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Optimization of multi-temporal generation scheduling in power system under elevated renewable penetrations: A review

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The traditional power generation mix and the geographical distribution of units have faced structural reform with the increasing renewables. The existing scheduling schemes confront the optimization challenges of multi-source collaborative and multi-temporal coordination. This paper reviews the optimization of generation scheduling in power systems with renewables integration in different time scales, which are medium- and long-term, short-term and real-time, respectively. First, the scheduling model and method are summarized. The connections and differences of the multi-source mathematic model with uncertainty, as well as the market mechanism, including thermal power, hydroelectric power, wind power, solar energy, and energy storage, are also indicated. Second, the scheduling algorithm and approach are sorted out from the two dimensions of certainty and uncertainty. The innovation and difference in algorithm between the traditional scheduling and the scheduling problem with renewables are presented. Meanwhile, the interaction and coupling relationship among the different time scales are pointed out in each section. The challenges and shortcomings of current research and references future directions are also provided for dispatchers.

KEYWORDS

optimization, generation scheduling, multi-temporal, renewables integration, power system

1 Introduction

The traditional power system in which thermal units account for the vast majority will face structural reform with the increasing penetration of renewables (Chen et al., 2021a). According to the "Renewable Energy Installed Capacity Statistics 2022" report released by the International Energy Agency, the world in 2021 added almost 257 GW of renewables, increasing the stock of renewable power by 9.1 per cent and contributing to an unprecedented 81 per cent of global power additions. Furthermore, renewables are predicted to reach around 40 per cent in total energy generation across all sectors by

2030. Thus, the original power balance will be changed due to the more complex generation mix and more dispersed geography distribution of power units (Wang et al., 2021). New challenges are proposed to be confronted for the traditional generation scheduling schemes.

However, existing generation scheduling schemes will experience shortfalls with the increasing proportion of renewables in the future. A comprehensive optimal solution under the new power system will be hard to be obtained, resulting in curtailment of wind and solar, frequent congestion of power flow, and even power outages. Two main reasons cause the problem. First, the output characteristics of various power generation entities require scheduling schemes to achieve multi-temporal coordinated optimization. The actual output of hydropower is often determined in medium- and long-term scheduling, while the output of wind power and solar energy can only be accurately considered in short-term and real-time scheduling. Second, higher requirements are put forward for the optimization and coordination of comprehensive energy including thermal power, hydroelectric power, wind power, solar energy, and energy storage (Tiwari et al., 2021). The optimization of generation scheduling is realized efficiently by the complementarity coordination of comprehensive energy.

Several overviews have been conducted on the optimization of generation scheduling (Boqiang and Chuanwen, 2009), (Howlader et al., 2019). On one hand, generation scheduling schemes have been extensively summarized. Reference (Boqiang and Chuanwen, 2009) reviewed the traditional economic dispatch method considering wind power integration. The optimization problem was reviewed based on unit commitment (UC) (Abdi, 2021), and the impact of the renewable energy injection system on UC was also analyzed (Abujarad et al., 2017). However, all the reviews only analyzed the scheduling optimization problem of a single time period in a fragmented manner, and cannot effectively integrate the methods in each part, revealing the correlation among different scheduling schemes. On the other hand, the multi-temporal generation models of power sources were summarized. Reference (Liu et al., 2022) summarized photovoltaic output models and prediction methods at multiple temporal and spatial scales. Wind power generation forecasting methods were reviewed in reference (Jiang et al., 2019). Energy storage applications in various scenarios were also summarized (Ai and Dong, 2015); (Howlader et al., 2019). However, such studies only analyzed the multi-temporal output of a single power source. The applications in scheduling optimization methods were barely summarized. Meanwhile, no existing literature comprehensively integrated all power sources including wind power, photovoltaics, hydropower, thermal power, and energy storage, revealing their optimized coordination methods.

This paper reviews the optimization of multi-temporal generating scheduling in power system with renewables integration. The traditional scheduling optimization scheme and the scheme based on the integrated energy dispatch are sorted out in detail from the perspective of multiple time scales, and the connections and differences between the two schemes are also indicated. In the context of the previous research, our paper provides the following contributions.

