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Robust Optimal Scheduling of Integrated Energy Systems Considering the Uncertainty of Power Supply and Load in the Power Market

Lang Zhao [1,2,*], Yuan Zeng [1], Zhidong Wang [2], Yizheng Li [2], Dong Peng [2], Yao Wang [3] and Xueying Wang [2]

[1] Key Laboratory of Smart Grid of Ministry of Education, Tianjin University, Tianjin 300072, China
[2] State Grid Economic and Technological Research Institute Co., Ltd., Beijing 102209, China
[3] Economic and Technical Research Institute, State Grid Shanxi Electric Power Company, Taiyuan 030002, China
* Correspondence: zldyx123123@163.com

Abstract: The integrated energy system is a complex energy system that involves multi-stakeholder and multi-energy coordinated operations. The key to improving its scale and sustainable development is to construct a better-integrated energy system dispatching method which is suitable for the power market. However, the randomness of the supply side and load side of the integrated energy system brings further challenges to system planning and scheduling. Therefore, the optimal scheduling method of an integrated energy system considering the uncertainty of supply and demand in the market environment is studied in this paper. Firstly, the uncertainty models of the supply side and load side of the integrated energy system are established. Then, the optimal scheduling model based on robust chance constraint is established. The reserve capacity constraint is set as a chance constraint with a certain confidence level to maximize the system profit in the power market. Finally, simulations show that the proposed method not only guarantees the robustness of the system but also improves the economy of the system. The method provides ideas for exploring the development mechanism and strategy of integrated energy systems in the electricity market environment.

Keywords: integrated energy system; uncertainty; chance constraint; robust optimization

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1. Introduction

With the continuous development of multi-energy grid-connected technology and the continuous improvement of renewable energy penetration, the integrated energy system involving multi-stakeholder and multi-energy coordinated operations has been widely applied. The key to the scale and sustainable development of integrated energy systems in the future is to construct an integrated energy trading strategy and dispatching method suitable for the power market [1–3].

Among them, the power-gas coupling system, which realizes bidirectional coupling between the power system and natural gas system through Power to Gas (P2G), is expected to become a basic form of modern energy supply. Compared with the traditional power system, the electric-coupled system can provide a new way for the consumption of renewable energy such as wind power and enhance the peak cutting and valley filling capacity of the system. However, the high proportion of renewable energy has changed the characteristics of resource allocation in the electricity market. The strong uncertainty of renewable energy makes the boundary of the market gap blurred. This is different from the traditional thermal power unit. With the existing deterministic market gap model, it is difficult to calculate the elastic resource cost required to smooth the uncertainty of renewable energy. This results in the uneven distribution of system resources. The unreasonable allocation of spare capacity leads to the uneven distribution of system resources [4–6]. Load demand response in the market environment has an impact on power grid stability and power quality [7,8]. Meanwhile, in the context of demand response policies and measures, uncertainty on the load side also affects the economy of the system [9–11]. Therefore, it is important to establish a mathematical model that reflects the uncertainty of power side and load side. An accurate model is helpful to realize the planning, distribution and coordinated operation of integrated energy system in market environment.

There have been some studies on the uncertainty in the process of integrated energy system optimization. Sperstad et al. presented a framework to describe distributed wind and photovoltaic power generation with energy storage devices. The method can account for uncertainties beyond the planning horizon [12]. Liang et al. proposed a two-stage adaptive robust optimization method for wind power uncertainties. By comparing simulation results, it is verified that the robust optimization method is conducive to improving wind power output and system economy [13]. Bai et al. analyzed the potential risks of wind power uncertainty. A robust transmission planning method is proposed for high-penetration wind power based on adaptive uncertainty set optimization [14]. Li et al. reported that the security of natural gas network and the uncertainty of wind power bring new challenges to the operation of power system. The robust optimization analysis of integrated energy system containing wind power is carried out [15]. Carli et al. proposed a data-driven robust optimization model considering wind power uncertainty and a multi-demand response plan for the integrated energy system; the system contains power-to-gas devices and traditional cold-thermal co-generation [16]. Jiang et al. proposed a robust model predictive control approach to minimize the total economical cost. The approach satisfies the comfort and energy requests of the final users [17]. In conclusion, the robust optimization algorithm is an effective method to solve the uncertainty problem of wind power.

However, the above references only optimize the uncertainty of the power supply side or load side. There is a lack of analysis on the impact of these two uncertain behaviors on the optimal scheduling of the system. Moreover, there are few relevant types of research on the background of the electricity market. This paper studies the optimal scheduling method of an integrated energy system considering the uncertainty of supply and demand in the electricity market. The main contributions of this paper are:

- The electric–gas coupling model of the integrated energy system is established, and the uncertainty model of the supply side and load side of the system is further established based on this model.
- An optimal scheduling model based on robust chance constraints to maximize system profits in the electricity market is presented. The model is solved by converting chance constraints into deterministic constraints.
- The effectiveness of the proposed method is verified by simulations. The proposed method not only guarantees the robustness of the system but also improves the economy of the system. It provides ideas for exploring the survival and development mechanism and strategy of integrated energy systems in the electricity market environment.

