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Full-length article

Multi-timescale robust dispatching for coordinated automatic generation control and energy storage

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Abstract: The increasing penetration of renewable energy into power grids is reducing the regulation capacity of automatic generation control (AGC). Thus, there is an urgent demand to coordinate AGC units with active equipment such as energy storage. Current dispatch decision-making methods often ignore the intermittent effects of renewable energy. This paper proposes a two-stage robust optimization model in which energy storage is used to compensate for the intermittency of renewable energy for the dispatch of AGC units. This model exploits the rapid adjustment capability of energy storage to compensate for the slow response speed of AGC units, improve the adjustment potential, and respond to the problems of intermittent power generation from renewable energy. A column and constraint generation algorithm is used to solve the model. In an example analysis, the proposed model was more robust than a model that did not consider energy storage at eliminating the effects of intermittency while offering clear improvements in economy and efficiency.

Keywords: Automatic generation control, Energy storage, Intermittency, Coordinated dispatching, Robust optimization.

1 Introduction

There is a global call for the vigorous development and application of renewable energy [1], [2]. However, a power grid must run synchronously at a uniform frequency. Renewable energy sources such as wind and solar do not have the inertial response characteristics of traditional generators [3]; the output power varies intermittently over time, so large-scale grid penetration can make dispatch and control more difficult [4]. Most power grids that use automatic generation control (AGC) to achieve a balanced dispatch rely on thermal power. However, AGC units generally have a basepoint decision interval of 15 min. With the increasing prominence of intermittent power sources, the climbing rate of AGC units is too slow. Developing an approach with a feasible basepoint decision interval is urgently needed for the effective acceptance of renewable energy.

In response to the above problems, energy storage is an emerging resource that offers the advantages of low environmental pollution, flexible charge and discharge, and a fast response rate [5], [6]. Coordinating with energy storage for dispatch can greatly reduce the pressure on AGC units and increase the proportion of renewable energy utilization. Song et al. [7] proposed that the key to the application of energy storage in power grids is coordination with AGC units. Zhang et al. [8] proposes that deploying a flexible and fast-response system can increase the demand for renewable energy. The participation of energy storage

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in power grid dispatching has become a research hotspot at home and abroad. Energy storage has been considered for application to transmission and distribution networks, but most research has been focused on smoothing peaks and valleys [5], improving the renewable energy utilization rate [9], smoothing the output power of renewable energy [10], or improving the power quality [11].

Many previous studies have described the uncertainty of energy storage over long time scales, which cannot reflect the uncertainty of intermittency in practice. Intermittency is a complex problem that will only increase in prominence with the large-scale grid penetration of uncertain energy connections in the future [12]. Sun et al. [13] proposed using the Fourier transform to separate selected frequencies so that energy storage can be targeted to absorb short-term intermittency and give guidance on control direction. Su and Gamal [14] proposed an energy storage strategy for suppressing fluctuations that can effectively reduce the oscillation amplitude of the output power and reduce intermittency. However, they failed to consider the cost issue, the energy storage configuration was large, and their approach was not economical. Qin et al. [15] proposed a new type of dynamic coordination between energy storage and economic dispatch. Although their approach could maintain an instantaneous power balance, the basepoint decision interval was 1 h, and the actual running behavior at any instant was ignored.

With the increasing prominence of intermittent characteristics, the feasibility of considering each moment must be questioned. Wang et al. [16] analogized the laws of kinematics given a range of harsh scenarios, and they established an economic dispatch model for intermittent power grid intervals. However, they limited their study to single-time economic dispatch and neglected to coordinate between dispatches, so their method is not representative. Weiss et al. [17] used the deviation between the short-term predicted value and real-time operating data to generate a rapid slope and match it with the energy storage response to achieve intermittent consumption. However, they only considered the possibility of intermittent phenomena within expected values, so their approach was inaccurate under actual conditions. Li et al. [18] coordinated energy storage with dispatch adjustment for a given predicted wind power scenario on a fixed hourly schedule; their approach actually sacrificed the rapid response advantage of energy storage and did not consider the constraints of intermittency in a period. Although Zhao et al. [19] established multiple constraints to describe uncertainty and determine the distribution of prediction errors, they still could not determine the feasibility of instantaneous containment, and the decisions made between periods were not necessarily fully realized. Li et al. [20] characterized the intermittency of wind power in terms of the range, rate, and variation differential, which provided a good idea for dealing with intermittent characteristics.

