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Optimization of unit commitment considering multiple stochastic factors and interruptible load under chance constraints

Baodi Ding, Mingxin Zhao, Xiaohui Qin & Shuqi Chen✉

After the integration of high-proportion renewable energy into the power system, the output volatility and load forecasting deviation significantly increase the uncertainty of system operation, posing new challenges to unit commitment. Demand Response (DR), as an important means to improve system flexibility, can guide users to adjust their electricity consumption behaviour when the power grid is in tight operation. Among various DR measures, Interruptible Load (IL) has been widely applied in the power market due to its fast and flexible response characteristics. This paper proposes a unit commitment model based on chance constraints, which comprehensively considers wind power output fluctuations, load forecasting errors, and IL response uncertainty. Multiple scenarios are generated through Monte Carlo simulation, and combined with mixed-integer linear programming for solving, to achieve the dual goals of minimizing system operation costs and maximizing renewable energy absorption capacity. Case study results on the modified New England-39 bus system show that the proposed method can effectively balance the system operation cost and IL compensation cost, reduce the volatility of unit output, and significantly improve the wind power absorption level. The results verify the effectiveness of the proposed method in enhancing system economy and flexibility.

Keywords Demand response, Interruptible load, Chance constraint, Unit commitment, Power system

With the proposal of the "dual carbon" goals (carbon peaking and carbon neutrality), China's energy structure is undergoing a profound transformation, and the installed capacity of renewable energy such as wind power and photovoltaic (PV) continues to expand. According to relevant statistics, by the end of 2024, the cumulative installed capacity of wind power and PV in China reached 520.68 GW and 886.66 GW respectively, accounting for more than 42% of the total national power generation installed capacity[1]. It is expected that by 2050, renewable energy will gradually replace traditional thermal power and become the main source of power supply. In this process, although the grid connection of high-proportion new energy is conducive to carbon reduction and sustainable development, its randomness and intermittency lead to a significant increase in the volatility of system net load, bringing severe challenges to economic dispatch and system operation security.

To address this issue, Demand Response (DR), as a market-oriented regulation mechanism for coordination between supply and demand sides, has gradually attracted widespread attention[2]. Through price signals or economic incentives, users can actively reduce or shift their electricity consumption when the power grid is in tight operation, thereby playing an important role in peak shaving, reducing reserve demand, and improving system flexibility. Reference[3] constructs an optimal dispatch model for an integrated energy system with electrical and thermal loads, introducing three types of demand response loads: transferable, curtail able, and substitutable. Through the coordination of demand response and a stepped carbon trading mechanism, this study effectively reduces system operation costs and carbon emissions, and improves the absorption level of renewable energy.

Among them, Interruptible Load (IL), as a typical form of incentive-based demand response, has been practically applied in many countries and regions. IL users agree to interrupt part of their load when the power grid needs it in exchange for economic compensation. This not only enables IL to participate in dispatch as virtual reserve capacity but also plays a buffering role when new energy fluctuates sharply. From the perspective of distribution network dispatch, Reference[4] proposes an optimal method for interruptible load based on dynamic regulation. By optimizing the calling time and power of IL, it reduces the system operation cost while

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significantly improving the absorption level of intermittent energy, reflecting the practical role of IL in promoting renewable energy absorption and enhancing system flexibility. Reference[5] incorporates interruptible load and electric vehicles into a coordinated dispatch framework and applies it to the optimal operation research of wind power-integrated power grids, which effectively improves the power supply reliability of wind power-integrated power grids and reduces the electricity consumption cost on the user side, providing a reference for multi-type adjustable loads to participate in renewable energy absorption. However, due to factors such as user response willingness, compensation and penalty mechanisms, the actual response of IL has significant uncertainty. If not properly handled in dispatch, it may lead to economic and fairness issues.

To solve the uncertainty problem of Interruptible Load (IL) participating in dispatch under high-proportion new energy grid connection, scholars have carried out extensive research. Reference[6] addresses the issue of island division in active distribution networks after upper-level power grid failures, incorporates IL compensation costs into the comprehensive outage loss model, and realizes the orderly shedding of interruptible loads through robust optimization to reduce economic losses. However, this study does not combine the coordinated dispatch of interruptible loads and energy storage, resulting in the failure to fully exploit the regulatory potential of interruptible loads, and its supporting capacity for island power balance is limited under the scenario of high-proportion new energy output fluctuations. Reference[7] classifies interruptible loads into multi-time scale dispatch of active distribution networks, optimizes IL curtailment and compensation costs, and simultaneously regulates reactive power to ensure voltage security. However, this study does not couple the coordinated impact of IL response uncertainty and source-load fluctuations, only considering source-load forecasting errors independently, leading to insufficient dispatch robustness under the scenario of overlapping multiple stochastic factors.

In summary, existing studies have made positive progress in renewable energy absorption and system economic improvement, but there are still two shortcomings: first, most studies focus on single uncertainty modelling, lacking comprehensive consideration of multi-source factors such as wind power output, load forecasting, and IL response uncertainty; second, the modelling of IL compensation and penalty mechanisms remains inadequate, as existing approaches typically consider only fixed compensation, without capturing the deviation between the scheduled interruption amount and the actual IL response, nor incorporating economic penalties for insufficient or non-compliant responses, making it difficult to fully reflect users' actual response behaviour. As a result, it is difficult for dispatch schemes to balance economy and robustness.

To address the above issues, this paper proposes a power system economic dispatch method based on chance constraints, which comprehensively considers wind power fluctuations, load forecasting deviations, and IL response uncertainty. The method generates multiple scenarios through Monte Carlo simulation and combines with mixed-integer linear programming for solving, to minimize operation costs and improve renewable energy absorption capacity while ensuring system security. The main contributions of this paper are as follows:

(1) A power system economic dispatch model based on chance constraints is proposed, which simultaneously considers wind power output fluctuations, load forecasting errors, and interruptible load response uncertainty.
(2) A modeling method including interruptible load compensation costs and risk costs is established to characterize user response characteristics and balance the economic relationship between the power grid and users.
(3) Combined with Monte Carlo scenario generation and mixed-integer linear programming methods, efficient dispatch solving under confidence level constraints is realized.
(4) Finally, a case study is carried out on the New England-39 bus system. The results show that the method can reduce operation costs, alleviate unit output volatility, and improve renewable energy absorption level.

Chance constraint model

Chance-Constrained Programming (CCP)[8] is an important method in stochastic programming. By introducing probabilistic constraints into the model, this method enables decisions under uncertain conditions to meet constraint requirements at a certain probability level, thereby improving the reliability and feasibility of decision results. As a classic means to deal with uncertainty problems, chance-constrained programming has attracted widespread attention in the optimization field and has shown good application value in various practical scenarios such as supply chain management, risk control, and resource allocation.

