theory to construct a robust optimization model, and the construction method of the wind power's uncertain set can be given [120–122]. By adjusting the boundary of the uncertain set, the conservative type of the robust optimization model can be controlled to realize the economy and safety balance of decision making. The polyhedron set in the robust optimization method can also be used to describe the uncertainty of the wind power output, and a robust conservative regulation factor is introduced to reduce the conservatism of problem solving. It should be noted that the key point of constructing the output uncertainty set is how to select a robust set to ensure the rationality of the decision results [123–126].

In practical running, hydro-wind-solar power systems should face various uncertainties, such as routine overhauling or unit failure under natural disasters. Aside from that, these faults show multi-dimensional uncertainties in occurring objects, periods, and durations. In order to reasonably portray the uncertain operating states of components in unexpected outages or failures, discrete state uncertainty sets have been constructed for different fault uncertainties in hydro-wind-solar power systems [127]. Figure 7 displays the traditional methodologies frequently applied in power optimization problems under uncertainty.

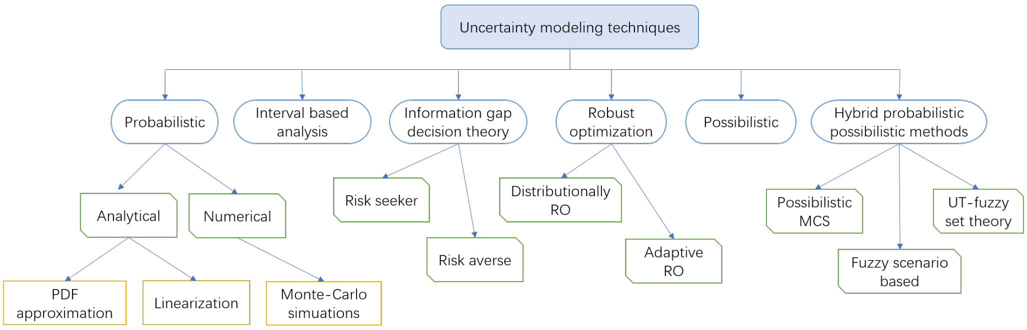

Figure 7. Uncertainty modeling techniques.

The risk management system of the hydro-wind-solar hybrid system can be established under the framework of "risk identification–risk assessment–risk control". The role of risk identification is to identify various uncertain factors and potential safety hazards faced by the power grid, collect data related to system load, and evaluate the impact scope of hydraulic power, wind speed, and photovoltaics based on micro-meteorology.

The role of risk assessment is to evaluate the predicted power grid security risk level and find the values of all kinds of operation risk indicators. Different from the reliability assessment methods generally applied in the planning stage, risk assessment is generally used in the real-time operation stage [128], and the main evaluation methods are the analytical method and simulation method. Among them, the analytical methods mainly include the fault tree analysis method, state space method, and network method. The basic principle of the analytical method is to idealize the running process of the system, describe the running process of the system with a mathematical model and then solve the model. Finally, the required risk index is obtained.

The main advantages of the analytical method are that the physical concept is clear and the calculation speed is fast, so it is generally suitable for small-scale systems, and it is difficult to apply to large power systems with multi-energy sources. The simulation method belongs to the category of stochastic optimization, which can directly study the power distribution characteristics of hydro, wind, and photovoltaic power to help participate in the load-side assessment. Common simulation methods include the Monte Carlo method [97], Latin hypercube method [98], and state selection method. The typical representative is the Monte Carlo method. According to whether the timing of the simulated events is considered, the Monte Carlo simulation method can be divided into two modes: non-sequential simulation and sequential simulation. In the large-scale application of non-sequential simulation, the sampling efficiency and convergence speed of Monte Carlo simulations are generally improved by reducing the sample variance. In practice, the duration of each state of the reservoir, wind turbine, and photovoltaic panels is random, so it is necessary to consider the limitations of applying sequential simulation to a multi-state model. The limited samples obtained by the Latin hypercube method can describe the distribution of variables more accurately. Then, according to the predicted wind and photovoltaic power generation and the simulated prediction error, a set of wind and photovoltaic power generation scenarios which can describe the uncertainty of prediction are generated [129] (see Equations (5)–(7)):

$$N^{\mathrm{h}} = N_f^{\mathrm{h}} + e^{\mathrm{h}} \quad (5)$$

$$N^{\mathrm{w}} = N_f^{\mathrm{w}} + e^{\mathrm{w}} \quad (6)$$

$$N^{\mathrm{p}} = N_f^{\mathrm{p}} + e^{\mathrm{p}} \quad (7)$$

where N_f^{h}, N_f^{w}, and N_f^{p} are the predicted hydro, wind, and photovoltaic power outputs, respectively, and e^{h}, e^{w} and e^{p} are the forecast errors of the hydro, wind, and photovoltaic power outputs simulated by the Latin hypercube method, respectively.