Several algorithms are available for dealing with intermittent uncertainty, such as stochastic optimization [21], [22], reinforcement learning [23], [24], and robust optimization [25], [26]. Stochastic optimization has the prerequisite of obtaining the probability distribution of the transition model for each scenario in advance. For a model that expresses the intermittent probability incorrectly, its decisions cannot be realized in practice. Reinforcement learning does not have complete proof of convergence, it is highly sensitive to the parameter values, and the results are not universal. These two algorithms only focus on dealing with uncertainties, such as limited probabilistic scenario approximation or interval expression, but they cannot reflect the transient imbalances of intermittency. Thus, they are difficult to apply to the problems described above. Liu et al. [27] used the duality principle and linear approximation to transform a two-stage robust optimization model into a deterministic problem. However, this linear approximation method has stringent requirements for applicable models, which results in poor universality. Zhang et al. [28] used the column and constraint generation (C&CG) algorithm to solve a mixed-integer nonlinear model that includes nonlinear equations and Boolean variables. Their results indicated that not only can the C&CG algorithm improve the calculation speed and quality of a solution, but it can also be used for nonlinear problems having Boolean variables with wide applicability.

This paper proposes a two-stage robust optimization model that uses energy storage to compensate for intermittency when dispatching power. The fast response speed of energy storage can be used to make up for the slow response speed of traditional AGC units, which improves the climbing ability and realizes the adjustment potential. The uncertainty of intermittency is fully considered in the modeling process, which abstracts control by tracking the energy storage and AGC units between any two moments. The proposed model not only improves the ability of AGC units to cope with the impact of intermittency within the calculation period (set to 15 min in this study), but also the improves the mitigation impact of energy storage. Compared with a model that does not consider intermittency, the proposed model has greater robustness, can effectively reduce the cost of energy storage, clearly increases the charge and discharge efficiency, and improves the economy and security of the overall power grid.

2 Problem of energy storage considering intermittent processes

The uncertainty due to intermittency exists on a very short time scale, and the slope constraint of AGC units limits their ability to cope with the intermittency of renewable energy. It is impossible for AGC units to manage a scenario with highly intermittent fluctuations in energy. In this paper, the entire calculation period is divided into many infinitesimally short segment, and each segment can approximate the uncertainty by using a straight line with a slope and express it as a linear equation. In this section, an uncertainty range is used to describe how energy storage coordinates with AGC units to eliminate the effects of intermittency. Fig. 1 shows the process of using energy storage to eliminate intermittency in coordination with AGC units. The shaded part shows the coordination of the energy storage with AGC units to compensate for energy overflow or inadequacy. For example, if the intermittent power output increases suddenly, then the output trace is C → D. The AGC units send a dispatch signal to adjust the output, but the receiving trace is only A → B. With the participation of energy storage, area ABCD compensates for insufficient climbing in the form of charging, which reduces the dispatch pressure on the AGC units.

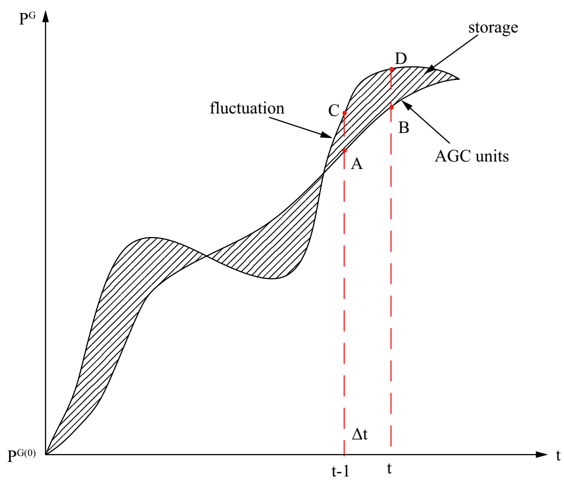

Fig. 1 Energy storage coordinating with AGC units to absorb intermittent changes

Increasing the maximum rate of change of the intermittency makes the climbing constraints more rigorous. This in turn increases the pressure on the dispatched AGC units and impact of the decided solution. Adding energy storage not only increases the acceptance of AGC units of intermittency but also reduces the dispatch pressure. Therefore, coordinating energy storage with AGC units to eliminate the effects of intermittency is an important problem for the application of energy storage to power grids. Energy storage can not only absorb the volatility of renewable energy during a given period but also apply its rapid response characteristics to power consumption. The proposed two-stage robust optimization model maximizes the use of energy storage.