The core idea of chance-constrained programming is to ensure that the system can meet certain specific constraint conditions at a given confidence level during the decision-making process despite the existence of uncertainty. This method introduces "probabilistic constraints", i.e., the probability that constraint conditions are satisfied, thereby considering the impact of uncertainty in the decision-making process and optimizing the objective function of the system. The chance-constrained programming model is usually expressed as the following formula[9]:

$$\left\{ \begin{array}{c} \max f(x,\xi) \\ s.t. \mathrm{P}_r\left\{ g_j(x,\zeta) \leqslant 0, j=1,2,\cdots,p \right\} \geqslant \alpha \end{array} \right. \tag{1}$$

where: x represents n-dimensional decision variables; ξ denotes random uncertain variables; $f(x,\xi)$ is the objective function; $g_j(x,\zeta) \leqslant 0$ represents constraint conditions; $\mathrm{P}_r\{\}$ denotes the probability that the constraint conditions are satisfied; α is the required confidence level.

Uncertainty analysis of wind power output and load forecasting

In the operation and dispatch of power systems, the accuracy of wind power output and load forecasting plays a decisive role in the stability and economy of the system. As a typical intermittent energy source, wind power output is affected by multiple factors such as wind speed, wind direction, and meteorological conditions, showing significant randomness and volatility. At the same time, the accuracy of load forecasting is also disturbed by various uncertain factors such as climate change, holiday effects, and user electricity consumption behaviour patterns. If these uncertainties are not effectively characterized, the feasibility and economy of the dispatch scheme will be difficult to guarantee. For this reason, probabilistic distributions are often used in research to model forecasting errors. Among them, the normal distribution is widely used to characterize the deviation of actual wind power output and load forecasting errors due to its good mathematical properties and reasonable approximation ability. Based on this assumption[10], the wind power output and load forecasting errors can be expressed as:

$$\begin{gathered} \Delta P_t^{\boldsymbol{w}} \sim N\left(\mu_{\mathrm{w}}, \sigma_{\boldsymbol{w}}^2\right), \Delta P_t^l \sim N\left(\mu_l, \sigma_l^2\right) \\ \mu_{\mathrm{w}}=0, \mu_l=0 \\ \sigma_{\boldsymbol{w}}=\frac{P_t^{Wy}}{\alpha}+\frac{W_{wind}}{\beta} \end{gathered} \tag{2}$$

where:$\Delta P_t^{\boldsymbol{w}}$ is the wind power deviation of the wind turbine in time period *t*; ΔP_t^l is the load forecasting deviation in time period *t*; $\mu_{\mathrm{w}}$and$\sigma_{\boldsymbol{w}}$are the mean and standard deviation of the normal distribution of wind power deviation respectively; μ_l and σ_l are the mean and standard deviation of the normal distribution of load forecasting errors respectively; P_t^{Wy} represents the forecasted wind power output in time period *t*; W_{wind} is the rated capacity of the wind turbine; α and β are the coefficients of the standard deviation of the normal distribution of wind power deviation.

Then, the actual wind power output in time period *t* is:

$$P_t^W=P_t^{Wy}+\Delta P_t^{\boldsymbol{w}} \tag{3}$$

The actual load power is:

$$P_t^l=P_t^f+\Delta P_t^l \tag{4}$$

where:P_t^f is the load forecast value in time period *t*.

Uncertainty model for demand response based on baseline load

At present, China has not yet formed a sound flexible electricity price mechanism, which restricts the promotion of price-based demand response. In contrast, incentive-based demand response based on interruptible load is more feasible in implementation and has been widely applied in power grid dispatch. This paper takes the user's baseline load as the core, establishes an interruptible load response model considering uncertainty, to evaluate the user's load curtailment potential and set the optimal adjustment range. The model also introduces uncertainty costs and compensation mechanisms to enhance the effectiveness of IL-based incentive demand response measures[11].

Interruptible load settlement cost model in demand response

In terms of settlement costs, after users who have signed contracts execute the load curtailment instructions, the power company shall settle the fees according to the pre-agreed compensation unit price and penalty unit price[12]. However, due to differences in users' curtailment willingness, there may be phenomena of under-response or over-response, resulting in certain uncertainty in settlement fees. To address this issue, the article uses random variables to describe the deviation between the user's reduced load and the actual required reduction in load, and calculates the settlement cost for each user per period, with each period lasting for 1 h. The fixed compensation cost and uncertainty cost in the formula are based on the baseline load and dynamically adjusted in combination with the unit contract price signed by the user, so as to ensure that the model is applicable to complex market environments. The random variable X_j is the difference between the actual curtailment load of user *j* and the required curtailment load. The settlement fee of user *j* in time period *t* is:

$$C_{ILj}^t=C_{ILj,fc}^t+C_{X_j}^t \tag{5}$$

$$C_{ILj,fc}^t=P_{ILj}^t r_{ILj,fc} \tag{6}$$

$$C_{X_j}^t=\begin{cases} 0 & X_j \geqslant 0 \\ X_j\left(r_{ILj,fc}+r_{ILj,pen}\right) & -P_{ILj}^t<X_j<0 \\ X_j r_{ILj,pen}-P_{ILj}^t r_{ILj,fc} & X_j \leqslant -P_{ILj}^t \end{cases} \tag{7}$$

where:$C_{ILj,fc}^t$ is the fixed cost of user *j* in time period *t*; $C_{X_j}^t$ is the dynamic uncertainty cost of user *j* in time period *t*; P_{ILj}^t is the load curtailment amount required for user *j* in time period *t*; $r_{ILj,fc}$ is the compensation unit price signed by user *j*; $r_{ILj,pen}$ is the penalty unit price signed by user *j*.

Interruptible load risk cost model in demand response

Based on power system risk theory, risks originate from the probabilistic attributes of events, among which random equipment failures and load uncertainty are the main risk factors. Risk management usually includes risk quantitative assessment, risk reduction strategy formulation, and risk threshold setting, among which risk quantification relies on the construction of a system risk index system. For demand response, load curtailment deviations may lead to economic risks for power enterprises: if users fail to curtail the load as required, the power company needs to purchase electricity at a high price to maintain the balance between supply and demand; if users over-respond, it may lead to a decline in electricity sales revenue. For this reason, a probability distribution model of user response can be constructed based on historical statistical data to quantitatively assess the risk cost. Specifically, the power company can use this model to characterize the response uncertainty of users in each time period, thereby calculating the risk cost under different scenarios, which is expressed as follows:

$$C_{ILj,risk} = r\left(\xi_j\right) \times EENS\left(\xi_j\right) = \int_{-\infty}^{+\infty} r\left(\xi_j\right)\left|\xi_j\right| f\left(\xi_j\right) d\xi_j \tag{8}$$

$$r\left(\xi_j\right) = \begin{cases} r_s & \xi_j > 0 \\ 0 & \xi_j = 0 \\ r_0 & \xi_j < 0 \end{cases} \tag{9}$$

where:r_s and r_0 respectively represent the electricity sales price and unit outage loss; ξ_j is the random uncertainty quantity for user *j*, encompassing all random variables affecting scheduling, and functions as a random variable in probabilistic operations within opportunity constraints. $f\left(\xi_j\right)$ is the probability density function of ξ_j.