On the basis of risk identification and assessment, the probability or severity of the risk can be reduced by implementing a risk-based control program. Figure 8 shows the schematic diagram for the operation scheme of wind-solar-hydro power while considering the risks. In addition, risk-averse decision making [99] and stochastic optimization methods [128] are also common methods for dealing with uncertainty in the investment and management of hydro-wind-solar hybrid systems. For example, Columbia scholars expressed the short-term power balance as a probability constraint, optimized a long-term operation plan based on risk aversion, and greatly simplified the uncertainty of hydro, wind, and photovoltaic power and load to improve the calculation efficiency and the safe operation of the system [130]. Mazidi et al. presented a risk-averse decision-making tool to guide the short-term operation of a distribution network operator that considered uncertainties including wind generation, load demand, and electricity's price [131]. Xiao et al. established a risk-averse multi-objective optimization model to enhance the risk control ability of a distribution network and further increased the penetration of renewable energy in a power grid [132].

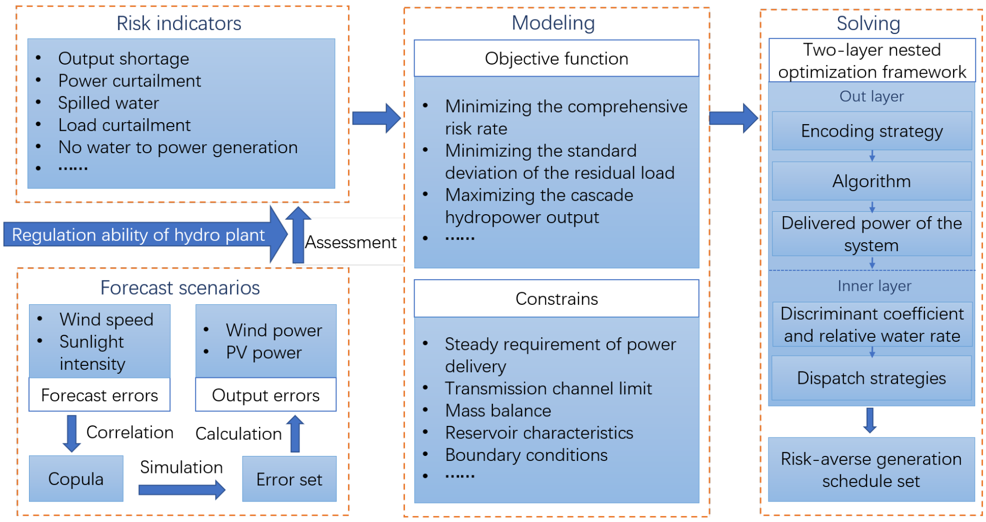

Figure 8. Schematic diagram for the operation scheme of wind-solar-hydro power considering risks.

4.3. The Research Status of a Hydro-Wind-Solar Hybrid System's Dispatching Optimization

The cluster management mode of renewable energy power generation has its own advantages in solving large-scale renewable energy access and local consumption. The cluster management mode has the characteristics of "weak coupling between groups to division of labor and strong connections within groups to cooperate", which can improve the stability of the hydro-wind-solar hybrid system and the simplicity of scheduling [133,134]. Based on this feature, the cluster division index is usually based on electrical distance, describing the degree of coupling between nodes and focusing on the coupling of the cluster and the utilization of the internal power supply of the cluster, such as the index reflecting the strength of the cluster structure and the index reflecting the autonomous ability of the cluster.

In addition, while considering the power quality, the economic related index is also an important factor that cannot be ignored. Based on the above-mentioned indicators, the cluster division criteria can be further constructed, and the constraint method and weighing method are generally used to convert multi-objective optimization into a single-objective optimization problem solution or establish a multi-objective programming model [60,135–139]. The multi-objective optimization method is used to solve the problem directly (see Equation (8) below):

$$\max / \min f(x) = \max / \min[f_1(x), \ldots, f_M(x)] \tag{8}$$

where $x = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \in S$ is the decision variable and S is the n-dimensional decision space. When M = 1, the above is a single-objective optimization problem, and when M > 1, the above is a multi-objective optimization problem.

At present, multi-objective optimization methods are mainly metaheuristic methods, which use the concept of the Pareto principle to obtain trade-off solutions, namely Pareto-optimal solutions. Katsigiannis et al. [140] developed a multi-objective optimization model to generate a Pareto front and minimize the total cost of energy and total greenhouse gas emissions of an HRES during its lifetime by using a non-dominated sorting genetic algorithm (NSGA). An optimization problem using PSO to solve the PV-wind capacity coordination for a time-of-use rate for industrial users was introduced in [141] with the aim of maximizing the economic benefits of investing in wind and PV generation systems. Metaheuristic methods, such as genetic algorithms (GAs), particle swarm optimization (PSO), and evolutionary algorithms (EAs), have gradually become effective tools to solve multi-objective optimization problems due to their good convergence and search performance. The use of metaheuristics for the planning of hydro-wind-solar systems can effectively overcome the limitations of traditional algorithms and achieve the simultaneous optimization of multiple objectives in solving problems.