2.1 Modeling of intermittent processes

From the perspective of robust optimization, an uncertainty set has definite upper and lower bounds. The characteristics and historical information of a region can be used to determine the expected output P_t^U of each period and the upper and lower limits of the fluctuation range. If the actual output power of a scenario is $\tilde{P}_t^U$ for a calculation period, then the uncertainty set can be expressed as

$$U=\begin{cases}\tilde{P}_t^U=P_t^U+\Delta P_t^U\\ \left|\tilde{P}_t^U-\tilde{P}_{t+1}^U\right|\leqslant P_{\Delta t}^U\\ P_{\Delta t}^U\in R^U\end{cases} \tag{1}$$

$$\tilde{P}_t^U\in[P_t^U-\Delta P_t^U,P_t^U+\Delta P_t^U]$$

where U is the set of uncertain fluctuation variables and $P_t^U=(P_{u,t}^U,u\in U)$ is the predicted output power of a scenario at time t. ΔP_t^U is the vector of uncertain fluctuation at time t, which can be determined empirically from historical data. $P_{\Delta t}^U$ represents the amount of deviation between the intermittency at each time period in the inequality of (1) and is also known as the "uncertainty budget." For two extremely short periods, the actual output power $\tilde{P}_t^U$ can be regarded as linear. By determining the value of $P_{\Delta t}^U$, the deviation from the expected fluctuation can be controlled within a certain range. Changing the size of $P_{\Delta t}^U$ can change the degree of conservativeness of the robust optimization to cope with fluctuations. As $P_{\Delta t}^U$ increases, the range of the uncertainty set also increases, which makes the solution for robust economic dispatch more conservative.

2.2 Model for considering intermittent processes

An AGC unit automatically adjusts an imbalance in the grid power through a participation factor to maintain the system within the specified frequency range. The upper and lower limits of the output power of the AGC unit are affected by the operation basepoint of each unit $P_i^{G(0)}$ and the climbing rate r_i within a certain period. When energy storage participates in dispatching, its characteristics are included in the decision-making, which reduces the disturbance of AGC units. The participation factor needs to be determined to release the ability of the AGC unit to reduce the deviation between the dispatch basepoint and optimal economic operating point. Considering the charge and discharge of energy storage can reduce the disturbance to an AGC unit and optimize the coordination area. The upper and lower limits of the operation of the i-th AGC unit are as follows:

$$\begin{aligned} \bar{P}_i^{\mathrm{G}} &= \max\{P_i^{\max}, P_i^{\mathrm{G}(0)} + r_i\Delta t + \Delta P_{k,t}^s\} \\ \underline{P}_i^{\mathrm{G}} &= \min\{P_i^{\min}, P_i^{\mathrm{G}(0)} - r_i\Delta t - \Delta P_{k,t}^s\} \end{aligned} \tag{2}$$

where $P_i^{\max}$、$P_i^{\min}$ are the allowable upper and lower limits of the AGC unit output power and $\bar{P}_i^{\mathrm{G}}$、$\underline{P}_i^{\mathrm{G}}$ are the upper and lower limits of the coordination area for AGC unit operation. When the energy storage is charged, the AGC unit can be defined by the maximum upper limit; when the energy storage is discharged, the AGC unit can be defined by the minimum lower limit.

The participation of energy storage increases the maximum up-slope and down-slope climbing capacity Δr_{ui}^G、Δr_{di}^G of the AGC unit within a shorter time scale Δt:

$$\begin{cases} \Delta r_{ui}^G = \dfrac{\bar{P}_i^{\mathrm{G}} - P_i^{\mathrm{G}(0)}}{\max\limits_{i\in G}\{r_i\}\Delta t} r_{ui} \\ \Delta r_{di}^G = \dfrac{P_i^{\mathrm{G}(0)} - \underline{P}_i^{\mathrm{G}}}{\min\limits_{i\in G}\{r_i\}\Delta t} r_{di} \end{cases} \tag{3}$$

$$\Delta P_{ri}^G = \begin{cases} \Delta r_{ui}^G \Delta t & \textit{Climb up} \\ \Delta r_{di}^G \Delta t & \textit{Climb down} \end{cases} \tag{4}$$