Interruptible load unit commitment optimization model considering multiple stochastic factors

Objective function

Considering the uncertain factors of interruptible load and combining with the optimal unit combination problem, the objective function of the model aims to minimize the expected total dispatch cost, which is specifically as follows:

$$\begin{aligned} \min F = F_G + E\left(F_{IL}\right) = & \sum_{t=1}^{T}\sum_{i=1}^{N_G}\left[f_{Gi}\left(t\right)u_{Gi}\left(t\right) + S_{Gi}\left(t\right)\left(1 - u_{Gi}\left(t-1\right)\right)u_{Gi}\left(t\right)\right] \\ & + E\left(\sum_{t=1}^{T}\sum_{j=1}^{N_{IL}} f_{ILj}\left(t\right)u_{ILj}\left(t\right)\right) \end{aligned} \tag{10}$$

$$S_{Gi}\left(t\right) = \begin{cases} h_{ci}\left(t\right), T_i^{off}\left(t\right) \leqslant T_i^{cold}\left(t\right) + DT_i\left(t\right) \\ c_{ci}\left(t\right), T_i^{off}\left(t\right) > T_i^{cold}\left(t\right) + DT_i\left(t\right) \end{cases} \tag{11}$$

$$f_{Gi}\left(t\right) = a_{Gi}\left(P_{Gt}\left(t\right)\right)^2 + b_{Gi}P_{Gt}\left(t\right) + c_{Gi} \tag{12}$$

$$f_{ILj}\left(t\right) = C_{ILj}\left(t\right) + C_{ILj,risk}\left(t\right) \tag{13}$$

where: T is the total number of scheduling time periods; N_G and N_{IL} are the number of generating units and interruptible loads respectively; $f_{Gi}\left(t\right)$ is the power generation cost function of unit *i* in time period *t*, which is generally a quadratic function; $u_{Gi}\left(t\right)$ is the on/off state variable of unit *i* in time period *t*, $u_{Gi}\left(t\right)$=0 means the unit offline, and $u_{Gi}\left(t\right)$=1 means the unit online; $S_{Gi}\left(t\right)$ is the start-up cost of unit *i* at time *t*; $f_{ILj}\left(t\right)$ is the calling cost of interruptible load *j* in time period *t*; $u_{ILj}\left(t\right)$ is the calling state of interruptible load in time period *t*, 0 means not called, 1 means called; $P_{Gi}\left(t\right)$ is the active power output of unit *i* in time period *t*; $h_{ci}\left(t\right)$ represents the hot start-up cost of unit *i*; $c_{ci}\left(t\right)$ represents the cold start-up cost of unit *i*; $T_i^{off}\left(t\right)$ is the cumulative offline time of unit *i* in time period *t*; $T_i^{cold}\left(t\right)$ is the cold start-up threshold of unit *i*; $DT_i\left(t\right)$ is the minimum offline time of unit *i*; a_{Gi}、b_{Gi}、c_{Gi} are the cost coefficients of the quadratic function of the unit operation cost respectively; $E\left(\cdot\right)$ denotes the expectation. In this paper, the average of the generated scenarios is used for approximation.

Constraint conditions

(1) Power Balance Constraint.

In the day-ahead economic dispatch, the load forecast and wind power output are random, and the response of interruptible load is also uncertain. Therefore, this paper uses a chance constraint model to describe it:

$$P_r\left(\sum_{j=1}^{N_{IL}} P_{ILj}\left(t\right)u_{ILj}\left(t\right) + \sum_{j=1}^{N_G} P_{Gi}\left(t\right)u_{Gi}\left(t\right) + P_w\left(t\right) - P_l\left(t\right) - P_b\left(t\right) \geqslant 0\right) \geqslant \alpha \tag{14}$$

where:$P_{ILj}\left(t\right)$ is the interrupt amount of interruptible load *j* at time *t*; $P_{Gi}\left(t\right)$ is the power generation of generating unit *i* at time *t*; $P_w\left(t\right)$ is the total actual wind power output of the wind turbine at time *t*, which obeys the normal distribution; $P_l\left(t\right)$ is the actual load at time *t*; $P_b\left(t\right)$ is the spinning reserve capacity at time *t* .

(2) Unit Operation Constraints.

Output Upper and Lower Limit Constraints:

$$P_{Gi\min}u_{Gi}(t) \leqslant P_{Gi}(t) \leqslant P_{Gi\max}u_{Gi}(t) \tag{15}$$

where:$P_{Gi\min}$ is the minimum active power output of generating unit *i*; $P_{Gi\max}$ is the maximum active power output of generating unit *i*.

Minimum Online and Offline Time Constraints for Unit:

$$[u_{Gi}(t) - u_{Gi}(t-1)]\left[T_{Gi}^{on}(t-1) - T_{Gi\min}^{on}\right] \leqslant 0 \tag{16}$$

$$[u_{Gi}(t-1) - u_{Gi}(t)]\left[T_{Gi}^{off}(t-1) - T_{Gi\min}^{off}\right] \leqslant 0 \tag{17}$$

where:$T_{Gi}^{on}(t-1)$ is the continuous online time of unit *i* up to time *t*; $T_{Gi}^{off}(t-1)$ is the continuous offline time of unit *i* up to time *t*; $T_{Gi\min}^{on}$ is the minimum online time of unit *i*; $T_{Gi\min}^{off}$ is the minimum offline time of unit *i*.

Unit Ramping Constraints:

$$-r_{Gi,down} \leqslant P_{Gi}(t) - P_{Gi}(t-1) \leqslant r_{Gi,up} \tag{18}$$

where:$r_{Gi,down}$ is the downward ramping rate of generating unit *i*; $r_{Gi,up}$ is the upward ramping rate of generating unit *i*.

Interruptible Load Interruptible Capacity Constraints:

$$P_{ILj\min}u_{ILj}(t) \leqslant P_{ILj}(t) \leqslant P_{ILj\max}u_{ILj}(t) \tag{19}$$

where:$P_{ILj\min}$ is the minimum interruptible capacity of interruptible load *j*; $P_{ILj\max}$ is the maximum interruptible capacity of interruptible load *j*.

Interruptible Load Minimum Interruptible Time Constraints:

$$[u_{ILj}(t) - u_{ILj}(t-1)]\left[T_{ILj}^{off}(t-1) - T_{ILj\min}^{off}\right] \leqslant 0 \tag{20}$$

where:$T_{ILj}^{off}(t-1)$ is the cumulative interrupt time of interruptible load *j* up to time *t*;$T_{ILj\min}^{off}$ is the minimum interruptible time of interruptible load *j*. This constraint is used to ensure the minimum interruption duration. That is, after the load is interrupted, it must remain in the interrupted state for the minimum duration before it can resume.