The complementary coordination of hydro, wind, and solar energy can be analyzed from two aspects: one is the coordination and optimization of multiple types of power sources on a long-term scale, and the other is the short-term joint operation optimization of multiple energy sources. Figure 9 shows the methodology for dispatching rules for the hydro-wind-solar complementary power system.

In fact, under the condition of high permeability of renewable energy connected to the grid, the net load (the load obtained by the electricity load without the output of new energy) fluctuates most obviously during the month. It is important to carry out long-term analysis and research on the water-solar hybrid system. This research has also attracted the attention of scholars (Table 3).

On the one hand (the first category), the input of the hydro-wind-solar dispatch model includes uncertain runoff, wind energy, and solar energy, which is a stochastic optimization problem under multiple uncertainties (see Equation (9)). How to establish a suitable stochastic dispatch model and how to construct an efficient solution algorithm is the focus and difficulty of this research. Many studies use scenario simulation to describe the output scenarios of wind and solar power generation [142–145], determine quarterly or monthly representative scenarios of wind and solar power generation, and serve as the boundary conditions for the optimal operation of hydropower stations and reservoirs in the complementary system. Deterministic or stochastic optimization techniques are used to reconstruct power plant dispatching and operation rules. Based on a long series of actual operating data, scene generation methods such as continuous probability distribution discretization [146] and the autoregressive moving average (ARMA) model [147] are adopted:

$$\max \sum_{s=1}^{S} Pr_s \cdot \left\{ \sum_{t=1}^{T} \begin{pmatrix} d_t \sum_{n=1}^{N} P_{s,n,t} \cdot \Delta t - \\ d_t E_{s,t}^{curt} - d_t E_{s,t}^{short} \end{pmatrix} \right\} \tag{9}$$

where Pr_s is the probability of scenario s, d_t is the electricity price of a period t, $P_{s,n,t}$ represents the average output of the power station n in the period t under scenario s, Δt is the length of each time, $E_{s,t}^{curt}$ is the additional power generated by the system compared with the planned generation, and $E_{s,t}^{short}$ represents the shortage of power generated by the system compared with the planned generation.

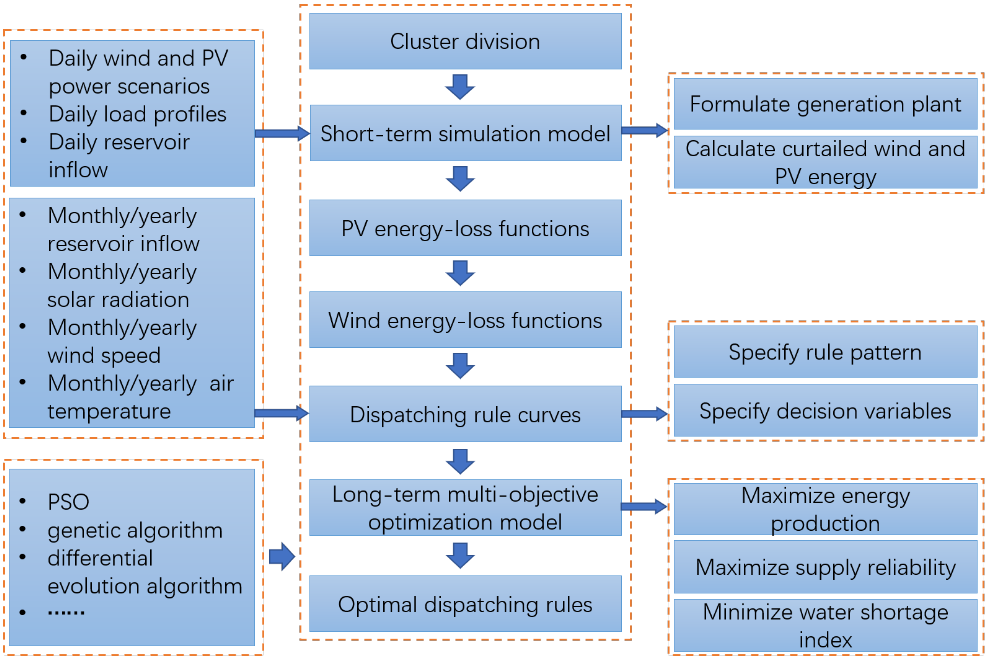

Figure 9. Dispatching rules for the hydro-wind-solar hybrid system.

On the other hand (the second category), some studies directly construct a description method for the multiple uncertainties of water, wind, and light or predict the output of new energy and analyze the prediction error by using the predicted output and fluctuation interval as the system input to establish a system with the maximum total benefit, minimum abandoned power, and minimum water consumption [148,149]. At the same time, the research on the solution algorithm of this complex model was carried out, and a multi-stage and sub-module solution method was proposed [150,151]. Some scholars found another way to combine intelligent algorithms to make up for each other's shortcomings and improve the efficiency and accuracy of the solution.