1) We summarize the traditional scheduling optimization methods and the methods in the new power system with renewables integration. The mathematic models of multiple power sources, including thermal power, hydroelectric power, wind power, solar energy, and energy storage, are also reviewed, revealing their inherent connections and differences with consideration of uncertainty.
2) We summarize the optimization of scheduling algorithm and approach from the two dimensions of certainty and uncertainty. The innovation and difference of algorithm between the traditional scheduling and the scheduling problem with injection of renewables are indicated.
3) We sort out the similarities and differences of scheduling schemes from the perspective of multiple time scales, which are medium- and long-term, short-term and real-time, respectively, and point out the coordination and relationship in scheduling optimization among three terms.

The structure of the paper is the following: Section 2 reviews the optimization of multi-temporal scheduling method with multiple power sources mathematic models. Section 3 reviews the optimization of multi-temporal scheduling algorithm and approach. The summary of current works and corresponding suggestions for future research are analyzed in Section 4. Conclusions are presented in Section 5.

2 Scheduling model and method

In this section, common methods and recent developments of scheduling models in medium- and long-term, short-term and real-time scales are concluded in sequence, including mathematical optimization models for each power source as well. Then the interaction and coupling relationship among the different time scales are summarized. What's more, market mechanism to promote renewables integration is also reviewed. The difference in time dimension such as the scheduling cycle, time resolution between multi-temporal dispatches, as well as the input data and the output results connecting these dispatches are presented in Table 1.

2.1 Medium- and long-term scheduling

Medium and long-term power generation scheduling focus on system operation for several weeks, months or a year. Long-term scheduling is generally considered with investment

TABLE 1 The difference in three time dimensions.

Time dimension	Scheduling cycle	Time resolution	Input	Output
Medium- and Long-term scheduling (MLS)	several weeks, months or a year	1 h	Power demand, solar and wind forecast data, physical constraints	Generator output and maintenance plan, cost and benefit
Short-term scheduling (STS)	1 day or a week	1 h or 15 min	Constraints given by MLS, power demand	Generator output and up/down plans, detail cost and benefit
Real-time scheduling (RTS)	1 day	15 or 5 min	Constraints given by STS, power demand	Generator output, detail cost and benefit

planning and medium-term scheduling gives correction to short-term scheduling instructions based on long-term scheduling results (Flatabø et al., 1998). With the difference in system scale, spatial and temporal resolution, and optimization target, there exist multiple modelling methods with different degrees of accuracy and technological properties.

2.1.1 Model for large-scale power systems with high temporal resolution

The model involves various generation sources and numerous operational constraints, which are simulated from months to a year with hourly resolution. These scheduling models are generally designed to be deterministic and linear for the purpose to reduce the computational burden, such as several representative European electricity system models—IDILES (Iterative Optimization of Investment in Large Energy Systems), JMM (Joint Market Model) and ELTRAMOD (Electricity Transshipment Model) (Misconel et al., 2022).

For large-scale systems, the total system costs, including operational costs, investment costs and environmental costs, are commonly used as the optimization targets (Schmid and Knopf, 2015), (Schinko et al., 2019). With high renewable penetration in future power system, how to model wind and solar generation more accurately is important for power balance. To obtain time series of potential wind and solar generation with an hourly resolution, meteorological reanalysis is a popular method in many studies. Liam et al. modelled long-term offshore wind generation by using ERA5 reanalysis, the results indicated that ERA5 (European Centre for Medium-Range Weather Forecasts Reanalysis v5) reanalysis can effectively reduce prediction error of capacity factor compared to MERRA2 (Modern-Era Retrospective Analysis for Research and Applications, version 2) reanalysis (Hayes et al., 2021). Luis et al. generated hourly time series of solar generation by ERA5 reanalysis and validate the result using actual data (Camargo and Schmidt, 2020). Moreover, flexible resources like fast responding thermal units, hydropower and energy storage are critical to reducing system costs with renewable penetration elevated (Yang et al., 2018). For thermal units, the traditional unit commitment model is inapplicable in long-term scheduling problems due to amounts of binary variables. Hence, Han et al. (2019) proposed a fast unit commitment model (FUC) to reconstruct traditional chronological constraints with a linear formulation based on unit grouping techniques, and linear relaxation was considered for the simplification in reference (Palmintier and Webster, 2015). Due to the highly non-convex and nonlinear structure in output characteristics (Taktak and D'Ambrosio, 2017), hydropower generation is generally linearized in these problems (Namely fixed hydraulic head and turbine efficiency) (Liu et al., 2019a). As for storage, charge-discharge characteristics are the main constraint for long-term scheduling which is commonly considered a linear model (Chen et al., 2021a). Besides, Sonja et al. introduced a novel system-states framework to optimize storage operation in medium- and long-term power scheduling (Wogrin et al., 2015) and combined it with Net-constraints in a subsequent study (Tejada-Arango et al., 2017).