Interruptible Load Minimum Interrupt Time Interval Constraints:

$$[u_{ILj}(t-1) - u_{ILj}(t)]\left[T_{ILj}^{on}(t-1) - T_{ILj\min}^{in}\right] \geqslant 0 \tag{21}$$

where:$T_{ILj}^{on}(t-1)$ is the cumulative non-interrupt time of interruptible load *j* up to time *t*-1; $T_{ILj\min}^{in}$ is the minimum interrupt time interval of interruptible load *j*. This constraint is used to prevent the intermittent load from being interrupted again shortly after its restoration.

Interruptible Load Maximum Interruptible Duration Constraints:

$$\sum_{t=m}^{m-1+T_{ILj\max}^{off}} u_{ILj}(t) \leqslant T_{ILj\max}^{off} \tag{22}$$

where: *m* is the interrupt start time; $T_{ILj\max}^{off}$ is the maximum sustainable interrupt time of interruptible load *j*. This constraint indicates that the duration of each interruption of the controllable load should not be too long.

Interruptible Load Maximum Interruptible Times Constraints:

$$\sum_{t=1}^{T} u_{ILj}(t)\left[1 - u_{ILj}(t-1)\right] \leqslant N_{ILj\max}^{off} \tag{23}$$

where:$N_{ILj\max}^{off}$ is the maximum number of interruptions of interruptible load *j*. This constraint limits the maximum number of times that the interruptible load can be called within the scheduling period.

Solution strategy

Since the unit power generation cost function involved in the original model is a quadratic nonlinear form, and the model contains multiple random variables, the complexity of direct calculation using analytical methods is high, and it is difficult to obtain a dispatch solution within a short time. Therefore, in this paper, a linearization transformation method is adopted. Firstly, the transformation of the chance-constrained model is carried out, and the specific method can be found in Reference[13]. Secondly, by segmenting and linearizing the original model, the quadratic nonlinear objective function is transformed into a mixed integer linear stochastic optimization model, thereby reducing the computational complexity and improving the solution efficiency.

The quadratic function of unit power generation cost is usually expressed as the quadratic convex function in Eq. (12), which can be expressed as follows through piecewise linearization:

$$f_{Gi}(t)\,u_{Gi}(t) \geqslant A_{Gi}u_{Gi}(t) + \sum_{l=1}^{L} C_{l,Gi}\delta_{l,Gi}(t) \tag{24}$$

where:A_{Gi} is the fuel cost of generating unit *i* at the minimum active power output; *L* is the number of linear segments of the power generation cost function; $C_{l,Gi}$ is the unit power generation cost of generating unit *i* in the l^{th} segment; $\delta_{l,Gi}(t)$ is the active power output of generating unit *i* in the l^{th} segment in time period *t*.

The constraints on the active power output of unit *i* in time period *t* and the active power output of each segment are as follows:

$$P_{Gi}(t) = P_{Gi\min}u_{Gi}(t) + \sum_{l=1}^{L}\delta_{l,Gi}(t) \tag{25}$$

$$0 \leqslant \delta_{l,Gi}(t) \leqslant K_{l,Gi} - K_{l-1,Gi} \tag{26}$$

where:$K_{l,Gi}$ is the upper limit of the active power output of unit *i* in the l^{th} segment, $K_{L,Gi} = P_{Gi\max}$, $K_{0,Gi} = P_{Gi\min}$.

The linearization accuracy is directly related to the number of segments. The more segments there are, the smaller the difference between the fitted curve and the real curve, and the higher the accuracy[14]. However, an increase in the number of segments will also lead to an increase in model complexity. Therefore, under the premise of ensuring that the accuracy requirements are met, the number of segments should be reduced as much as possible. This paper selects 3 segments for linearization. The schematic diagram of the linearized segments of the power generation cost of unit *i* is shown in Fig. 1.

Through the above processing, the original nonlinear dispatch problem is transformed into a mixed-integer linear programming model, which can be efficiently solved with the help of modern optimization tools. For its solution, the mainstream method adopts the branch-and-cut algorithm, which integrates the branch-and-bound framework and cutting plane technology, and realizes the optimal solution search by constructing a dynamic relaxation tree. The specific process is as follows: first, generate the root node relaxation problem and relax the integer variables into continuous variables; then, generate mutually exclusive sub-problem spaces through variable branching, where each sub-node represents a specific fixed value state of the integer variable; iteratively perform branching operations until the leaf nodes exhaust all discrete combinations, and at the same time use the node lower bound for pruning optimization. In this process, the introduction of cutting plane technology can effectively tighten the relaxation model and accelerate the search process.

This paper uses the Gurobi 11.0.1 optimizer for solving. This tool integrates advanced branch-and-cut algorithms and parallel computing architectures, and supports users to customize heuristic strategies and cutting plane generation rules. The overall solution steps and model solving are shown in Fig. 2.

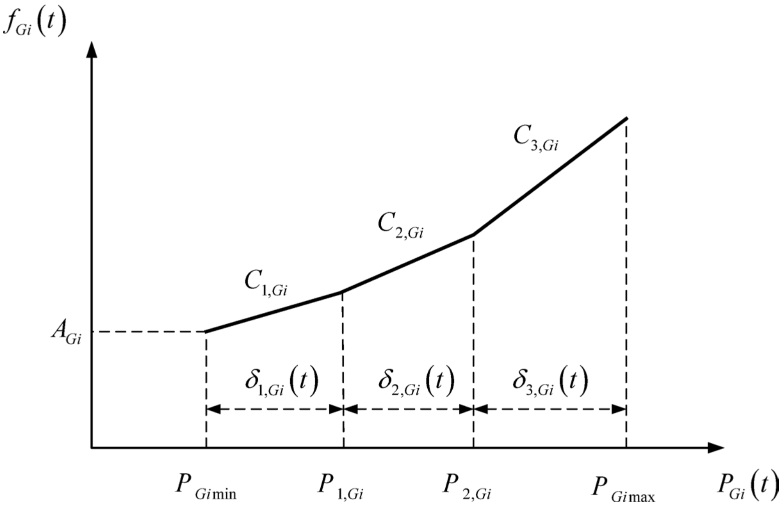

Fig. 1. Schematic Diagram of Piecewise Linear Generation Cost of Units.