In fact, the hydraulic connection leads to multi-scale coupling and influence in the long-term and short-term of the hydro-wind-solar hybrid system, and the mid- and long-term power coordination results of hydropower are usually an important basis for determining the boundary conditions of short-term complementary operation. Therefore, it is very meaningful to establish a multi-time scale dispatch model to realize the optimal dispatching of a power grid from multiple time levels.

The short-term optimal scheduling of a hydro-wind-solar hybrid system is mainly studied from two aspects: flexibility evaluation and the short-term complementary operation strategy of hydro, wind, and photovoltaic power. The objects of power system flexibility evaluation (see Equation (10)) can be divided into the power supply side, load side, and system flexibility. The evaluation indexes of power-side flexibility include the climbing capacity, minimum start-stop time, start-up time, response time, and minimum stable output, which are mainly used to compare the flexibility adjustment capacity of different resources and are often used as input parameters for the dispatching model. The load-side flexibility evaluation index includes the net load ramp rate and ramp acceleration, which is mainly used to analyze the characteristics of the load curve and quantify the flexibility demand. The system flexibility evaluation index has the flexibility insufficiency probability and expectation, which can also be subdivided into the upregulation flexibility insufficiency probability and expectation and downregulation flexibility insufficiency probability and expectation, which are mainly used to evaluate the overall flexibility level of the system.

Table 3. Summary of reviewed articles to show the status of long-term scheduling.

Type	Ref.	Solution	Outcomes	Remarks
The first category	[139]	GFM-MOEA	Maintained calculation accuracy and reduced problem dimensions	Enhanced the reliability of the risk- informed complementary operation strategy
	[146]	SDP, Fortran 90	Improved the long-term complementary operation	The results of operations are relatively rough
	[152]	CPLEX	Determined the optimal working position and capacity of each power plant	Provided guidance for mid-to-long term dispatching
	[153]	GLPK	Found a key constraint in systems with high penetration of renewables	The uncertainty of new energy output and input data is not considered
	[154]	NSGA-II	Proposed model optimizing both quality and quantity of hydro and PV power	Analyzed the complementary operations in different typical years
the second category	[57]	Dynamic programming technique	Maximized the total generation output and system reliability	Explored the long-term operating rules required for a hydro-PV system
	[86]	Solver	Trade-off effects and influencing mechanism identified	Operation behaviors under multiple uncertainties should be investigated
	[150]	MOCS	No conflict between maximizing energy production and power supply reliability	Represented short-term constraints in long-term energy models
	[151]	DP	Estimated the expected net revenue of the PV plant	Optimized the size of a PV plant using cost–benefit analysis and considered variations in downstream water level
	[155]	Solver	Proposed a model for decision making in electricity market	The extension should focus on rolling optimization with updating the forecasting in different time scales
	[156]	PVGIS platform	Assessed hydrological and solar irradiation information on a monthly scale	Examined the degree of time complementarity between small hydropower stations and PV systems

The wind-solar complementary short-term scheduling model is mainly divided into two categories. The first category is using the uncertainty description method described above to describe the output of wind power and photovoltaic power [157] and then couple it with conventional power sources such as hydropower to construct a joint scheduling model. The optimization criteria of the model usually include three aspects: the first is the clean energy consumption criterion [158], the second is the benefit criterion [159], and the third is the system's stable operation criterion [160]. The second category is realizing the joint dispatching of wind and solar power stations and adjustable power sources through constraints, which is usually described as reasonably scheduling constraints to optimize the operation plan of complementary regulatory power sources such as hydro-wind-solar power. The common method is to allocate a reasonable reserve capacity according to the fluctuation in prediction error to ensure the power balance in real-time operation and to borderize the uncertainty problem:

$$\begin{aligned} S_t^{UR} &= \sum_{s=1}^{S}\left(D_{s,t}^{UR} - CA_{s,t}^{UR}\right)Pr_s \\ S_t^{DR} &= \sum_{s=1}^{S}\left(D_{s,t}^{DR} - CA_{s,t}^{DR}\right)Pr_s \end{aligned} \tag{10}$$

where S_t^{UR} is the expectation of insufficient flexibility upregulation, which refers to the expectation of the difference between the demand for flexibility and the capacity for flexibility due to insufficient capacity at time t, S_t^{DR} is the expectation of insufficient flexibility downregulation, which refers to the expectation of the difference between the flexibility adjustment demand and the flexibility adjustment ability caused by an insufficient adjustment ability at time t, $D_{s,t}^{UR}$ and $D_{s,t}^{DR}$ represent the flexibility to adjust to demand, and

$CA^{UR}_{s,t}$ and $CA^{DR}_{s,t}$ denote the flexibility upregulation ability and flexibility downregulation ability, respectively.