2.1.2 Model for specific optimization strategy with diverse resolution

The models in the previous section are aimed to minimize the total system costs, however, there exist many studies focusing on other specific optimization strategies, such as renewable curtailment, energy generation and output fluctuation. Scheduling for hybrid power system with reservoirs has gradually become a hot topic. Considering the impact of uncertainty caused by wind and solar power generation, such problems are generally presented as multi-objective and multi-stage optimization models with small-scale systems and daily or monthly resolution (Liu et al., 2019b), (Shen et al., 2020). In some hydro-dominated systems like Norway and Brazil power system, the optimization scheduling of hydropower is a critical component in power dispatch. Linear programming (LP), decomposition techniques and energy equivalent reservoir (ERR) methods have been proposed to model the scheduling of large-scale reservoirs (Brandao, 2010). Stochastic dynamic programming (SDP) and stochastic dual dynamic programming (SDDP) are available for systems with few reservoirs (Zambelli et al., 2006), (Helseth et al., 2017). Meanwhile, a novel econometric model based on water value model has been applied in the deregulation system for reservoir operation (Jahns et al., 2020).

From the aspect of the electricity market, reference (Yao et al., 2020) analyzed renewable energy integration in the Ningxia electricity market while the ancillary service market is yet to be established. The generation contract transfer trading (GCTT) is adopted to ensure the cost recovering of thermal generators. Reference (McPherson and Bryan, 2014) analyzes the new law aiming to promote wind energy by mandating long term power purchase tenders in Panama, as well as the power generation and system marginal cost.

2.2 Short-term scheduling

The total optimization horizon for short-term scheduling ranges from 1 day to 1 week with an hourly interval. Unit commitment (UC) and Economic dispatch (ED) models are universally applied in power system to determine on-off states and production plans of units. Classical UC and ED model has been widely discussed in many reviews (Saravanan et al., 2013)-(Bhardwaj et al., 2012), while this paper focuses on the latest development in modelling techniques. Matija et al. compared four clustering methods in Dispa-SET UC model and their results indicated that the differences between the methods and the traditional UC model are acceptable (Pavičević et al., 2019). Luis et al. proposed a frequency-constrained stochastic UC model to efficiently schedule diverse frequency services (Badesa et al., 2019). Brito et al. developed seven piecewise linear generation models for hydro UC problems and compared the corresponding performance in Brazil's hydro system (Brito et al., 2020). Furthermore, some studies improved traditional ED under the rapid development of distributed energy (Velasquez et al., 2019), (Jian et al., 2020) and combined ED with environmental dispatch (Razeghi et al., 2016).