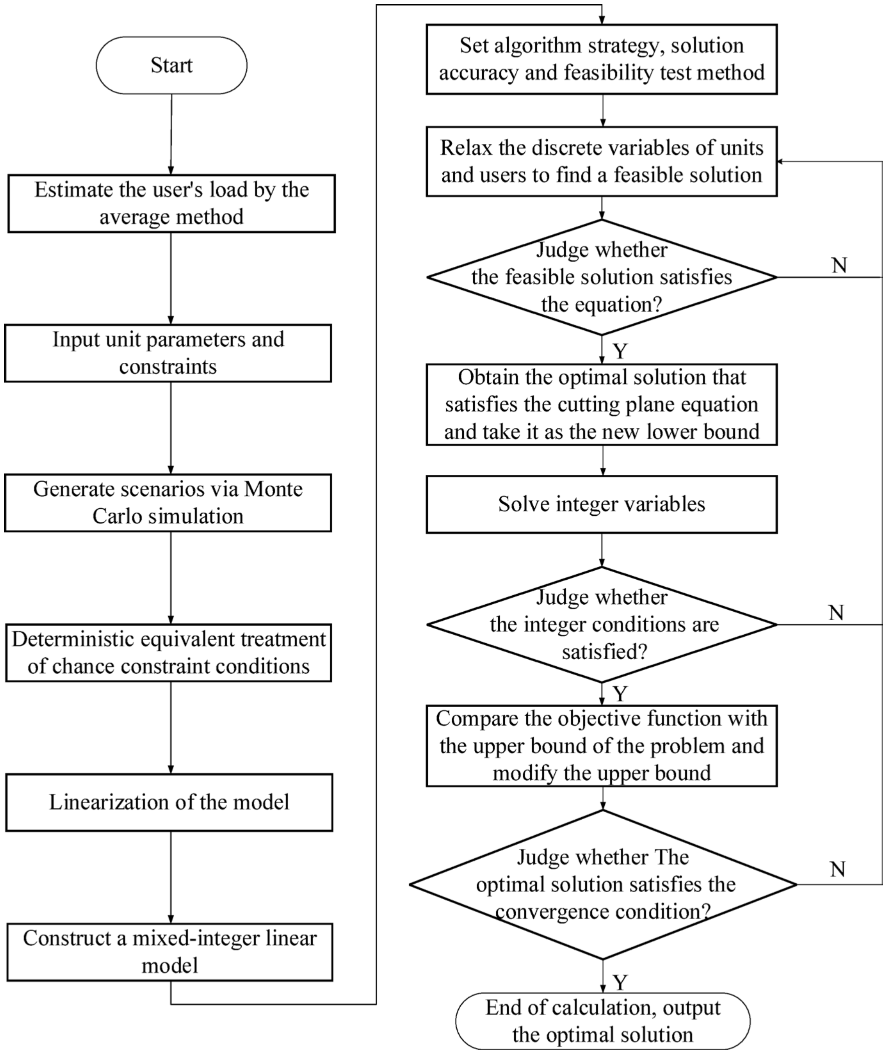

Fig. 2. Solution Steps of the System and Solution Diagram of the Optimization Model.

Case analysis
Case introduction
To verify the effectiveness of the constructed economic dispatch model, the modified New England-39 bus test system is used in the study. The test system is equipped with 10 generators, and its basic parameters and daily load forecast curve are set with reference to Reference[15] During the system operation, the load distribution ratio coefficient and power factor of each node remain constant, and the power factor also does not change. It is assumed that a wind farm with an installed capacity of 200 MW is connected to node 8. The improved system is shown in Fig. 3. The parameters of the system's generating units are shown in Appendix Table 5.

The variance of load forecast and wind power output forecast is 1% of their mean values, and the confidence level is 0.9. The wind power forecast output curve in different time periods is shown in Fig. 4. After completing the day-ahead wind power forecast, the Monte Carlo simulation method is used to randomly sample the output deviation to simulate the actual wind power fluctuation characteristics. The values of the standard deviation calculation coefficients α and β were set according to reference[10], being 5 and 50 respectively, and a total of 1000 random samples were generated to simulate various fluctuation scenarios.

In the case, 1/3 of the load nodes are defined as interruptible load access points, and 10 interruptible users are configured in total. The interrupt cost and time parameters of the interruptible load are set with reference to References[16–18] In the initial state, the continuous interrupt duration of all nodes is zero, and the power factor of each node remains unchanged during the interrupt period. The detailed parameter configuration is shown in Table 1.

Economic dispatch cost analysis
To analyze the role of interruptible load in economic dispatch, this paper adopts an optimization model based on chance constraints, combines wind power output fluctuations, load forecast deviations, and interruptible load response uncertainty, and constructs a day-ahead economic dispatch framework. Multiple scenario samples

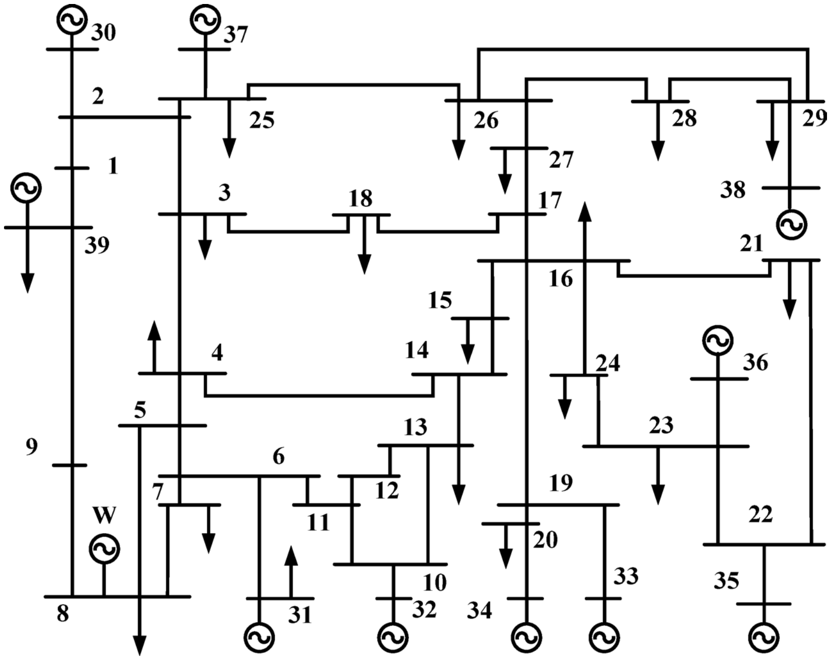

Fig. 3. Structure Diagram of the Improved New England-39 Node System.

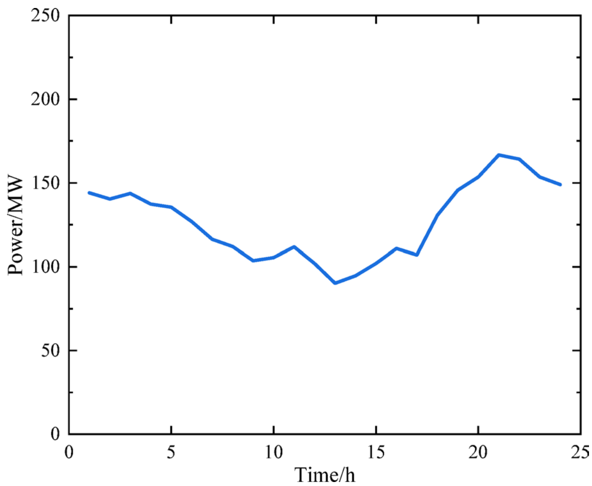

Fig. 4. Wind Power Output Prediction Curve.