The rest of this paper is organized as follows. In Section 2, the uncertainty characteristic models of the power supply side and load side are established. Then a power system optimal scheduling model based on robust chance constraint is established in Section 3. The simulation and experimental results are shown in Section 4. At last, the conclusion is given in Section 5.

2. Modeling of the Integrated Energy System

2.1. Power Output Equipment

The integrated energy system is a complex energy system that involves multi-interest subjects and a multi-energy coordinated operation. The network in the integrated energy system mainly includes a power network, a heat network, and a gas network. The energy conversion process mainly includes energy input, energy conversion, and energy storage [18–20]. The power-gas coupling system in the integrated energy system is relatively mature, and mainly uses the P2G technology to complete the conversion between electric energy and gas energy. The system structure is shown in Figure 1.

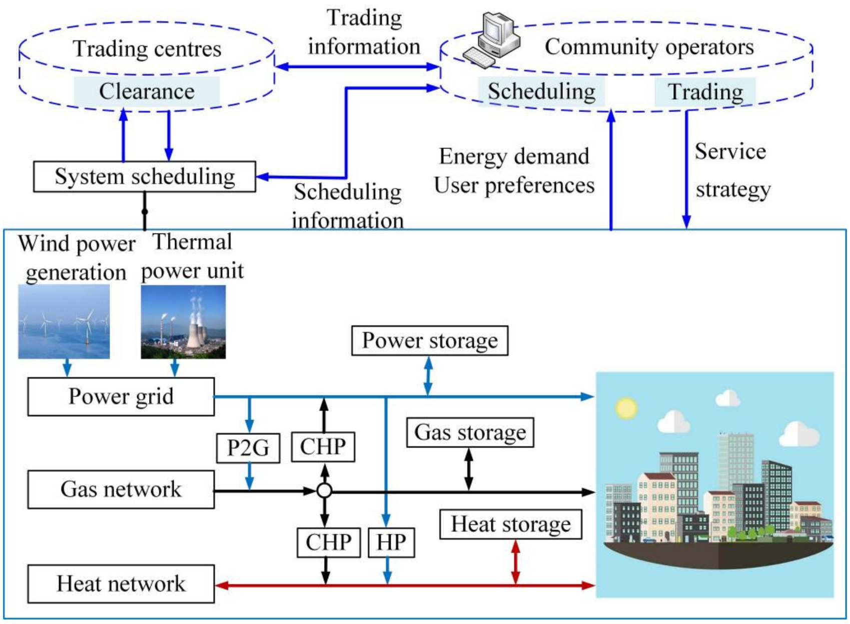

Figure 1. Structure diagram of the integrated energy system.

Energy sources include wind power generation and thermal power units. The grid side includes the power grid, gas network, and heat network. The electric–gas coupling system is realized by P2G technology. The networks can be coupled with each other by the Combined Heat and Power (CHP) units, and the power grid and thermal network can also be coupled through Heat Pumps (HP). In the optimal scheduling problem, the mathematical description of source, load, and energy conversion units is established at first. Then, the robust chance constraints are added to the mathematical model to balance the economy and robustness. Finally, the scheduling scheme is obtained after calculating the optimal solution of the mathematical model.

The integrated energy system operation center is responsible for energy supply services and energy transactions within the system. The goal of the operation center is to pursue the optimization of operating costs under the premise of ensuring the reliability of the energy supply. According to the regulations of the trading center, the system is divided into internal and external services. The internal service meets the full-time and efficient energy supply demand through cooperation with various energy equipment in the community. External service means that operators gather all kinds of flexible resources in the system. More operational benefits are obtained through energy substitution, demand response, or purchase and sale strategy, trading surplus or deficit energy with other entities. Through external services, the operators provide services such as peak shaving and frequency modulation for the power grid, thus obtaining more operational benefits.

2.1.1. P2G Model

The working principle of P2G is to realize the two-way transmission of electricity and gas through the combination of surplus power and chemical reaction to produce corresponding gas. Considering the conversion efficiency, the principle can be expressed as

$$G_{\mathrm{P2G}} = \eta_{\mathrm{P2G}} \cdot P_{\mathrm{P2G}} \tag{1}$$

where G_{P2G} is the gas power generated by P2G equipment; P_{P2G} is the electric power consumed by P2G; η_{P2G} is the conversion efficiency of P2G equipment.