Uncertainty is becoming an inevitable factor for short-term power scheduling with the increasing share of intermittent resources. As the main source of uncertainty, wind and solar power output should be built more carefully in short-term scheduling, instead of being considered as time series in medium- and long-term models. One of the ways is to approximate power output by probability distribution function which is based on historical data and large amounts of scenarios generated by Monte Carlo simulation (MCS) and other mathematical methods (Zakaria et al., 2020). Another way is to define the uncertainty set by a set of parameters, which includes all possible scenarios (Yi et al., 2018). The two ways mentioned above are universally applied in uncertainty methods such as stochastic optimization and robust optimization. Reference (Kuznia et al., 2013) presents a stochastic mixed integer programming model for a hybrid power system, which consists of thermal units, renewables, storage considering network constraints, for remote areas. Reference (Madaeni and Sioshansi, 2013) combines stochastic optimization and demand response to mitigate the uncertainty of wind power. Li et al. (2020) proposed a stochastic programming for power system with renewables integration. It reduces energy costs with electric heaters and effectively manages renewables with fluctuating output. The two-stage robust optimization solved by the column-and-constraint generation is first proposed in reference (Zeng and Zhao, 2013), which greatly improve the scheduling speed. Based on that, An and Zeng. (2014) further present the expanded robust unit commitment and the risk constrained robust unit commitment model. What's more, to cope with the wind power penetration, the uncertain sets based on multi-band uncertainty set considering the temporal correlation (MBUSCTC) can be added to the modeling of multi-power units. The method can rigorously and realistically describe the output of wind power sources (Chen et al., 2020). Meanwhile, the outage probability of units and transmission lines can be considered in solving unit commitment problems, which effectively reduce the conservatism of traditional robust contingency constrained unit commitment (Chen et al., 2019).

Moreover, the influence of load uncertainty is reckless to ignore in short-term scheduling problems (Dey et al., 2020). Batteries, pumped-hydro and other energy storage techniques are generally used to deal with these uncertainties. Wai et al. analyzed the advantages and disadvantages of storage operation based on daily cycles and weekly cycles respectively, the results showed that storage operated in daily mode is more advisable for renewables intermittency (Ho et al., 2016). Toubeau et al. (2020) presented a two-stage mixed-integer linear programming (MILP) model by data-driven methodology to optimize the day-ahead dispatch of storage systems. In addition, the data-driven robust state estimation (DDSE) method through off-line learning and on-line matching can be used to simplify the calculation of network parameters and effectively improve the scheduling efficiency (Chen et al., 2021b). At the same time, to cope with the uncertainty of renewables, it is possible to further consider the data-driven PF (DDPF) method based on historical/simulated data that includes an offline learning stage and an online computing stage in scheduling optimization (Chen et al., 2021c). Furthermore, multi-type demand response resources are gradually becoming a new direction for tackling uncertainty (Baek and Shin, 2022). For short-term hydro scheduling, MILP is one of the most effective approaches to accurately model the operation of hydropower stations with head-dependent prohibited operation zones (Su et al., 2020), while the uncertainty of reservoir inflow data is commonly handled with the stochastic programming (SP) model (Fleten and Bjørdal, 2020).

From the aspect of the electricity market, in order to cope with the elevated renewable penetrations of wind power, reference (Liu and Xu, 2021) increases corporate profits by analyzing bidding regulations and imbalance pricing mechanism, thereby promoting renewable accommodation. Reference (Zhang et al., 2022a) further using the Stackelberg game model analyze the relationship between renewable energy generation companies (GENCOs) and the day-ahead electricity market. The renewable accommodation in the day-ahead market can be effectively promoted by adjusting the bidding strategy.