	IL3	IL4	IL7	IL8	IL15	IL16	IL20	IL21	IL23	IL27
Maximum Adjustable Capacity (MW)	30	35	20	40	30	35	40	20	20	30
Capacity Compensation Price ($/MW)	0.5	0.5	0.4	0.8	0.5	0.5	0.8	0.4	0.4	0.5
Penalty Price ($/MWh)	20	20	20	25	20	20	25	20	20	20
Interrupt Electricity Compensation Price ($/MWh)	12.9	12.9	12.9	14.7	12.9	12.9	14.7	12.9	12.9	12.9
Maximum Interruptible Duration (h)	4	4	4	4	4	4	4	4	4	4
Minimum Interruptible Duration (h)	2	2	2	2	2	2	2	2	2	2
Minimum Calling Time Interval (h)	6	6	6	6	6	6	6	6	6	6
Maximum Number of Interruptions	1	1	1	2	1	1	2	1	1	1

Table 1. Interruptible load Parameters.

With/Without IL	Average Total Cost ($)	Maximum Total Cost ($)	Average Unit Operation Cost ($)	Average Unit Start-up Cost ($)	Average IL Calling Cost ($)
Without	583,999.6	594,845.3	580,693.3	3,297.6	—
With	578,468.1	583,700.5	556,059.8	2,124.1	20,294.2

Table 2. Comparison of economic dispatch Costs.

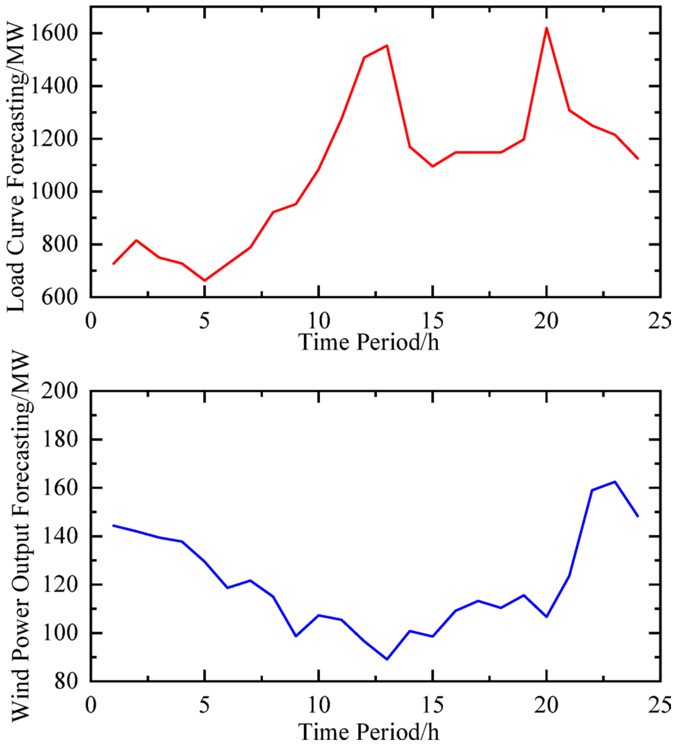

Fig. 5. Wind Power Prediction Output and Load Prediction Curve.

are generated through Monte Carlo simulation, and mixed-integer linear programming is applied for solving to achieve the dual goals of minimizing system operation costs and improving renewable energy absorption capacity.

Under this framework, the system calculates the costs under two scenarios: considering IL participation and not considering IL participation. Table 2 shows the optimal dispatch results under the two scenarios. By comparing the average and maximum values of the optimal total power generation cost, the average values of unit start-up and operation costs, and the average IL calling cost, the following conclusions can be drawn: when IL is introduced as a virtual regulation resource, the average total power generation cost of the system decreases by 12.7%, the unit start-up cost decreases by 23.4%, the operation cost decreases by 9.8%, and the total cost decreases by 0.95%. This indicates that IL participation in system optimal dispatch can significantly improve economic efficiency.

High power generation cost scenario analysis

The intermittency and volatility of new energy power generation pose severe challenges to the system power balance. To quantitatively analyze the impact of wind power randomness on economic dispatch, 1000 sets of wind power output fluctuation samples are first generated through Monte Carlo simulation, and then the extreme case with the maximum total power generation cost is selected as a typical analysis case. The rationality of this selection strategy is reflected in two aspects: the maximum cost sample can effectively reveal the economic performance of the system under the most unfavourable scenario; it provides strong support for subsequent comparative analysis. As shown in Fig. 5, the actual wind power output curve in this scenario shows a significant "double peak and double valley" characteristic, which will cause the system to face severe power balance pressure.

In this scenario, the volatility of wind power is very strong, especially from 10:00 to 13:00 and 20:00 to 23:00, showing obvious anti-peak regulation characteristics, which brings great challenges to system dispatch. In the case of no IL participation, to cope with this fluctuation, the system needs to start small-capacity units from 19:00 to 21:00 to make up for the shortage of wind power output. However, these small-capacity units have high power generation costs and low efficiency, resulting in poor system operation efficiency.

Figures 6 and 7 show the changes in the output curves of generating units in each time period under the economic dispatch conditions without IL participation and with IL participation respectively. The observation

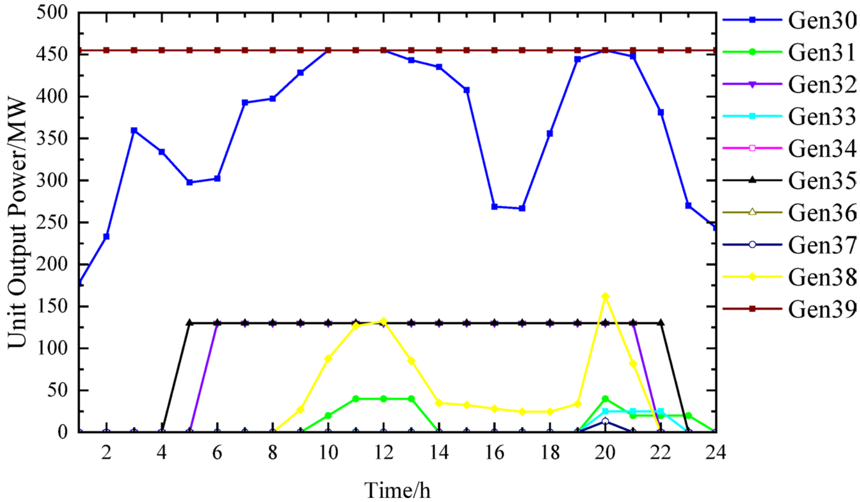

Fig. 6. Output Curves of Each Unit without IL Participation.