In the complementary joint operation of hydropower, wind power, and solar power, hydropower stations, wind farms, and photovoltaic power stations are operated and managed as three different stakeholders. Distributed optimization is very important for solving multi-energy coupling optimization problems. It has the advantages of saving computing resources and ensuring user information security. Common distributed optimization algorithms include the dual method, consistency method, and alternating direction of multipliers method (ADMM). At present, the ADMM only has a theoretical convergence guarantee for solving two-block or three-block coupled convex optimization problems, and its convergence rate is also very sensitive to the penalty parameters. Therefore, the improved ADMM has also received a lot of attention and research, such as the fast ADMM and adaptive ADMM.

These research results can be summarized as two types: (1) studying the joint dispatching strategy from the perspective of a power generation company [40,161–163], which aims to minimize the power output fluctuation or maximize the generation revenue of the hybrid system, and (2) studying the coordinated dispatching of the whole power system [164–167], including renewable energy sources, with the aim to increase the penetration of renewable energy sources, minimize the system operation cost, or reduce the probability of power supply loss through the complementarity of hydropower and other renewable energy [168]. Table 4 summarizes the short-term optimal scheduling outcomes, solutions, and critical remarks of hydro-wind-solar hybrid systems based on the above classifications.

Table 4. Summary of reviewed articles to show the status of short-term scheduling.

Type	Ref.	Solution	Outcomes	Remarks
The first category	[90]	ARMA	Maximized the power generation	Ensured more reasonable power transmission planning
	[163]	GCH	Proposed a double-layer model	The distinct constraints and the operating errors should be considered
	[162]	ARMA	Established a coordinated model in the energy and ancillary service markets	Increased the expected benefits for the system
	[40]	MOCS	Increased the power generation and decreased the power output fluctuation	The uncertainty of new energy output and input data is not considered
	[157]	GA	The uncertainty of new energy output and input data is considered	The solution process needs to be strengthened
	[137]	NSGA-II	The Pareto frontier of power generation and output fluctuations is obtained	The complementary role of hydropower in the coordination is discussed
	[161]	Solver	Improved the stability of power output for hydro-wind-solar systems	The required hydropower compensation capacities in different quarters are discussed
the second category	[36]	Gurobi 6.5	Minimized the system operation cost	Derived relatively stable operation cost in the presence of uncertainties
	[167]	MATPOWER	Minimized operating costs for the hybrid system	Tracked wind-photovoltaic power's and load demand's effective variations
	[165]	GAMS	Optimized the electricity generated by each reservoir	Damped the fluctuations of renewable energies and minimized energy cost
	[164]	Three-stage algorithm	Minimized the operating cost and renewable energy loss of the power	Summarized specific scheduling strategies in different natural scenarios
	[166]	Solver	85% of the cost benefits of the optimal grid expansion can be captured	Grid bottlenecks inside each country are not considered in the model

The modeling and solving ideas of multi-energy complementary optimal scheduling can be divided into two categories: (1) solution methods based on a linear model [169–171] and (2) solution methods based on a nonlinear model [172–174]. Among them, the solving methods based on nonlinear models, such as the particle swarm optimization algorithm [175], genetic algorithm [176,177], and differential evolution algorithm [178], have the advantage of high modeling accuracy, but the algorithm has weak convergence, a slow solution speed, and high dependence on specific solvers. The effectiveness of the algorithm requires the modelers to be highly skilled, which will cause the model to be less versatile. On the contrary, a linear model needs to linearize the device in the modeling process, sacrificing the accuracy of the model for its solving speed. This kind of model has many mature solvers, such as the commercial solvers Cplex, Gurobi, and Mosek, and open-source solver such as Scip, GLPK, and Lpsolve. These solvers encapsulate the solving process such that the scheduler does not have to pay attention to the solving process and can concentrate on the construction of the model. Therefore, the linearized model is still the mainstream of industrial applications, such as microgrid [179], a park-integrated energy linear programming model.

5. The Prospect of Power Generation Scheduling Optimization for Hydropower, Wind, and Solar Renewable Energy

The previous section introduced the current situation of power generation in a hydro-wind-solar hybrid system, and this section analyzes and looks forward to the hydro-wind-solar hybrid operation problems summarized above.

5.1. The Prospect of Wind and Solar Power Generation Forecasting and Description

A single forecasting method has advantages in dealing with specific forecasting problems, while the random volatility of new energy power systems puts forward higher requirements for the generalization performance of forecasting methods. The combination method based on multiple forecasting models can integrate the advantages of multiple methods and realize the flexible application of multiple scenarios [180]. The combination forecasting method refers to the forecasting method formed by the weighted combination of physical methods, statistical methods, artificial intelligence methods, and other different forecasting methods based on the characteristics of photovoltaic power data and meteorological data. The combination forecasting method can maximize the prediction advantages of each single forecasting method and improve the forecasting accuracy of wind energy and photovoltaic power.