2.3 Real-time scheduling

Real-time generation scheduling mainly focuses on intraday dispatch problems with 15 min, 5 min or shorter temporal resolution. Accurate prediction information is a critical input for reasonable results in real-time scheduling. Thus, an ultra-short-term forecast is necessary for the violent fluctuation of wind and solar power output. Time series regression models, machine learning techniques, and other approaches such as image-based methods and decomposition methods are practicable to obtain the forecast information of minutes and hours ahead (Tawn and Browell, 2022). Recently, the combination of different methods called hybrid prediction model has been widely used in renewable forecast (Wang et al., 2020). For dynamically updating real-time prediction information, rolling dispatch based on model prediction control (MPC) has been widely used in many studies. Zhang et al. (2021) proposed a multi-objective rolling dispatch model to handle the intermittency of renewable resources in the optimization of active distribution network scheduling. Sheng et al. (2021) developed a mixed-integer second-order cone model with rolling optimization to eliminate the impact of renewable fluctuation on transmission networks. Meanwhile, uncertainty methods such as distributionally robust optimization and stochastic optimization in real-time scheduling has some novel developments. Distributionally robust optimization (DRO) is used to ensure security constrained economic dispatch and assess operating cost expectations affected by renewable energy sources (RES) uncertainty (Lu et al., 2018). Reference (Yang and Wu, 2018) improves the conservativeness in real-time scheduling by the distributionally robust optimization, where the uncertainty of distributed generation output is characterized with the first-order and second-order moments. Overvoltage problems can be eliminated effectively through the combination of ED and corrective control strategies. Based on DRO, reference (Liu et al., 2021) further considers automatic generation control (AGC) in SCED, which reduces the total cost of power generation and frequency regulation. Lin et al. (2020) took a mean-tracking model into stochastic ED to get optimal dispatch solutions with minimal tracking errors. Morteza proposed a two-stage stochastic model to optimize the operation of a hybrid system with the target of maximizing the system owner's profit (Li et al., 2019).

Real-time scheduling of energy storage is usually determined by markets price and uncertainties. Fang et al. (2018) developed a mean-variance optimization method for the scheduling of storage system, which modelled the uncertainty of day-ahead and real-time price with a Gaussian distribution and aimed at reducing revenue volatility. Gao et al. (2018) introduced a MILP model which considered the impact of battery wear-cost and demand uncertainty based on rolling dispatch. With an intensive coupling relationship between upstream and downstream reservoirs, hydropower system is rarely dispatched at intervals of less than a quarter of an hour. While MILP is the universal approach to model the operation of hydropower system in real-time scheduling (Zhang et al., 2022b).

From the aspect of the electricity market, an integrated dynamic market mechanism (DMM) was proposed combining real-time market and frequency regulation. Renewable generators and flexible consumers can negotiate electricity prices to maximize the profitability of unit output (Shiltz et al., 2015). Reference (Yuan et al., 2021) further proposes a real-time pricing mechanism based on demand-response. The upper and lower models are aimed at maximizing the profit and welfare of suppliers respectively. The scheduling results can effectively reduce the peak-to-valley difference and optimize the output data of each unit.

To sum up, we have sorted out the commonly used methods and recent developments of multi-temporal power generation scheduling models. Power scheduling is generally ordered from longer time scales to shorter time scales. For instance, medium- and long-term model determines the annual scheduling plan for large reservoirs and takes it as the boundary of short-term model, while units on/off states are obtained from the output of short-term model and then directly applied in real-time model. The scheduling models of multiple time scales are closely coupled, where they have commonalities but are different from each other. They are interdependent and complementary to realize the smooth and safe operation of the power system.

3 Scheduling algorithm and approach

Here, we sort out common solution algorithms and approaches for various models at multiple time scales, which are medium- and long-term, short-term and real-time, respectively. Each part the mainstream algorithms based on deterministic schemes in traditional generation scheduling are introduced first. Then the improvement and optimization of the uncertainty algorithm for the renewables integration are presented. The approaches to coordinate with other time scales are introduced at last. We note that optimizers including GUROBI, CPLEX, MINOS, GSOMP and so on are widely used to address the optimization issues. These approaches will not be repeated here.

3.1 Medium- and long-term scheduling

The power generation scheduling in the medium- and long-term scales mainly focuses on the output schemes of the hydropower system. Meanwhile, relatively less uncertainty will be considered for renewable sources due to the long time scales. Hence, the medium- and long-term scheduling algorithms are mainly deterministic.

Reference (Nolde et al., 2008) proposed a multistage stochastic programming formulation solved *via* Nested Benders Decomposition. Model predictive control was setup to obtain the solution during the solving program. Horizon length and shape of the event tree were identified to optimize the computational power, and improved the performance and robustness by adjusting parameters.

In terms of co-optimization with other time scales, considering the randomness brought by inflow and varying temperatures, risk management and portfolio analysis were studied to face uncertainties in the Norwegian hydro system (Flatabø et al., 1998). Reference (Xinli et al., 2011) proposed a mixed numerical integral algorithm to simulate dynamically in scheduling. Multi-temporal phenomena were also united and coordinated to minimize the cost.