The relationship between the input flow and the output power of the gas turbine satisfies a second-order fitting relation

$$H_{GB,j} = \alpha_g + \beta_g P_{GB,i} + \gamma_g P_{GB,i}^2 \tag{2}$$

where $P_{GB,i}$ is the output power of the gas-fired boiler at node i of the power grid; $H_{GB,j}$ is the output heat of the gas-fired boiler at node j; α_g, β_g and γ_g is the fitting coefficient of the gas-fired boiler.

The conversion relationship from gas to heat is

$$F_{G,j} = \frac{H_{GB,j}}{GHV} \tag{3}$$

where $F_{G,j}$ is input gas flow of the gas turbine at node j of the connecting line of the natural gas system; $H_{GB,j}$ is the output heat of the gas-fired boiler at node j; GHV is the gas heat value.

2.1.2. Wind Power Model

The power output of the wind turbine is mainly related to the wind speed. When the wind speed is less than the cut wind speed or greater than the cut wind speed, the wind turbine does not work [21]. The mathematical model of wind power generators is

$$P_{w,t} = \begin{cases} 0 & v_t \le v_{in},\ v_t \ge v_{out} \\ P_{w,t,r}\frac{v_t - v_{in}}{v_{out} - v_{in}} & v_{in} < v_t \le v_r \\ P_{w,t,r} & v_r < v_t \le v_{out} \end{cases} \tag{4}$$

where $P_{w,t}$ is the generating power of wind turbine at time t; v_{in} is the cut-in wind speed; v_{out} is the cut-out wind speed; v_r is the rated wind speed of the wind turbine; $P_{w,t,r}$ is the rated power of wind turbine.

2.2. Supply and Demand Uncertainty Analysis of the System

2.2.1. Uncertainty Model of Wind Power Output

The source-side power generation system mainly includes thermal power units and renewable energy generating units, among which renewable energy generation is wind power generation. Because of the fluctuation and intermittency of wind power output, the source-side uncertain behavior is caused. The specific uncertainty model can be described by the prediction bias. Compared with the normal distribution, the Laplace normal mixed distribution can better reflect the probability density distribution of wind prediction deviation [22,23]. Therefore, this distribution is used to describe the prediction deviation of wind power output. The peak value of output k is

$$k = \frac{E(\Delta P_{r,w,t} - \mu_w)^4}{\sigma_w^4} \tag{5}$$

where $P_{r,w,t}$ is the predicted value of wind power output; $\Delta P_{r,w,t}$ is the forecast deviation of wind power output in time period t; $E(\Delta P_{r,w,t} - \mu_w)^4$ is the fourth order center distance of $\Delta P_{r,w,t}$, μ_w is the expectation of wind power output forecast deviation; σ_w is the standard deviation of forecast deviation of wind power output.

The probability density distribution function is as follows:

$$f(\Delta P_{r,w,t}) = \frac{a}{2b}\exp\left(-\frac{|\Delta P_{r,w,t} - \mu_w|}{b}\right) + \frac{(1-a)}{\sqrt{2\pi}\sigma_w}\exp\left[-\frac{(\Delta P_{r,w,t} - \mu_w)^2}{2\sigma_w^2}\right] \tag{6}$$

where $a = 2 - k/3$, $\sigma_w = \varepsilon_w P_{r,w,t}$, $b = \sqrt{\sigma_w^2/2}$, ε_w is the percentage of the predicted deviation of wind power output in the predicted value.

2.2.2. Load Uncertainty Model

The uncertainty of the load side mainly refers to the deviation of load prediction. Considering the uncertainty of load from the perspective of load prediction deviation, the probability density distribution function of forecast deviation can be used for analysis. It is found that the normal distribution can better reflect the probability density distribution of load prediction deviation [24,25]. Therefore, a normal distribution is adopted here to describe the load prediction deviation, and its specific probability density distribution function is

$$f(\Delta P_{r,l,t}) = \frac{1}{\sqrt{2\pi}\sigma_l} \exp\left(-\frac{(\Delta P_{r,l,t} - \mu_l)^2}{2\sigma_l^2} \right) \tag{7}$$

where $\sigma_l = \varepsilon_l P_{r,l,t}$, $P_{r,l,t}$ is the predicted load value of the system; $\Delta P_{r,l,t}$ is the load prediction deviation; μ_l is the expectation of wind power output forecast deviation; σ_l is the standard deviation of load prediction deviation; ε_l is the percentage of load forecast deviation in predicted value.

3. Optimization Scheduling Based on Robust Chance Constraints in Electricity Market

3.1. Objective Function

An integrated energy system in the context of the electricity market can be viewed as an operator that aims to provide safe, stable, and clean energy to the load side while pursuing its profit maximization. The goal of the system under the electricity market is to maximize the profit on the premise of meeting the load demand.

$$\max f = F_S - F_B - F_C \tag{8}$$

where F_S, F_B, and F_C are energy sales revenue, energy purchase cost, and total system operation cost of the integrated energy system, respectively.