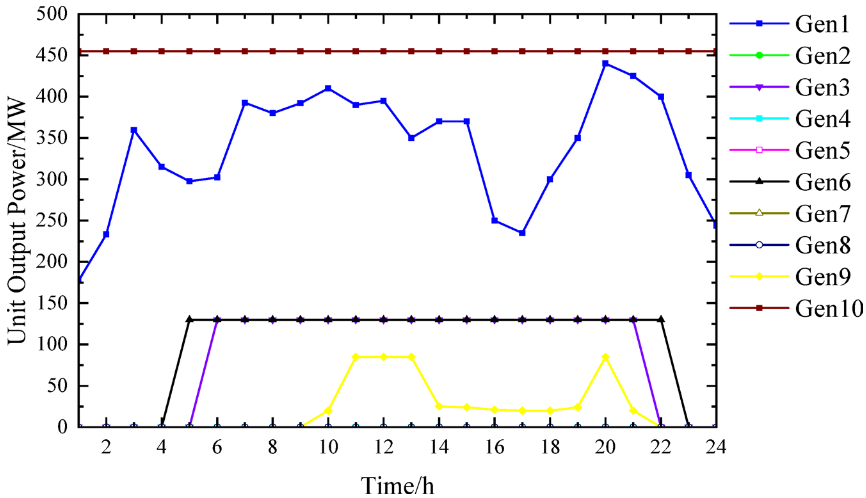

Fig. 7. Output Curves of Each Unit with IL Participation.

results show that when IL participates in economic dispatch, the output fluctuation of each unit in different time periods is significantly reduced, which indicates that the introduction of IL effectively smooths the ups and downs of unit output in each time period and enhances the stability of the system.

Figure 8 shows the impact of calling IL on the system's daily load curve when considering the participation of interruptible load in economic dispatch. The analysis results show that after introducing interruptible load, the system's daily load peak is effectively suppressed, and the fluctuation range of the load curve tends to be gentle. Therefore, the number of start-ups and shutdowns of generating units is significantly reduced, and the output fluctuation becomes more stable, thereby greatly reducing the economic operation cost of the system and improving the overall benefit.

These results indicate that even in the most unfavorable scenario where wind power fluctuations affect economic dispatch, introducing interruptible load as a dispatch resource can not only alleviate the impact of load and wind power fluctuations but also reduce the frequent start-up and shutdown of units, stabilize the output changes of units, and ensure more stable system dispatch. Although calling interruptible load requires a certain amount of compensation fees, the overall power generation cost of the system is reduced due to the reduction in unit start-up and operation costs. It can be seen that the participation of interruptible load in economic dispatch can promote the economy and stability of the system.

Unit output volatility analysis

Considering the volatility of wind power output and the randomness of unit output, this paper further analyzes the output fluctuation of units under different conditions. Table 3 compares the output fluctuation of units with and without IL participation in dispatch through standard deviation. The results show that after IL participates in dispatch, the unit output fluctuation is significantly reduced, and the standard deviation is significantly smaller

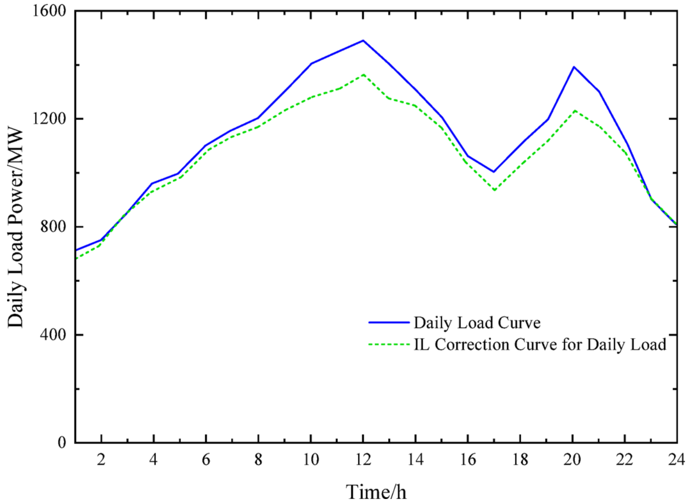

Fig. 8. Comparison of Daily Load Curves with and without IL Participation.

Time	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Without IL	17.92	31.69	28.42	34.26	32.93	33.39	39.01	36.47
With IL	13.43	27.25	25.51	25.33	24.34	21.21	27.60	26.55
Time	9	10	11	12	13	14	15	16
Without IL	32.35	29.86	39.25	40.77	32.50	29.72	31.35	17.32
With IL	15.23	19.11	36.41	31.75	31.47	15.31	25.76	13.85
Time	17	18	19	20	21	22	23	24
Without IL	4.477	6.23	7.45	4.54	5.37	21.54	35.35	21.64
With IL	4.47	6.13	2.32	4.48	5.70	20.46	33.87	19.55

Table 3. Standard deviation of overall unit output fluctuation in each time period (MW).

Time	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Without IL	0	0	0	0	0	25	33.6	48.3
With IL	0	0	0	0	0	0	0	25
Time	9	10	11	12	13	14	15	16
Without IL	71.8	99.9	107.9	88.7	104	63.8	60.2	25
With IL	54.8	64.9	99.6	90.6	81.4	35.2	30	25
Time	17	18	19	20	21	22	23	24
Without IL	25	32.6	14.7	0	28.7	25	0	0
With IL	25	25	28.9	52.2	24.1	0	0	0

Table 4. Maximum fluctuation of Gen38 output in each time period (MW).

than that in the scenario without IL, indicating that the addition of IL helps to alleviate the impact of wind power fluctuations on the system.

In addition, Table 4 lists the maximum fluctuation of unit Gen38 that may occur during the Monte Carlo simulation. Without considering IL, the unit output fluctuates greatly, especially in segment 13, where the fluctuation of unit Gen38 reaches 104 MW due to wind power fluctuations, reflecting the significant impact of wind power randomness on system dispatch. However, after considering IL, the maximum fluctuation is reduced to 81.4 MW, the unit output becomes more stable, and the system operation stability is significantly improved.

The above results indicate that introducing interruptible load to participate in dispatch not only helps to improve the economic benefits of the system but also plays a positive role in balancing wind power volatility, thereby promoting the economic and stable operation of the system.

Analysis of results under different confidence levels

Since this paper involves multiple stochastic factors, this section uses the confidence level alpha to measure the system's risk level.