3.2 Short-term scheduling

The short-term generation scheduling algorithms further solve the optimization in the hydro-thermal system. Different from medium- and long-term scheduling, the algorithms in short-term scheduling need more randomness and robustness due to the uncertain impacts of wind and solar energy. Hence, the short-term algorithms are innovated to adapt to the uncertainty due to the injection of renewables.

Reference (Ma et al., 2017) proposed a method to enhance the ability to accommodate wind power based on reciprocal peak-regulation trading of inter-regional grids. The uncertainty of wind power in day-ahead scheduling was reduced by the information gap decision algorithm. Reference (Liaquat et al., 2020) took into account the effects of photovoltaic energy in traditional power system. Auto-Regressive Integrated Moving Average (ARIMA) model was applied to solar energy forecasting. Non-linear problems could be addressed effectively by the accelerated particle swarm optimization and the Rey algorithm.

Meanwhile, as the essential hub of multi-temporal scheduling, short-term strategies have more interaction with other time scales. Several researches have been conducted on interaction with medium- and long-term scheduling. Reference (Marwali and Shahidehpour, 2000) proposed a coordination approach based on Monte Carlo simulation. The behavior of power system and potential forced outage scenarios in long-term scheduling were submitted to short-term scheduling, making sure the short-term scheduling and network constraints were satisfied. Three approaches, which are the primal-information approach, the dual-information approach and the marginal resource-valuation functions approach, respectively, were proposed to coordinate the medium-term planning and short-term scheduling. Profitability was increased by the combination of different decision levels (Reneses et al., 2006).

3.3 Real-time scheduling

Real-time scheduling algorithms demand higher precision in a shorter scheduling time period. Multiple power sources and inter-regional coordination are important issues that real-time scheduling algorithms need to address. Meanwhile, the greater randomness brought by renewables also puts forward higher requirements on the robustness of the algorithm.

First, deterministic algorithms have been reviewed. Traditionally, real-time scheduling based on security constrained economic dispatch (SCED) was solved by deterministic algorithms. Reference (Kang et al., 2018) proposed deferrable loads control scheduling algorithm, where the power resource utilization was improved. The difference between the total load curve and the supply curve was also reduced. Reference (Huang and Wang, 2007) proposed an approach to optimized real-time generation scheduling combining orthogonal least-squares (OLS) and enhanced particle swarm optimization (EPSO) algorithms. The three-layer network structure has been simplified. The fast response and precise scheduling could be obtained when the inputs of system load with the weight of cost were submitted.

Second, optimization algorithms for the uncertainty have been reviewed. The researches on real-time scheduling algorithms to improve robustness have also been conducted due to the higher uncertainty of real-time renewables. Reference (Patrinos et al., 2011) formulated a real-time optimal generation scheduling problem containing intermittent generation and storage energy system. Then a novel scenario-based stochastic model predictive control (SMPC) algorithm was proposed for the solution of the real-time scheduling problem. Reference (Wei et al., 2015) proposed the concept of real-time dispatch ability (RTDA) of power systems with variable energy resources. A polyhedral representation of RTDA was defined and an efficient Ad-CG algorithm generated its boundaries. Linear characteristics make the method easy to implement. A continuous-time modelling based robust unit commitment was presented to address beyond-the-resolution (BtR) wind power uncertainties (Zhou et al., 2021). The optimization scheduling problem was solved by the column-and-constraint generation algorithm in the function space. Then the results were recovered to algebraic space. Robustness was enhanced at the expense of economic costs. Uncertainties were further reduced by a two-level optimization structure by a

TABLE 2 Comparison of typical cited papers.