The types of combinations are generally as follows. First, there is combined prediction of the physical forecasting method and statistical forecasting method. The weather forecast information is first obtained based on a numerical weather forecast and then processed and selected. Finally, the needed data are sent to the statistical forecasting model established by historical data training to predict the power output. Second, there is combination forecasting of multiple statistical forecasting methods. Its essence is to combine the weights of multiple single forecasting methods. First, two or more single prediction models are selected through error analysis, and the constraint objective function is established according to the optimal weight allocation rule. Then, the weight coefficients of each forecasting method are obtained by realizing the optimal solution under the constraint conditions. Finally, the combination forecasting model is formed by superposition. The third type is the comprehensive application of different artificial intelligence technologies, such as fuzzy inference adaptive neural networks for ultra short-term wind energy prediction, where a genetic algorithm used to train the model of fuzzy wind speed, light intensity, and wind power. To a certain extent, the comprehensive use of various methods can improve its convergence speed and solve problems such as local minimization.

At present, the prediction model is mainly the classical network structure, which has the potential to improve the prediction accuracy. The network structure optimization of the prediction model needs to be further explored to improve the accuracy of the algorithm. The temporal and spatial scales of the data used in the research are mostly small. The subsequent research can collect photovoltaic and wind power data with a larger time range, more spatial distribution, and unstructured data by arranging experimental platforms in multiple regions to achieve more universal photovoltaic and wind power output power prediction. Further research on forecasting methods to achieve multi-step forecasting in advance is also a challenge to be faced by hydro-wind-solar projects in the future.

On the basis of the aggregation of wind and photovoltaic power stations, the generation output characteristics need to be further analyzed, and the following methods can meet the needs of different complementary operation modes. The first one is to fit the probability distribution while considering the time-varying characteristics of the output. The output process of wind and solar power generation is random and non-stationary, so it may be more conducive to predict the power generation law by considering the time-varying characteristics to establish a probability distribution. The second is the scenario description method of uncertain power output of power plant clusters. In order to avoid the influence of the change in installed capacity on the results, the installed utilization data sample will be constructed based on the long series of actual output data and the corresponding installed capacity, and the quantile regression theory can be introduced to construct a nonparametric probability prediction model. The appropriate distribution function is used to describe the output random variables. The quantile matrix is obtained, and the output scene set is generated by combining the predicted output sequence. For the clusters composed of different types of power stations, the idea of a Cartesian product can be used to determine the combined scene set. It should be noted that when the number of scenes leads to too much computation, it is necessary to introduce techniques such as scenario reduction for dimensionality reduction.

5.2. The Prospect of Hydro-Wind-Solar Hybrid System Risk Management

The key to the power generation of a hydro-wind-solar complementary system lies in the uncertainty of wind and solar output. For the risk management of grid-connected operation of a hybrid system, the power prediction error of wind and solar power is considered by reliability or the risk index. The quantitative description method of uncertain output of a power plant cluster is carefully studied, such as through the power shortage probability and system load loss index. The focus of these methods is how to determine the constraint boundary to realize the rationality and practicability of a hydro-wind-solar hybrid system. In the process of risk assessment, the single analytical method and simulation method have the disadvantages of low sampling efficiencies and poor computational convergence, and the combination of various methods seems to be more widely used in model solutions. For example, the mixed method of the Monte Carlo method and analysis method can reduce the sample variance to a certain extent and improve the sampling efficiency. However, there is no unified conclusion on how to realize the organic combination of the two probability methods, and further research is still needed.

In the current research, most of the research work on the risk transfer of fluctuating energy generation through the Internet adopts a linear propagation path. However, in the actual process, there are hierarchical, network, and chaotic transmission paths. The risk transfer probability and loss caused by different risk transmission paths are different. In future research, it is necessary to refine the risk transmission path, conduct research under different path conditions, and use different calculation models and theories when calculating losses. Moreover, in the process of risk decision making, there is a transformation loss between the qualitative concept and quantitative representation, so how to find a mathematical model with a better conversion efficiency and effect to meet the needs of practical projects is also an additional challenge in the future.

In order to carry out risk management of a hydro-wind-solar hybrid system more accurately, the load shedding risk, voltage out-of-limit risk, line active power out-of-limit risk, and overflow risk are introduced to comprehensively evaluate the operation risk of a power system with hydraulic, wind, and photovoltaic energy. The influence of water and landscape access on a power system's operation risk is comprehensively analyzed from the aspects of wind power, the photoelectric access node, hydropower access capacity, and hydro-wind-solar replacement capacity. It can provide reference information for the safe operation and operation planning of a power system with renewable energy.

5.3. The Prospect of a Hydro-Wind-Solar Hybrid System's Dispatching Optimization

The power generation scheduling of a hydro-wind-solar complementary system is also green generation scheduling; that is, it also involves controlling the abandonment rate of wind and solar power in a reasonable range to maximize power generation and achieve the maximum output of green electricity.