The high penetration by renewable energy of a power grid can cause fluctuations in the power generation and load balance. Energy storage is the main approach to compensating for these fluctuations. The base power value of the i-th AGC unit in the t-th period is P_i^G, and the actual output power $\tilde{P}_i^G$ of the AGC unit can be expressed as

$$\tilde{P}_{i,t}^G = P_{i,t}^G + k_{i,t}(\Delta P_{u,t}^U - \Delta P_{k,t}^s) + \Delta P_{ri}^G \tag{5}$$

where $k_{i,t}$ is the participation factor of AGC, $\Delta P_{k,t}^s$ is the amount of change in the charge and discharge of the energy storage, and ΔP_{ri}^G is the increase in the climbing ability of the AGC units. The above analysis shows that energy storage can not only suppress the fluctuations from renewable energy but also can coordinate with AGC units to be converted into climbing ability and response ability and mitigate the dispatch pressure.

3 Two-stage robust optimization model

3.1 Objective function

The proposed two-stage robust optimization model has the objective of reasonably arranging the energy storage and output power of AGC units under the constraints of uncertainty to deal with the effects of intermittency. Robust optimization is used to deal with the uncertainty of intermittency, avoid the multiple problems of energy storage charging caused by deterministic dispatch methods, and improve the economy of the power grid dispatch through optimal energy storage.

If the optimization objective is minimizing the total cost, then the optimal power basepoint of the AGC units and the optimal coordination with energy storage can be solved. The objective function of the two-stage robust optimization model is

$$\min\left\{\sum_{t=1}^{T}\sum_{i\in G}F_{i,t}(P_{i,t}^G) + \max min\sum_{t=1}^{T}\sum_{k\in S}F_{k,t}(P_{k,t}^s)\right\} \tag{6}$$

where $F_{i,t}(P_{i,t}^G)$ is the generation and standby costs of the i-th AGC unit in the t-th period, and $F_{k,t}(P_{k,t}^s)$ is the configuration and operating costs of the kth energy storage in the t-th period.

The generation cost of AGC units and the configuration and operating costs of energy storage are expressed as

$$F_{i,t}(P_{i,t}^G) = a_i(P_{i,t}^G)^2 + b_i P_{i,t}^G + c_i \tag{7}$$

$$F_{k,t}(P_{k,t}^s) = M_k\left(P_{ck,t}^s \eta_{ck,t}^s + \frac{P_{dk,t}^s}{\eta_{dk,t}^s}\right) \tag{8}$$

In (7), a_i, b_i, and c_i are the quadratic term coefficient, primary term coefficient, and constant term coefficient, respectively, of the generation cost, and $P_{i,t}^G$ is the output power of the i-th AGC unit at time t. In (8), $P_{ck,t}^s$、$P_{dk,t}^s$ is the charge–discharge power of energy storage, and M_k is the cost coefficient of the energy storage.

3.2 Constraint conditions

To ensure the safety and reliability of the system operation in feasible uncertainty scenarios, the model also considers safety constraints such as the charge and discharge of energy storage and the climbing speed. All values of uncertain quantities must meet the following constraints.

3.2.1 Power balance constraint

$$\sum_{i=1}^{G}P_i^G + \sum_{k=1}^{S}P_k^s + P^U = P^L \tag{9}$$

where P_k^s is the output power of energy storage, P^U is the output power of the uncertainty set, and P^L is the power load.

3.2.2 Climbing rate and operating threshold of the AGC units

$$\begin{cases}\Delta P_{i,t}^{G}=k_{i,t}(\Delta P_{t}^{U}+\Delta P_{t}^{L}-\Delta P_{k,t}^{s})\\ \sum_{i=1}^{G}\sum_{t=1}^{T}k_{i,t}=1\\ k_{i,t}\geqslant 0\end{cases} \tag{10}$$

$$\begin{cases}\underline{P}_{i}^{G}\leqslant P_{i,t}^{G}+k_{i}(\Delta P_{t}^{U}-\Delta P_{k}^{s})\leqslant \bar{P}_{i}^{G}\\ \underline{P}_{i}^{G}\leqslant P_{i,t+1}^{G}+k_{i,t+1}(\Delta P_{t+1}^{U}-\Delta P_{k+1}^{s})\leqslant \bar{P}_{i}^{G}\end{cases} \tag{11}$$