References	Main power source model	Modelling method	Solving approach	Uncertainty	Temporal scale
Chen et al. (2018)	Thermal, wind, solar	Linear programming	Optimizer (GUROBI)	—	Medium- and long-term
Wogrin et al. (2015)	Storage	Methodology of System states approximation	Optimizer (CPLEX)	—	Medium- and long-term
Liu et al. (2019b)	Wind, solar, hydro, batteries	Two-stage model with an proposed optimal operation strategy	—	Wind, solar	Medium- and long-term
Brandao. (2010)	Hydro	ERR model for hydropower	Optimizer (MINOS)	—	Medium- and long-term
Zambelli et al. (2006)	Hydro	SDP model with independent probability distribution function	—	inflows	Medium- and long-term
Jahns et al. (2020)	Hydro	Econometric approaches based on supply curves and water value	—	—	Medium- and long-term
Badesa et al. (2019)	Thermal	Stochastic UC model with clustering and a linear inner approximation	Optimizer (FICO Xpress)	Renewable	Short-term
Brito et al. (2020)	Hydro	MILP model with several piecewise linear approaches	Optimizer (GUROBI)	—	Short-term
Yi et al. (2018)	Wind, solar	Multi-objective robust model	NSGA-II algorithm	Wind, solar, demand response	Short-term, real-time
Toubeau et al. (2020)	Storage	Two-stage MILP model with data-driven methodology	Optimizer (GUROBI)	Energy storage	Short-term
Zhang et al. (2021)	Wind, solar, gas, storage	Rolling multi-objective model	MOEA/D-TSA algorithm	Wind, solar	Real-time
Sheng et al. (2021)	Storage, wind, solar	Mixed integer second-order cone programming based on MPC	Convex relaxation and solved with Optimizer	—	Short-term, real-time
Lin et al. (2020)	wind	Multi-objective stochastic ED model based on Mean-tracking	Optimizer (GSOMP)	Wind	Real-time
Li et al. (2019)	Storage	Dynamic constraints model with deterministic linear conversion	Optimizer (CPLEX)	Load, Power regulation	Real-time
Zhang et al. (2022b)	Hydro	MINLP model and linear approximation by improved special ordered sets	Optimizer (GUROBI)	—	Real-time
Nolde et al. (2008)	Hydro, thermal	Multistage stochastic programming based on MPC	Nested Benders Decomposition	Inflows, load	Medium- and long-term
Xinli et al. (2011)	Thermal	MINLP model with hybrid techniques	LR together with EA	—	Short-term
Marwali and Shahidehpour, (2000)	Thermal	Dynamic programming and two-state continuous-time Markov model	LA and Monte Carlo sampling algorithm	Lines and generating units availability	Medium- and long-term, Short-term
Reneses et al. (2006)	Thermal	Three approaches: the primal-information, the dual-information and the marginal resource-valuation functions	—	—	Medium- and long-term, Short-term
Patrinos et al. (2011)	Thermal, storage	Stochastic model based on MPC	SMPC algorithm	Load, market price, renewable	Real-time
Huo et al. (2015)	Storage	ED model with greedy control strategy	Iteration algorithm with Perturbed Markov decision process	Wind, storage	Real-time

policy iteration algorithm based on the Perturbed Markov decision process. The optimal real-time scheduling strategy combined with storage energy was also described (Huo et al., 2015).

In terms of co-optimization with other time scales, coordination strategies between real-time and short-term scales were also applied to improve the robustness of scheduling. Reference (Yu et al., 2018) proposed an improved two-stage robust optimization with recourse method considering the rolling trading of inner-day electricity market based on the analysis of time-varying prediction uncertainty of wind power. Day-ahead scheduling results had been combined with real-time scheduling to both reduce the reserve capacity and the imprecision.

To sum up, the optimization algorithm in medium- and long-term scheduling is mainly deterministic, which solves multi-level planning, and calculates revenue precisely. In short-term scheduling, algorithms with uncertain models are widely used, such as Benders decomposition algorithm, Monte Carlo algorithm and so on. The real-time scheduling algorithms are similar to the short-term ones. However, due to its short scheduling period, iteration algorithms such as SMPC are proposed innovatively. In addition, various integrated optimization solvers are applicable to all time scales.