In light of the huge number of power stations in the complementary system and the difficulty of centralized dispatching, the aggregation strategy of wind and solar power stations can be introduced to explore suitable aggregation criteria and integrate multiple wind power stations and photovoltaic power stations by taking advantage of the level of high-convergence power station clusters able to be scheduled, such as spatial smoothness and time complementarity, and by taking wind and wind power station clusters as the object to achieve complementary coordination with a hydropower system. Considering that the aggregation effect of wind and solar power is closely related to the size of the power station, how to divide the clusters of wind and solar power plants is very important. According to the distribution characteristics of wind and photovoltaic power stations in the multi-energy complementary project, the feasible idea is to comprehensively consider the zoning characteristics, output correlation, time-varying characteristics of wind speed and illumination, etc. step by step from a single power group to the whole wind-solar convergence, research the aggregation effect analysis method of the wind-solar power station, and establish the aggregation criterion of the power station group.

From the perspective of long-term operation, the short-term complementary ability of water, wind, and photovoltaic power depends to a large extent on the long-term water level control of hydropower station reservoirs. Through reasonable water level control rules, according to the electricity scale and power fluctuation in different periods of the landscape, the reasonable energy storage of each stage of the hydropower system can be determined, thus providing accurate boundary conditions for daily hydro-wind-solar power compensation. Therefore, considering the multiple uncertainties of wind and solar power generation and runoff, the research on the long-term coordinated control of hydropower station with a complementary system can be carried out with two ideas.

The first is to explore the stochastic optimal dispatching method of hydropower coupled with wind and solar power's uncertain output, including the modeling criteria and efficient solving methods. At the level of centralized control of the river basin, the joint operation of cascade hydropower, wind power, and photovoltaic power can be further discussed. By taking the cascade hydropower stations and the wind and photovoltaic power stations with the same stakeholders as the object, the maximum comprehensive benefit expectation model of a hydro-wind-solar hybrid system with long-term and short-term multi-time-scale coupling will be constructed.

The second idea is to study the key water level control rules of a hydropower station reservoir group with the complementary operation of water, wind, and solar power. Starting from the cascade and cross-basin stages, we will focus on the water level control of the main time nodes before a flood, at the end of a flood, and at the end of the year under the condition of complementary water, wind, and photovoltaic power. In the first stage, the dispatching level of a single river basin is mainly based on the combined scene of long series runoff and wind and photovoltaic power stations. The water level at the critical time nodes of the controlled hydropower station will be taken as the optimization object. Multi-objective evaluation criteria such as the maximum comprehensive power generation benefit and the minimum abandoned power of the hydro-wind-solar hybrid system will be constructed, and the multi-objective optimization algorithm is used to simulate the long-series optimal dispatching, and the non-inferior critical water level set of cascade hydropower stations is deduced, while the reasonable water level control intervals before a flood, at the end of a flood, and at the end of the year are analyzed and determined. According to the water level control rules of the main hydropower stations, the reasonable energy storage control range of the cascade hydropower stations is further analyzed to guide the joint operation of the cascade hydropower stations and the hydro-wind-solar power stations so as to stabilize the wind-solar fluctuation and realize the safe operation of the hydro-wind-solar hybrid system.

The short-term scheduling of renewable energy generally makes the mid-and long-term scheduling decision as the boundary constraint; that is, when the available water in the current scheduling period is given, an appropriate dispatching model is selected for optimization, and the water consumption in each scheduling period of the power station is allocated reasonably so as to determine the short-term scheduling operation strategy. One of the core tasks of the short-term operation of the hydro-wind-solar hybrid system is how to use the flexible regulation ability of hydropower to stabilize the intermittence and volatility of the new energy output. Therefore, it is necessary to carry out quantitative research on the flexibility needed to absorb new energy. We can proceed from two aspects. One is to analyze the probability distribution of the actual output of the power station, quantify the extreme value of the output or range of intraday fluctuations, and also compare and analyze the predicted power and the actual value. This focuses on the distribution law of power deviation to describe the flexibility regulation requirements in real-time operation. The second is to build appropriate flexibility evaluation criteria, where it is necessary to combine the flexibility requirements and scheduling capacity to formulate a quantitative flexibility up-and-down margin or deficiency indicators and then establish a suitable flexibility evaluation model according to the actual engineering characteristics of the complementary system.

Based on the quantification of flexibility demand, the short-term joint modeling method of hydro-wind-solar complementary operation can be studied in two ways. On the one hand, the output and fluctuation extreme values of a wind and solar power station cluster are described quantitatively, and the hydropower deterministic scheduling model is innovated through constraint integration, focusing on solving the peak regulation difficulties caused by the fluctuation in the wind and solar power output at critical time nodes, such as the load trough, peak, and maximum ramp or downgrade. On the other hand, based on the stochastic programming theory, a stochastic dispatching model can be constructed by combining the wind solar power output with hydropower to study the output stability and adjustability of the complementary system by considering the full-cycle power generation fluctuation of new energy sources. In addition, due to the time migration ability of the energy storage system with electric power, the new energy storage system will become a direct solution to a series of problems brought by the continuous improvement in the penetration rate of new energy in the future.

At the present stage, there have been many theoretical studies on the operation characteristics and economic benefits of hydro-wind-solar hybrid systems, but they are still imperfect. In the future, it is necessary to combine, sort out, and expand these aspects more comprehensively and build a comprehensive evaluation system for multi-energy complementary systems to adapt to the scheduling optimization of large-scale hydro-wind-solar hybrid systems.