$$-r_{Di}^{G}\leqslant P_{i,t+1}^{G}-P_{i,t}^{G}-k_{i+1}(\Delta P_{k,t+1}^{s}+\Delta P_{t+1}^{U}-\Delta P_{k,t}^{s}-\Delta P_{t}^{U})\leqslant r_{Ui}^{G} \tag{12}$$

where $k_{i,t}$ is the participation factor of the i-th AGC unit, $\bar{P}_{i}^{G}$、$\underline{P}_{i}^{G}$ are the upper and lower limits of the i-th AGC unit coordination, whose values do not exceed the maximum and minimum values reached from the previous period to the t-th period, and r_{Ui}^{G}、r_{Di}^{G} are the upper and lower limits of the climbing rate for the AGC unit.

3.2.3 Energy storage constraint

Coordinating the charge and discharge of the energy storage with the AGC units is important for reducing the dispatch pressure and cope with the intermittency of renewable energy. When there is limited generation from thermal power, renewable energy is a friendlier option. The base power of the k-th energy storage device in the t-th period is expressed as P_{k}^{s}, and the charge and discharge of the energy storage can be expressed as

$$\begin{cases}P_{k,t}^{s}=P_{c,k,t}^{s}\omega_{c}+P_{d,k,t}^{s}\omega_{d}\\ 0\leqslant\omega_{c}+\omega_{d}\leqslant 1\\ \omega_{c},\omega_{d}\in[0,1]\end{cases} \tag{13}$$

where ω_c and ω_d (values of 0 or 1) represent the control flag of the charging and discharging states, respectively, and $P_{c,k,t}^{s}$、$P_{d,k,t}^{s}$ are the charge and discharge power, respectively, of the energy storage.

The energy storage coordinates with the AGC units to reduce the dispatch pressure and free up capacity for the AGC units. The participation factor is adjusted to reduce the deviation between the dispatch basepoint and optimal economic operation point.

The charge and discharge of the energy storage can be expressed as

$$\begin{cases}E(t)=C_{soc}(t)E_{cap}\\ E^{0}(t)=E^{T}(t)\\ E_{c}(t)=E_{c}(t-T)+(\mathrm{P}_{t}^{U}+\mathrm{P}_{t}^{L})T\eta_{c}\\ E_{d}(t)=E_{d}(t-T)+\dfrac{(\mathrm{P}_{t}^{U}+\mathrm{P}_{t}^{L})T}{\eta_{c}}\\ E(t)=E_{c}(t)+E_{d}(t)\end{cases} \tag{14}$$

$$C_{soc}(t)=(1-\rho)C_{soc}(t-1)+\frac{\omega_{c}P_{ck}^{s}(t)\Delta t\eta_{c}-\omega_{d}P_{dk}^{s}(t)\dfrac{\Delta t}{\eta_{d}}}{E_{cap}} \tag{15}$$

$$\underline{P}_{k}^{s}\leqslant P_{k,t}^{s}+\Delta P_{k,t}^{s}\leqslant \bar{P}_{k}^{s} \tag{16}$$

where $C_{SOC}(t)$ is the remaining state of charge (SOC) at time t, $E(t)$ is the energy stored at time t, $E_0(t)$ and $E_T(t)$ are the energies stored at the initial and final moments, respectively, and $E_c(t)$ and $E_d(t)$ are the energies charged and discharged, respectively, by the energy storage. E_{cap} is the energy storage capacity, ρ is the self-discharge rate of the energy storage and was set to $\rho=0.95$. $P_{ck}^{s}(t)$、$P_{dk}^{s}(t)$ are the charge and discharge power, respectively, of the energy storage. $\bar{P}_{k}^{s}$、$\underline{P}_{k}^{s}$ are the upper and lower limits, respectively, of the charging and discharging power of the k-th energy storage.

4 Algorithm for solving the model

To consider the advantages of robustness and rapidity, the nonlinear model described in the previous section can be solved by combining the C&CG algorithm with external approximation [29]. The C&CG algorithm can be used to construct an equivalent unilateral optimization formula by enumerating the variables and constraints of each scenario in an uncertainty set. The monotonic optimization problem is transformed into the equivalent problem of finding the maximal convex function in a convex set. This is based on the principle that the maximum point for the function of a convex polyhedron must be at a vertex of this polyhedron. The values of the convex polyhedron vertex function are compared with the objective function to update the lower value of the iterative relaxation problem. When the error between the upper and lower bounds is less than a given value, the outer optimal solution y^* is obtained. When the optimal relaxation solution is less than the optimal solution of the constraint under consideration, this can be used to determine whether or not the outer optimal solution y^* is feasible. At this point, the second stage becomes a linear problem, which is easy to solve. Moreover, the optimal solution is less sensitive to changes in parameter values and is more generalized.