Among them, F_S adopts fixed electricity price to transfer synchronously to the load side, and does not adopt floating electricity price. Therefore, when the operating cost of the system is at its lowest, the maximum benefits of the system can be satisfied in the electricity market. The objective function of minimum total system operating cost can be described as

$$\min(F_C) = C_{H,t} + C_{W,t} + C_{OG,t} + C_{P2G,t} + C_{CW,t} \tag{9}$$

where $C_{H,t}$ is the operation cost of the thermal generating set; $C_{W,t}$ is the operating cost of wind power generating set; $C_{OG,t}$ is the gas storage cost of the gas storage tank in the gas system; $C_{P2G,t}$ is the operation cost of electricity to gas in the energy conversion device; $C_{CW,t}$ is the penalize costs for curtailment.

3.1.1. Operation Cost of Generator Set

The operation cost of issuing units mainly includes the cost of the thermal-generating unit and wind-power-generating unit, and the calculation method is

$$\begin{cases} C_{H,t} = \sum\limits_{i=1}^{H_t} \left[\left(a_i P_{h,i,t}^2 + b_i P_{h,i,t} + c_i \right) \right] \cdot h_{i,t} \\ C_{W,t} = \sum\limits_{j=1}^{W_t} d_j P_{w,j,t} w_{jt} \end{cases} \tag{10}$$

where $h_{i,t}$ is the generation time of thermal power unit i at time t; a_i, b_i, and c_i are the fitting coefficient of generator operation cost of the thermal power unit i, respectively; $P_{h,i,t}$ is the active power output for the thermal power unit i; w_{jt} is the generation time of wind turbine j at time t; d_j is the operating cost fitting coefficient of wind power generator j; $P_{w,j,t}$ is the active output of the j-th generator unit.

3.1.2. Gas Storage Cost of Gas Storage Tank in Natural Gas System

The operating cost of natural gas systems only takes the storage cost of the gas storage tank into consideration.

$$C_{OG,t} = \sum_{t \in T} \sum_{i \in \Omega_S} OC_{S,i}^{in} G_{S,i,t}^{in} + OC_{S,i}^{out} G_{S,i,t}^{out} \tag{11}$$

where $OC^{in}_{S,i}$ is the unit intake cost of the i-th gas storage tank; $G^{in}_{S,i,t}$ is the natural gas flow injected by the i-th gas storage tank at time period t; $OC^{out}_{S,i}$ is the unit pumping cost of the gas storage tank; $G^{out}_{S,i,t}$ is the natural gas flow extracted from the i-th gas storage tank at time period t; $C_{OG,t}$ is a collection of gas storage tanks in the system.

3.1.3. Operation Cost of P2G Conversion Device

When transporting natural gas, the natural gas system consumes energy only when the gas storage tank is used or the compressor is used to pressurize the gas, resulting in the operation cost. The operation cost resulting from the operation process of P2G equipment can be expressed as

$$C_{P2G,t} = \sum_{t \in T} \sum_{n \in \Omega_{P2G}} OC_{P2G,n} L_{P2G,n,t} \tag{12}$$

where $OC_{P2G,n}$ is the unit operating cost of the n-th P2G equipment; $L_{P2G,n,t}$ is the active power consumed by the n-th P2G equipment in time period t.

3.1.4. Penalty Cost of Wind Abandonment

The penalty cost of abandoning wind is expressed by

$$C_{CW,t} = \sum_{t=1}^{T} a_{\mathrm{CW}} P_{\mathrm{CW},t} \tag{13}$$

where a_{CW} is the penalty cost coefficient of wind abandonment; $P_{\mathrm{CW},t}$ is the wind abandonment power at the moment.

3.2. Constraints

Since there are uncertain factors such as wind power output and load in the system, the stochastic programming method is an effective method to deal with the model containing uncertain factors [26,27]. Therefore, the stochastic programming method is used to process the model. Among stochastic programming methods, one of the most important is chance constrained programming, which refers to the optimization of artificially set goals under a certain probability [28,29]. The constraints in this paper include system output constraints, power and energy constraints, power balance constraints, gas storage constraints, node traffic balance constraints, and chance constraints.

When constraint conditions are set up, if there are random variables under the constraint, chance constrained programming can solve this problem well. Chance constrained programming needs to make decisions in advance when observing random variables. Specifically, a confidence value β is set in advance so that the probability of meeting the constraint conditions is not less than β, which can be described as

$$\Pr\{g_i(z,\xi) \geq 0, i = 1, 2, \ldots, m\} \geq \beta \tag{14}$$

where z is the decision variable; ξ is a random variable with known probability density; $g_i(z,\xi)$ is the chance constraint function; $\Pr\{\cdot\}$ is the probability that the condition is satisfied in the expression; β is the confidence level.