4 Discussion

We have sorted out the typical scheduling methods and their algorithms with consideration of uncertainty in multiple time scales as shown in Table 2. The optimization of main power source models is also listed in detail. The review results show that the existing multi-temporal generating scheduling will confront the challenges under elevated renewable penetrations in the future. A comprehensive optimal solution will be difficult to be obtained, resulting in insufficient accommodation of renewables, frequent congestion of power flow, and even power outages. Two main reasons cause the problem. First, it is hard to achieve a unified scheduling scheme under multiple time scales due to the different physical characteristics of each power source. The actual output of hydropower is often determined in medium- and long-term scheduling, while the output of wind power and solar energy can only be accurately considered in short-term and real-time scheduling. Second, higher requirements are put forward for the optimization and coordination of comprehensive energy under elevated renewable penetrations. In order to ensure the balance of electricity, the comprehensive power abandonment rate of renewables will be very small, where some places require the full accommodation.

Meanwhile, we further found that the existing researches have the following shortcomings through the above review. In terms of scheduling models, no practical modelling method was proposed to ensure computing efficiency for large-scale systems in medium- and long-term scheduling when taking into account the uncertainty of renewable. Meanwhile, the participation of hydroelectric units, especially pumped storage plants, and energy storage were hard to be considered in real-time scheduling. From the perspective of scheduling algorithm and approach, the lack of effective algorithms to efficiently solve the medium- and long-term scheduling problem with consideration of renewables is also worth studying. Furthermore, current studies mainly focus on the coupling relationship between short-term and real-time scheduling models while few studies are concerned about the linkage between medium- and long-term and short-term scheduling. The above problems are demanded to be addressed in future research.

Therefore, future researches can focus on the following directions:

1. The medium- and long-term scheduling optimization problem in large-scale systems considering the hydro-thermal system should be investigated, where the large-scale cascade hydropower can be mainly considered. In particular, the optimization of output curves of various hydropower stations considering constraints such as maintenance plans is worthy of further study.
2. The optimization of scheduling strategies from medium- and long-term to short-term is worth studying. The coordinated operation of hydro-thermal and renewables can effectively improve the accommodation. Meanwhile, the connection of dispatch results including constraints and generator output between medium- and long-term dispatching and short-term dispatch is the focus of research.
3. The multi-source optimization model and cooperating strategy in real-time scheduling demand further improvement. The participation of pumped hydro and energy storage is an essential issue to be addressed. In addition, researchers can conduct the research on electricity market mechanism to address the problem of uncertainty under elevated renewables penetrations considering network constraints.
4. The trading mechanism of the electricity market can be further improved. The mechanism design of agency power purchase in the medium- and long-term scale, the renewables bidding strategy and the clearing model in the spot market are all worth studying.

5 Conclusion

The original power generation mix and the geographical distribution of units have changed with the increasing transition of power generation structure from fossil energy to renewable energy. Therefore, traditional optimization of scheduling methods based on the deterministic model has experienced shortfalls, while coordinated operation of hybrid system considering various uncertainties has gradually become concerned. This paper first introduces generation scheduling models and the latest improvement of mathematical modelling methods systematically, including wind power, photovoltaic, hydropower, thermal units and energy storage, from the perspective of multiple time scales. The coupling relationship and coordinated operation mechanism in different scheduling time scales are also indicated. The scheduling algorithms and approaches to problems at different time scales are reviewed then. The deterministic algorithms and the improved optimization algorithms for the uncertainty brought by renewables are introduced in detail. The medium- and long-term to short-term, short-term to real-time scheduling coupling algorithms and approaches are summarized as well. Furthermore, this review also points out the shortcomings of current research on large-scale systems in medium and long-term scheduling, as well as the lack of a strategic mechanism for the coordination between medium and long-term and short-term scheduling. Three references are presented for future research directions.

This review summarizes detailed multi-temporal generation scheduling schemes and corresponding algorithms with the purpose of providing assistance for dispatchers. The basis can be referenced for corresponding scheduling to face the increasing proportion of renewables injection.

Author contributions

KC, QS, BZ, QY, HP, and TJ: Data analyze, writing–original draft preparation SL: Supervision and editing.

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Conflict of interest

KC, QS, BZ, and SL were empolyed by the System Operation Department, Yunnan Power Grid Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Publisher's note

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