Therefore, the C&CG algorithm can be used to make dispatch decisions for AGC units in the first stage. Then, the dispatch decisions for energy storage in the second stage are robust against all uncertain fluctuations. Moreover, the second stage has sufficient adaptability to uncertainty. This approach to solving the two-stage robust optimization model can obtain a decision for the first stage and an adaptive scheduling strategy for the second stage that is immune to uncertainty because the cost of the worst case in the uncertainty set is minimized. The second stage can be solved after the first-stage decision is taken and its uncertainty is revealed.

The C&CG algorithm performs better than the traditional Benders decomposition algorithm. It can generate constraints without using a dual solution for the second stage, and it can be simplified to solve the equivalent mixed-integer programming problem. The variable type in the second stage does not matter, and the C&CG algorithm has wider applicability. The external approximation algorithm guarantees the feasibility of the solution; it provides a fast convergence speed and improves the optimal solution.

This is a mixed-integer programming problem, which is difficult to solve and has many variables. The flow of the C&CG algorithm is as follows:

1. Define the initial pole set and pole direction set to solve the main problem. The initial set should be a subset of the entire set or an empty set.

2. During processing, the inner layer is transformed into a maximization problem: $\min c^T y+\eta$, get $Q(y)=\max\{(\mathbf{E}-\mathbf{G}y-\mathbf{h}u)^T\lambda\}$ $\lambda\geqslant 0$ and solve to obtain the optimal solution (y^*,π^*) for the initial pole set and pole direction set.

3. Generate the cutting plane $\eta\geqslant\left(\mathbf{E}-\mathbf{G}y-\mathbf{h}u^*\right)^T\pi^*$.

4. Update the lower bound $LB=c^T y^*+\eta$ of the objective function. If the constraint set of the lower limit LB is an empty set ϕ, the objective function has no solution. If it is not the empty set ϕ, then the pole and direction of the constraint set can be found.

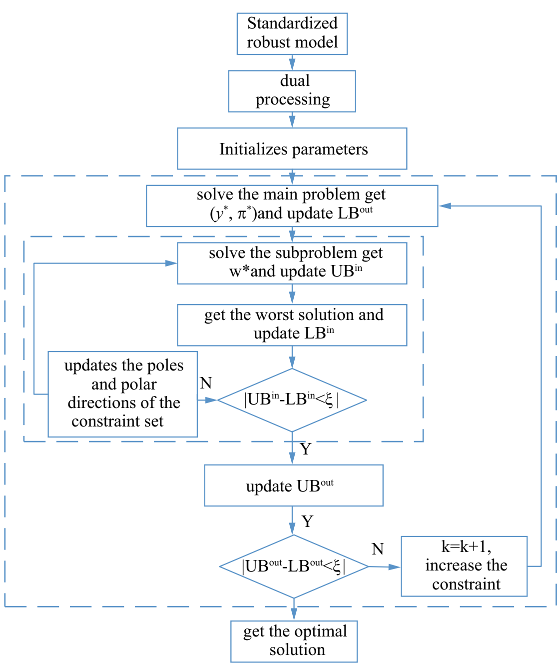

Fig. 2 Solution flow of the robust optimization model

5. Substitute the solution into the sub-problem: Substitute the obtained function as a known value into the sub-problem, and update the upper bound $UB=\min\left\{UB,c^T y^{*\prime}+\eta^{*\prime}\right\}$.

6. If the optimal value of the objective function LB is $y>\delta$, then the optimal solution is y^*, and the dual optimal solution is w^*. If the optimal solution $(x^*, y^{*\prime})$ is obtained, then the algorithm stops. If there is no solution, the constraint $\eta\geqslant\boldsymbol{b}^T x^{*\prime}$ is added to the main problem, the constraint $Gy+Dx>E-hu^{*\prime}$ is updated, and $Q(y^{*\prime})$ is solved again.