According to the system model and planning objectives, the main constraints of the system include the following constraints.

3.2.1. System Output Constraint

System output constraints include thermal power units and wind turbine unit output constraints, which are limited by the maximum and minimum values.

$$\left\{ \begin{array}{l} P_{h,i,t,\min} \leq P_{h,i,t} \leq P_{h,i,t,\max} \\ P_{w,j,t,\min} \leq P_{w,j,t} \leq P_{w,j,t,\max} \end{array} \right. \tag{15}$$

where $P_{h,i,t,\min}$ and $P_{h,i,t,\max}$ are the minimum and maximum output of the thermal power unit, respectively; $P_{w,j,t,\min}$ and $P_{w,j,t,\max}$ are the minimum and maximum output of the wind turbine, respectively.

3.2.2. Power and Energy Constraints

The total output of the system at time t should be limited by the load demand. Similarly, the total power of the system at time t should meet the demand of the system.

$$\begin{cases} \sum\limits_{i=1}^{H_t} P_{h,i,t} + \sum\limits_{j=1}^{W_t} P_{w,j,t} \geq P_{D,t} \\ \sum\limits_{i=1}^{H_t} P_{h,i,t} T_{h,i} + \sum\limits_{j=1}^{W_t} P_{w,j,t} T_{w,j} \geq E_t \end{cases} \tag{16}$$

where $P_{D,t}$ is the total power load demand at time t; E_t is the total energy load demand at time t; $T_{h,i}$ and $T_{w,j}$ are the output time of thermal power unit i and wind power unit j, respectively.

3.2.3. Power Balance Constraints of the Power System

The power balance constraint of the power system can ensure the balance between generating power and consuming power in the same period of time. It can ensure the stable operation of the system.

$$\sum_{i=1}^{H_t} P_{h,i,t} + \sum_{l=1}^{G_t} P_{g,l,t} + \sum_{j=1}^{W_t} (P_{w,j,t} - P_{BW,j,t}) = \sum_{k=1}^{D_t} P_{D,k,t} + \sum_{n=1}^{P2G_t} P_{P2G,n,t} \tag{17}$$

where $P_{g,l,t}$ is the output value of the gas unit l at time t; $P_{BW,j,t}$ is the wind abandon power of the j-th wind field at time t; $P_{P2G,n,t}$ is the active power consumed by the n-th P2G device in the time period t.

3.2.4. Constraints of Gas Storage Tank

Gas storage tank can temporarily store gas when there is a large flow of natural gas, and provide natural gas supply when the load demand is too high. Constraints of gas storage tanks include total storage constraints and inbound and outbound natural gas flow constraints as

$$\begin{cases} G_{\mathrm{S},i,t} = G_{\mathrm{S},i,t-1} + G_{\mathrm{S},i,t}^{in} - G_{\mathrm{S},i,t}^{out} \\ 0 \leq G_{\mathrm{S},i,t}^{in} \leq G_{\mathrm{S},i,\max}^{in} \\ 0 \leq G_{\mathrm{S},i,t}^{out} \leq G_{\mathrm{S},i,\max}^{out} \\ G_{\mathrm{S},i,\min} \leq G_{\mathrm{S},i,t} \leq G_{\mathrm{S},i,\max} \end{cases} \tag{18}$$

where $G_{\mathrm{S},i,t}$ is the storage gas volume of the i-th node gas storage tank at time t. $G_{\mathrm{S},i,\max}^{in}$ is the upper limit of natural gas intake of the i-th gas storage tank; $G_{\mathrm{S},i,\max}^{out}$ is the upper limit of gas output flow of the i-th gas storage tank; $G_{\mathrm{S},i,\min}$ and $G_{\mathrm{S},i,\max}$ is the upper and lower limits of gas storage capacity of the i-th gas storage tank.

3.2.5. Constraints on Node Traffic Balance

In gas network, node flows, in and out, are conserved, and the node flow balance constraint is conserved as follows

$$G_{\mathrm{O},i,t} - G_{\mathrm{S},i,t}^{\mathrm{in}} - \sum_{j \in \Omega_3} G_{ij,t} + G_{\mathrm{P2G},i,t} = \sum_{l \in \Omega_{j,l}} GL_{\mathrm{com},l,t} + GL_{\mathrm{d},i,t} + GL_{\mathrm{G2P},i,t} \tag{19}$$

where $G_{\mathrm{O},i,t}$ is the compressor set supplied by node i; $G_{\mathrm{P2G},i,t}$ is the natural gas injected by P2G equipment of node i at time t; $GL_{\mathrm{d},i,t}$ is the gas load demand of node i; $GL_{\mathrm{G2P},i,t}$ is the gas consumed at time t.