By and large, for the hydro-wind-solar hybrid system, there are many cascade power stations in a basin, and each cascade power station has different wind and solar resources. In the actual project at this stage, the basin compensation between the mutual hydropower stations has not yet been implemented. In addition, there is the development of new wind and solar resources, peak regulation of the water potential, matching of corresponding electric charges, energy storage, frequency regulation, and other auxiliary services. There is a large number of stakeholders in the overall operation, and the stakeholders in the system are more complex. At this level, how to achieve the balance of economic interests is still an issue worthy of consideration and innovation, and it is also the main direction of future research.

6. Conclusions

Renewable energy sources such as hydro, wind, and solar power continue to develop rapidly, even as economies are struggling under the pressure of the COVID-19 pandemic. In particular, the issue of green recovery has been put forward to vigorously promote clean energy reform around the world, and the use of hydro-wind-solar hybrid renewable energy systems is increasing day by day. In the future, second-generation energy systems dominated by hydro-thermal power will gradually develop to the third generation of new power systems with wind and solar power, as well as other new energy generation, as the main body. At the same time, there will be a series of challenging theoretical and technical problems in power generation forecasting, renewable energy consumption, complementary and coordinated operation of multi-energy sources, and system stability control. No matter which link is explored, the optimization method used will show limitations in a certain aspect. It can be concluded that, thus far, there is not a superlative uncertainty handling technique.

This paper focuses on the generation scheduling problem of hydro-wind-solar hybrid systems from the following aspects: (1) mainly analyzing the long-term and short-term coordinated operation of the system, (2) focusing on the prediction and description of the power generation law of wind and photovoltaic power stations, (3) the risk management of hydro-wind-solar hybrid systems, and (4) the modeling and solution of joint dispatching of a hydro-wind-solar power station group. This paper summarizes and analyzes the current research and development situation of hydro-wind-solar hybrid systems and discusses the research ideas of these problems one by one from different perspectives. It provides a referential technical solution for the power generation scheduling of hydro-wind-solar hybrid systems and helps to overcome the key problems in the dispatching and operation of a new power system, which has a certain reference value for overcoming the challenges and complexity in the research of safe operation and scheduling optimization of hydro-wind-solar hybrid systems.The following is a look forward to the challenges and opportunities in the future research of hydro, solar, and wind power generation dispatching to open up ideas for scholars' follow-up investigations:

1. Taking into account that the occurrence of uncertainty has specific time sequences in power system scheduling, which means that the decision-making process for uncertainty in the upcoming period should be based on the outcomes of the previous periods;
2. Scheduling issues could involve nonlinear objectives or constraints, which would make the scheduling model non-convex;
3. Fault uncertainties attract more attention due to their potential for destruction, so operators intend to contact a variety of sources to deal with unexpected failures;
4. Flexible operational approaches that take resource features into account;
5. Evaluation of comparative costs and the environment;
6. The use of current hydroelectric facilities as PHS;
7. Research-based networks;
8. Suitable geography;
9. The economics of hydro-wind-solar systems.

7. Patents

This section is not mandatory, but it may be added if there are patents resulting from the work reported in this manuscript.

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Abbreviations

The following abbreviations are used in this manuscript:

UC	Unit commitment
SCUC	Security-constrained unit commitment
ED	Economic dispatch
SCED	Security-constrained economic dispatch
ARIMA	Autoregressive integrated moving average
KF	Kalman filter
ANN	Artificial neural network
BP	Backpropagation
RBF	Radial basis function
GAN	Generative adversarial network
FWNN	Fuzzy wavelet neural network
ARMA	Autoregressive moving average
ADMM	Alternating direction of multipliers method
SDP	Semi-definite programming
CO	Convex optimization
SO	Stochastic optimization
RO	Robust optimization
DRO	Distributionally robust optimization
ARO	Adjustable robust optimization
GHG	Greenhouse gas
CO_2	Carbon dioxide
MILP	Mixed-integer linear programming
MG	Microgrid
TVPP	Technical virtual power plant
OPF	Optimal power flow
ROPF	Robust optimization-based AC optimal power flow
SOCP	Second-order conic program
LP	Linear programming
BD	Bender decomposition
EMS	Energy management systems
CVAR	Conditional value at risk
CCG	Column-and-constraint generation
SNP	Stochastic nonlinear programming
DO	Deterministic optimization
GEP	Generation expansion planning
OA	Orthogonal array
GCH	Global complementary hydropower
MOCS	Multi-objective cuckoo search algorithm
GLPK	GNU linear programming kit
EA	Evolutionary algorithm
PSO	Particle swarm optimization
GA	Genetic algorithm
NSGA-II	non-dominated sorting genetic algorithm
DP	Dynamic programming
CF	Capacity factors
HRES	Hybrid renewable energy system
PHS	Pumped hydro storage

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