As this process is repeated, more constraints are placed on the main problem, and the obtained optimal solution increases and converges to the actual optimal solution.

5 Example analysis

As an example, a power grid was simulated by connecting three AGC units, one windfarm, and one photovoltaic farm. The parameter settings are shown in Table 1. The effectiveness of the proposed model was analyzed. For the analysis, the Cplex solver was used with YA1MIP in MATLAB on a computer configured with 4.0 GHz 8 GB RAM and a Windows 10 operating system. The optimization process of all calculation examples was completed within 5 min.

Table 1 AGC unit parameter settings

Generator number	Output upper bound (MW)	Output lower bound (MW)	Climbing limit (MW/h)	Fuel consumption curve parameters		
				a	b	c
1	110	25	10	0.00756	7.52	261
2	150	40	15	0.00451	7.94	357
3	150	30	20	0.00418	7.83	315

The two-stage robust optimization model presented in Section 2 could calculate the best matching energy storage configuration for any given scenario. Fig. 3 shows an example. The energy storage significantly improved the climbing ability of AGC units for a given calculation period. The charging and discharging of the energy storage was scheduled first to reduce the dispatch pressure on AGC units and realize the large-scale acceptance of renewable energy.

The following scenarios were considered for the coordination of energy storage with AGC units for economic dispatch:

1) Energy storage only works with increased capacity:

The energy storage only cooperates with AGC units to increase capacity. Thus, the improved climbing capacity with energy storage is not considered in the objective function.

2) Energy storage improves the climbing ability of AGC units.

Fig. 4 shows that Scenario 1 had a high consumption and low abandonment rate, but it also reduced the adjustable range of AGC units and increased costs. For Scenario 2, the rapid adjustment of the energy storage coordinated with AGC units to improve the climbing ability and increase the coordination area. Although some capacity was sacrificed and the abandonment rate of renewable energy increased, the overall system cost decreased.

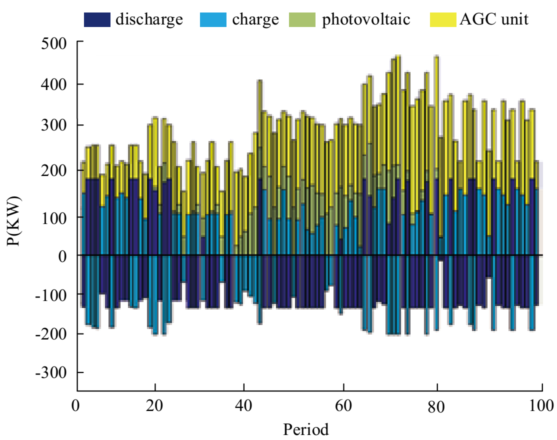

Fig. 3 Energy storage participation in optimizing the dispatch results

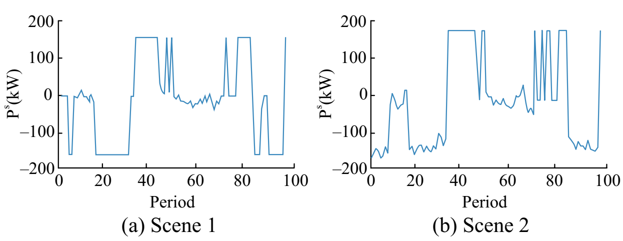

Fig. 4 SOC with charging and discharging of energy storage battery

Scenario total energy storage adjustment total/MW abandon wind and light rate/% optimal ratio (AGC: energy storage) total cost/¥

The above analysis results showed that, because of the limited climbing capacity of the AGC units, if the energy storage only absorbed renewable energy, the energy storage adjustment was 1064 MW, and the abandonment rate of renewable energy was only 6.49%. However, the coordination ability after energy storage was sacrificed, which is not conducive to the overall scheduling of the power grid. In Scenario 1, the climbing ability of the overall system did not meet the maximum fluctuation demand, so the rapid response of the energy storage was not fully utilized to supplement the AGC units. The AGC units needed to be mobilized further, which increased the total costs. In Scenario 2, the energy storage coordinated with the AGC units to deal with intermittency. This expanded the AGC schedule range and increased the climbing ability. The actual adjustable reserve capacity of the AGC units was 667 MW, and the climbing ability satisfied the maximum fluctuation demand. This reduced the deviation between the unit dispatch basepoint and optimal economic operating point, so the overall costs were low.