3.2.6. Chance Constraints

In the system, due to the randomness, volatility of wind power output, and the existence of load prediction deviation, the uncertain behavior of the supply side and load side will affect the net income of its participation in day-ahead trading. Therefore, the chance constraints in this paper mainly include new energy output prediction and load prediction.

$$\begin{cases} \Pr(\sum_{i=1}^{H_t} P_{h,i,t} + \sum_{l=1}^{G_t} P_{g,l,t} + \sum_{j=1}^{W_t} (P_{w,j,t} - P_{BW,j,t}) = \sum_{k=1}^{D_t} P_{D,k,t} + \sum_{n=1}^{P2G_t} P_{P2G,n,t} \geq \Delta P_{r,w,j,t} + P_{rl,t}) \geq \beta_1 \\ \Pr\left(\sum_{m=1}^{L_t} P_{l,m,t} + P_{re,t} \geqslant \Delta P_{rl,t} + \sum_{m=1}^{L_t} P_{r,l,m,t}\right) \geqslant \beta_2 \\ \sum_{j=1}^{W_t} P_{r,w,j,t} + \Delta P_{r,w,j,t} \geq P_{clr,w,t} \\ \sum_{t=1}^{T} (1-\varepsilon) = \Gamma, 0 \leqslant \varepsilon \leqslant 1 \end{cases} \quad (20)$$

where $P_{r,w,j,t}$ is the predicted power of wind power; $\Delta P_{r,w,j,t}$ is wind power prediction error; $P_{clr,w,t}$ is the clearing power of wind power; $P_{re,t}$ is the rotation reserve power; $P_{l,m,t}$ is the actual load; $\Delta P_{rl,t}$ is the predicted load shortage; ε is the probability that the constraint exceeds the limit; Γ is the robustness. The closer ε is to 1, the higher the security of the system, but it will lead to a waste of energy. The closer ε is to 0, the higher the economy will be, but the security of the system will be sacrificed.

As a cooperative optimization objective, a robust maximization objective is constructed as follows:

$$\max \Gamma = \sum_{t=1}^{T} (1-\varepsilon) \quad (21)$$

3.3. Solution Algorithm

The sampling method to solve the reduced chance constraint model includes the following steps. First of all, the distribution law of variables is calculated. Then, the data samples are substituted one by one for the test to see whether the result is greater than $1-\varepsilon$. Lastly, it is judged whether the opportunity constraint is established. This method needs many samples for verification, the calculation is large, and it is not easy to operate. Therefore, it is necessary to transform chance constraints into deterministic constraints to reduce calculation and ensure speed and accuracy.

The power balance constraint Equation (17) is processed through sample-based deterministic transformation. Considering economic objectives and robustness objectives, this paper uses the MOMDE (Multi-Objective Molecular Differential Evolution) algorithm to solve the model. By using the evolutionary variation mechanism based on inter-molecular forces, it can overcome the precocious convergence phenomenon effectively and achieve efficient depth optimization [30,31]. The flow chart of the solution process is shown in Figure 2. According to the initialization data, confidence level, and the source and load probability density function, the random numbers are generated. The chance constraint parameter values are substituted into the transformed deterministic parameter equation. The objective function optimization model with constraints is solved by the multi-objective optimization algorithm.

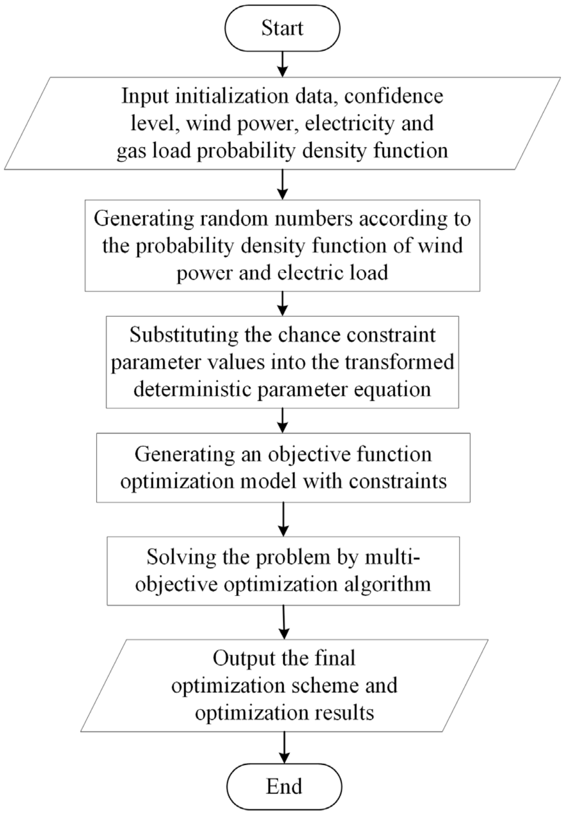

Figure 2. Solution process of the model.