It can be seen from Fig. 9 that the system cost, IL dispatch volume, and IL dispatch cost all increase with the increase of the confidence level, showing a positive correlation. When the confidence level increases from 0.9 to 1.0, the system cost increases from 578,468.1 to 601,607.3. This is because under a high confidence level, the system needs to ensure that the load demand and operation constraints are met with a higher probability, so it will increase the reserve capacity and call IL resources more frequently. These measures improve reliability but also increase the corresponding operation costs. The same applies to IL calling volume and dispatch cost. At a lower confidence level, the system can accept a certain amount of risk and has less dependence on IL; while at a high confidence level, the system needs to ensure that the load demand can be met in almost all cases, so it will call IL more to cope with load fluctuations and wind power uncertainty. Therefore, choosing an appropriate confidence level to balance operation cost and operation reliability is a problem that needs further research.

Conclusion

This paper proposes a day-ahead economic dispatch model for power systems based on chance constraints, which takes interruptible load as a demand-side response resource and comprehensively considers load forecasting errors, interruptible load response uncertainty, and wind power output randomness. Through Monte Carlo sampling and piecewise linearization modelling, combined with mixed-integer linear programming and

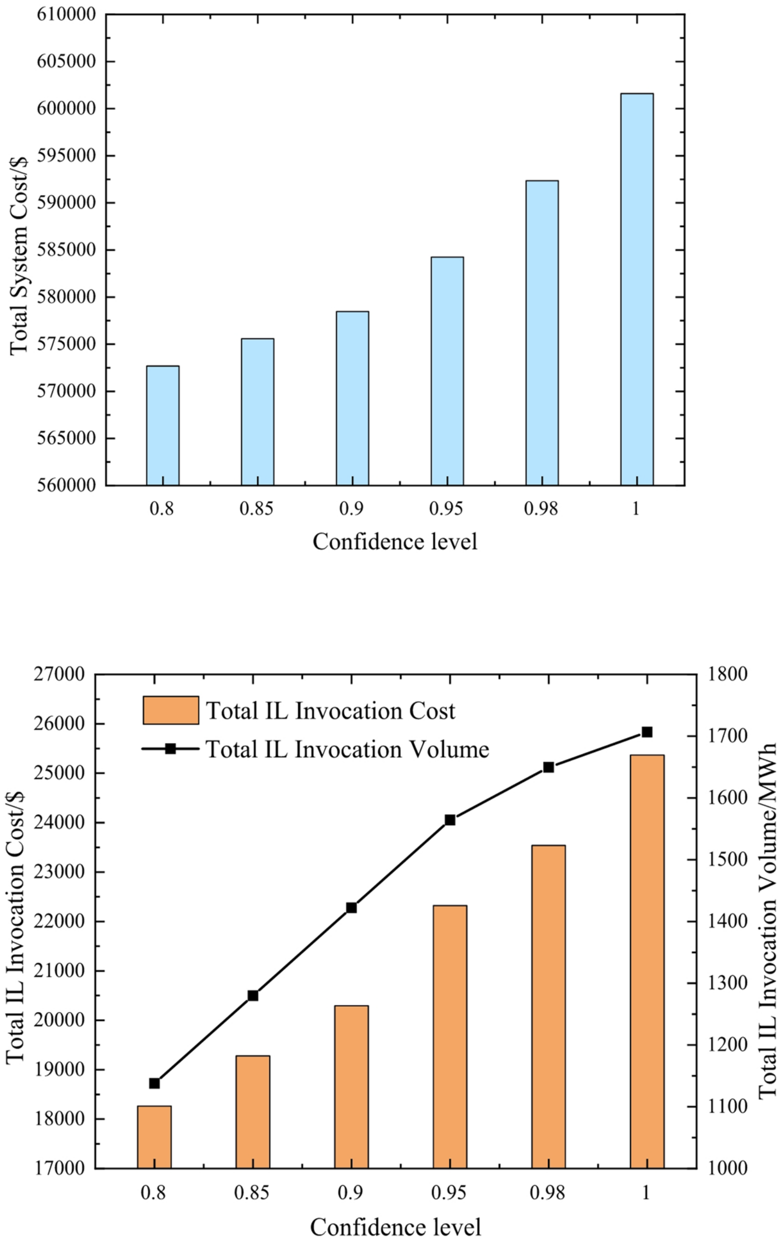

Fig. 9. System Cost, IL Dispatch Volume and IL Dispatch Cost at Different Confidence Levels.

	Gen30	Gen31	Gen32	Gen33	Gen34	Gen35	Gen36	Gen37	Gen38	Gen39
a (\$/MW^{2}h)	0.00048	0.00031	0.00200	0.00211	0.00398	0.00712	0.00079	0.00413	0.00222	0.00173
b (\$/MWh)	16.19	17.26	16.60	16.50	19.70	22.26	27.74	25.92	27.27	27.79
c (\$/h)	1000	970	700	680	450	370	480	660	665	670
h_c (\$/h)	4500	5000	550	560	900	170	260	30	30	30
c_c (\$/h)	9000	10,000	1100	1120	1800	340	520	60	60	60
T^{cold} (h)	5	5	4	4	4	2	2	0	0	0
DT (h)	8	8	5	5	6	3	3	1	1	1
P_{Gi}min (MW)	150	150	20	20	25	20	25	10	10	10
P_{Gi}max (MW)	455	455	130	130	162	80	85	55	55	55
r_{Gi} (MW)	80	80	50	50	50	15	15	15	15	15

Table 5. Generating unit Parameters.

branch-and-cut algorithms, efficient solving under confidence level constraints is realized, and verification is carried out on the modified New England-39 bus system. The research results show that:

1)The introduction of interruptible load effectively reduces the total power generation cost and unit start-up cost of the system, and improves the dispatch economy;

2)Participation significantly alleviates the impact of wind power fluctuations on system power balance and reduces the volatility of unit output;

3)Under different confidence levels, the system cost is positively correlated with the IL dispatch volume, indicating that risk preference has a significant impact on the dispatch results;

4)Even in extreme wind power fluctuation scenarios, the introduction of IL can still effectively peak shave and valley fill, smooth the load curve, and improve the stability of system operation.

In general, the proposed chance-constrained dispatch model shows good performance in balancing economy and reliability, and provides a useful reference for the coordinated optimal dispatch of interruptible load and renewable energy. Future research can further explore the joint dispatch strategy of IL with energy storage and multi-agent demand response to enhance system flexibility and robustness. Furthermore, this study focuses exclusively on chance-constrained modelling to represent uncertainty in unit commitment. Future work will consider incorporating modern risk measures such as CVaR, which captures the expected loss beyond the confidence level, provides a more comprehensive characterisation of risks and further enhance the robustness and practicality of the proposed model.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Appendix

See Table 5.

Received: 19 October 2025; Accepted: 2 December 2025
Published online: 16 December 2025

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Acknowledgements
This project is supported by Science and Technology Project of State Grid Corporation of China (No. 5100–202355778 A-3-7-CB).

Author contributions
Authors Ding Baodi and Zhao Mingxin primarily drafted the manuscript. Author Qin Xiaohui primarily conducted the programming work. Author Chen Shuqi primarily prepared the figures and tables. All authors reviewed the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

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