Table 2 AGC unit parameter settings

Scenario	AGC maximum adjustable capacity (MW)	Energy storage adjustment capacity (MW)	Abandonment rate of renewable energy (%)	Optimal ratio (AGC: energy storage)	Total cost (¥)
1	516	1064	5.74	1:0.3628	34479.38
2	667	938	6.43	1:0.2745	27698.62

Coordinating energy storage with AGC units for dispatch compensated for mismatches in energy scheduling mismatch on the time scale of seconds to minutes. Meanwhile, changes in available power were used to obtain more revenue. Fig. 5 shows that the energy storage was quickly charged and discharged during periods of high uncertainty, which compensated for the intermittent nature of wind and solar energy. Meanwhile, the SOC of the energy storage was between 30% and 80% during periods requiring high availability. Table 3 compares the cost and energy storage output power according to the C&CG algorithm and the Benders decomposition method.

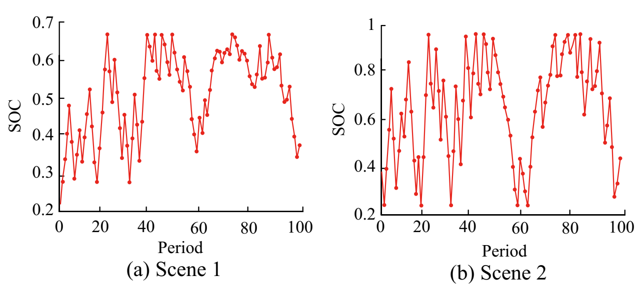

Fig. 5 SOC for energy storage battery

Table 3 Dispatch optimization results for various scenarios

Scenario	Single-stage dispatch with energy storage	Two-stage robust optimization dispatch with energy storage	
		Benders	C&CG
Storage charge (MW)	314	545	574
Storage discharge (MW)	289	437	467
Storage cost ($)	205.481	288.923	306.519
Abandoned capacity of renewable energy (MW)	412.87	62.81	35.7
Wind and light curtailment rate (%)	31.92	6.43	5.74
Total cost ($)	32358.819	21826.348	21021.207
Best configuration ratio (AGC: energy storage)	1:0.1187	1:0.3028	1:0.2745
Operation time (s)	10.1	122.7	78.4
Iterations	7	15	8
Operation time (min)	1.4	8.7	5.2

5.1 Comparison of dispatch results with and without energy storage

Compared with the single-stage dispatch model, the two-stage robust optimization model showed a significant reduction in the abandonment rate of renewable energy when energy storage was included. This led to positive effects on power generation and reduced the cost of coal consumed by the AGC units. This reduced the need to frequently start and stop large AGC units, which reduces the operating costs and extends the service life.

5.2 Comparison of accuracy with Benders decomposition method and C&CG algorithm

The Benders decomposition method is commonly used to deal with two-stage problems in robust optimization. However, the C&CG algorithm does not need to distinguish between types of variables in the model and has a wider range of applicability. Table 3 indicates that the results obtained with the C&CG algorithm not only lead to renewable energy acceptance with improved efficiency and higher economy but also greatly reduce the number of iterations and shorten the calculation time. Thus, the robustness and applicability of the two-stage robust optimization model were validated.

The results showed that coordinating energy storage with the dispatch system improved the operating efficiency of the power grid. This is because energy storage responds quickly and can flatten peaks, which allows large AGC units to operate at more cost-effective load levels. The robust optimization model can be used to solve the uncertainty and tradeoff between economy and safety for the dispatch decision-making process of a power grid.

6 Conclusion

To address the impact of large-scale renewable energy penetration of a power grid, a two-stage robust optimization model was built where energy storage is coordinated with AGC units to cope with intermittency for power dispatch. Examples were presented to validate the proposed model and synergy of energy storage. The main conclusions are as follows:

(1) The proposed model fully considers the intermittency of renewable energy and describes the coordination of energy storage with AGC units to effectively deal with the problems that this causes.

(2) The two-stage model not only exploits the rapid response of energy storage but also improves the climbing ability of the AGC units, which realizes the adjustment potential of the entire system. This allows the power grid to operate with better flexibility and economy.

(3) The two-stage model is characterized by complex decoupling and many iterations. The C&CG algorithm can be used to obtain an optimal solution that is less sensitive to changes in parameter values, that requires fewer iterations, and that has more universality.

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