4. Example Analysis

4.1. Simulation Parameters

In this paper, a 39-bus system is selected for analysis and calculation. Table 1 shows system parameters. The selection of system operation parameters refers to the integrated energy demonstration parks in North China.

Table 1. Main system parameters.

Parameter	Value (kW)
Power of CHP	200
Power of GB	300
Power of P2G	400
Output of thermal power unit	3000
Wind farm output	1000

Due to the uncertainty of renewable energy, in order to verify the effectiveness of this method, the distribution of prediction errors under different wind speeds during the test process is shown in Table 2. Among them, the predicted value of 24 h renewable energy output and load demand are shown in Figures 3 and 4, respectively. The maximum relative error of wind speed prediction is less than 3.2%. The wind power output is larger at night and smaller during daytime. The low temperature in the early morning leads to a high heating load. Residents conduct more activities in the afternoon and evening. During these two periods, the energy consumption load is relatively large.

Table 2. Error distribution of wind power prediction.

Wind Speed (m/s)	Error (%)	Standard Deviation	Wind Speed (m/s)	Error (%)	Standard Deviation
3–4	1.98	3.96	7–8	0.02	15.82
4–5	2.01	6.27	8–9	−0.71	14.25
5–6	1.45	15.83	10–11	−0.42	12.68
6–7	1.12	16.62	11–12	−3.2	10.23

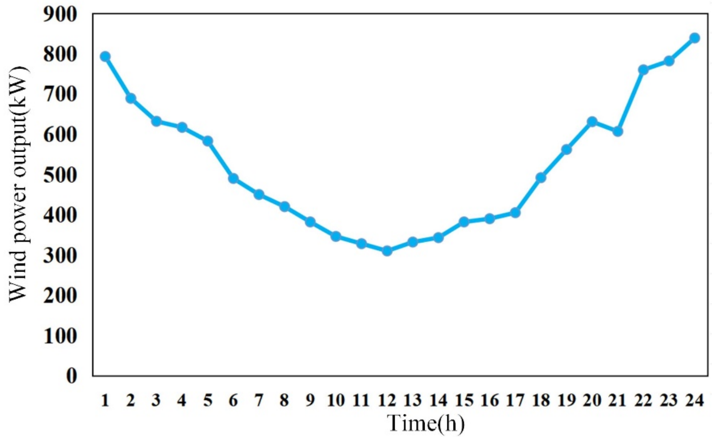

Figure 3. Forecast of wind power output.

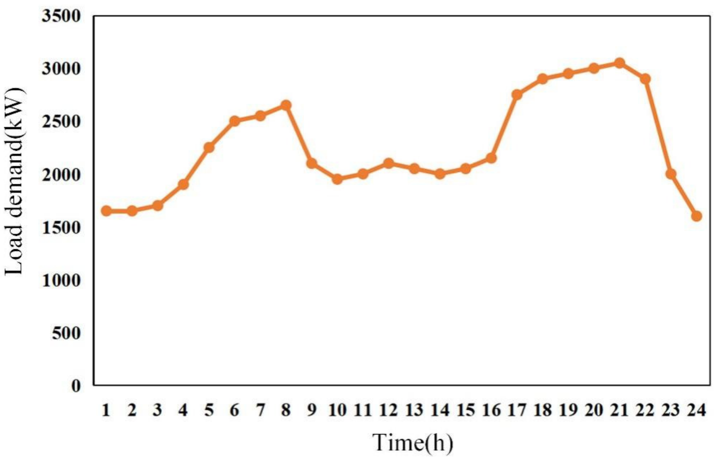

Figure 4. Forecast of load demand.

4.2. Analysis of Model Optimization

The chance constraint parameter is set to 0.1, and the corresponding optimal dispatching results of when the optimal solution is obtained through calculation are presented in Figures 5 and 6, respectively. In order to fully absorb wind power, P2G equipment starts to operate and convert electric energy into gas energy for storage at night. Especially from 02:00 to 04:00, the electric power consumed by P2G technology greatly increases the electric load and provides a lot of space for wind power consumption. At the same time, P2G technology can save costs by purchasing gas. Compared with [15], the uncertainty of the loads can be further considered in this paper by using chance constraints.

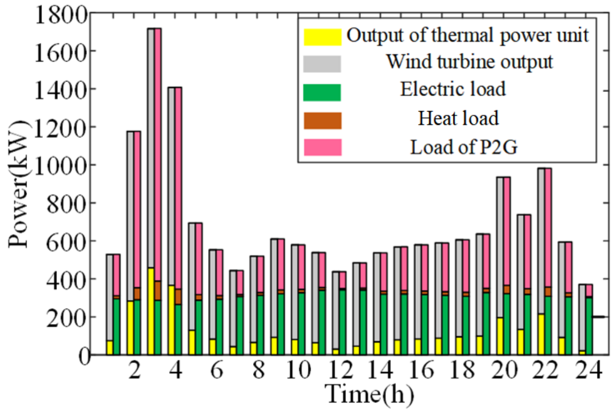

Figure 5. Dispatching of power grid equipment.

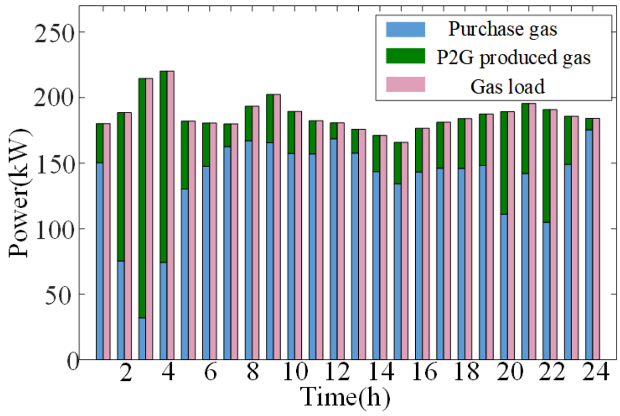

Figure 6. Scheduling of gas network equipment.

4.3. Impact of Robust Chance Constraints

The influence of parameter confidence on the economy and the robustness of the model in the chance constraint is analyzed. Table 3 indicates the different values used to achieve robust optimization of results. The price unit is Chinese Yuan (CNY).

Table 3. Economy of robust optimization with different confidence intervals.

E	W_{w}^{t} (CNY)	W_{v}^{t} (CNY)	F (CNY)
0.1	43,829	19,872	198,723
0.15	47,813	16,782	176,281
0.2	38,921	11,982	167,268
0.25	32,869	8729	142,784

It can be seen from Table 3 that with the increase of chance constraint parameters, the robustness becomes worse, the economy will be improved, and the cost will be reduced. The goal of robustness maximization is to eliminate the subjective restriction of preset robustness (confidence level) and obtain a more reasonable and robust economically optimal scheduling scheme. With the increase in robustness Γ, the confidence interval increases, the robustness of the system increases, and the economy decreases. Under the condition of reducing the robustness of the system, the operating cost of the system is reduced, which is mainly manifested in the reduction of the cost of abandoning wind and purchasing fuel. With the increase of the chance constraint parameter ε from 0.1 to 0.25, the total cost of the system is reduced by 28.15%.

4.4. Comparative Analysis of Different Schemes

To prove the effectiveness and correctness of the proposed method, through the calculation of the following four methods, it can be seen in Table 4 that the profits obtained by different methods are different. It can be concluded that the proposed robust chance constraint optimization scheme is more economical. Compared with [18], the influence of the market environment has been further reflected. Deterministic optimization does not consider the fluctuation of wind power, the result is too idealistic, and, therefore, the calculation cost is the lowest. Compared with stochastic optimization and robust optimization, when the chance constraint parameter is 0.1, the total system revenue increases by 17.61% and 10.99%, respectively. The cost of robust optimization is the highest because robust optimization considers the worst scenario and is too conservative. The economy of stochastic optimization is between deterministic optimization and robust optimization. The method proposed in this paper fully considers the uncertainty of wind power. The calculation is closer to the actual operation situation. At the same time, the shortcoming of traditional robust optimization has been improved. Therefore, it has more reference value.

Table 4. Economic comparison of different schemes.

Optimization Method	ε	Profit (CNY)
Optimization of deterministic	0	158,247
Optimization of stochastic	0	167,813
Optimization of robust	0	177,823
Chance constraints of robust optimization	0.1	197,362

5. Conclusions

In this paper, the optimal scheduling method of an integrated energy system considering the uncertainty of power load in the market environment is studied. The uncertainty models of the supply side and load side of the integrated energy system are established. Taking the integrated energy system as an operator, an optimal scheduling model based on robust chance constraints is established to maximize the system's profit in the electricity market. The model is solved by converting chance constraints into deterministic constraints. The simulations show that the proposed method can not only ensure the robustness of the system, but also improve the economy of the system. Compared with robust optimization, with the increase of the chance constraint parameter from 0.1 to 0.25, the total cost of the system is reduced by 28.15%. Compared with stochastic optimization and robust optimization, when the chance constraint parameter is 0.1, the total system revenue increases by 17.61% and 10.99%, respectively.

Since the research on uncertain pricing of renewable energy is still in its infancy, the results can provide a reference for exploring the survival and development mechanism and strategy of integrated energy systems in the electricity market environment.

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