Multi-objective optimization of integrated gas–electricity energy system based on improved multi-object cuckoo algorithm

Bowen Yang

School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China

Correspondence
Bowen Yang, School of Electrical and Electronic Engineering, North China Electric Power University, Beijing 102206, China
Email: 120181010915@ncepu.edu.cn

Abstract
With the depletion of sources of primary energy across the world, the prospect of a global energy crisis in the near future has raised considerable concern. Among the many sources of clean energy, wind energy is considered to be the most effective means of sustainable and environmentally friendly energy. Traditional systems of energy based on oil and natural gas still operate in a discrete manner, and the promise offered by the mutual coordination between energy systems to draw complementary benefits has not yet been fully exploited. This has prompted all energy sectors to examine the optimal integration of interconnected gas–electricity energy systems. In this context, this study proposes a multi-objective collaborative operational optimization model of P2G for an interconnected, integrated gas–electricity energy system in case of uncertain wind power. Based on the effect of carbon capture by using P2G, the effect of coupling gas and electricity, and the cost of low-capacity reserves, the authors use conditional risk values to design four targets of optimization—the operating cost of the system, rate of consumption of the natural gas system, total carbon emissions and capacity stand-by cost—according to the power system, natural gas system, thermal energy system, and their elements of coupling from multiple perspectives to clarify the constraints on the model. Moreover, to reduce the likelihood of the optimal solution falling into the local optimum, the improved cuckoo algorithm is used to optimize the multi-objective scheduling model. The authors used a 10-node power system and a six-node natural gas system as examples for simulation to verify the proposed model. The results of empirical analysis show the following: (a) Once the P2G equipment had been connected, it reduced the total operating cost and improved the consumption of wind power of the natural gas system regardless of whether backup services were provided. (b) The P2G equipment could be combined with gas-fired CHP units to “cut peaks and fill valleys” in the electrical load of the power system. These results verify the effectiveness of the proposed multi-objective optimal dispatch model of an interconnected gas–electricity energy system.

KEYWORDS
conditional risk value, cuckoo algorithm, integrated gas–electricity energy system, multi-objective optimal scheduling model
1 | INTRODUCTION

1.1 | Literature review

Because the international structure of energy supply is still dominated by energy based on fossil fuels, such as coal, the prospect of a global energy crisis in light of the depletion of such primary sources of energy has raised considerable concern. Among the sources of clean energy, wind is considered to be the most effective means of obtaining sustainable and environmentally friendly energy. According to energy statistics from the BP, China’s capacity for installed wind power had reached 229 GW by the end of 2019, a year-on-year increase of 37%, which is the highest in the world.¹

With the development of P2G technology, multi-energy systems composed of an electric power system and a natural gas system have been developed to form interconnected, dual-network gas–electricity systems.²³ P2G equipment converts surplus electrical energy into natural gas in time when the demand for power is low or the wind power generated by the system is redundant, where this helps solve the problem of wind abandonment.⁴⁻⁶ Chiang et al⁷ sought the optimal configuration of the capacity of P2G by setting the minimum number of gas turbines as the objective function while ensuring that the required load-related conditions of the integrated gas–electricity energy system were satisfied. Zhang⁸ proposed a method to predict wind power by studying the electrolysis reaction of P2G equipment in water and the principle of hydrogen-fired steam turbines. To quantify the capacity of P2G equipment to absorb remaining wind power, Costa et al⁹ built a complete scheduling model for an integrated gas–electricity energy system. Christidis et al¹⁰ proposed Benders’ decomposition technology combined with an electrolyzed water unit and a hydrogen gas turbine unit, and Yang et al² investigated whether the electricity-to-methanation reaction reduces carbon emissions.

In terms of the uncertain impact of wind power on integrated energy systems, Yan et al¹ quantified the uncertainty in the output of wind power to construct an optimized model for interconnected electrical systems. Mirzaei et al¹¹ studied various probabilistic simulations, and the results showed that characteristics of the output of a wind farm reduced error in its predicted output, which verified the correlation between this output and power flow in the system. Conditional value at risk (CVaR) can help achieve the maximum output at a known level of confidence of loss. Many scholars have applied CVaR theory to assess the economic component of system uncertainty. Nedjari et al¹² used CVaR theory to define and quantify the risk of demand for the system’s reserves. Wang et al¹³ also used this theory to describe this demand, with the goal of minimizing the expected value of wind curtailment through a rolling correction intra-day unit dispatch optimization model. Many researchers have modeled the collaborative optimization of an integrated gas–electricity energy system. Roviano et al¹⁴ considered the operational constraints on a natural gas pipeline and constructed an optimization model for it with the goal of minimizing power-related risk in the coupling between the natural gas system and the power system. Guoqian et al¹⁵ constructed a scheduling model for an interconnected natural gas–electricity energy system, where the objective function was designed to maximize system health, and studied the influence of changing factors on the operational state of the system. Chen et al¹⁶ used the energy center model to analyze the benefits of P2G equipment in consuming the remaining wind power of the system. Vila et al¹⁷ considered the safety-related constraints on the natural gas system and used examples of calculations to show that the results of scheduling obtained by considering safety-related constraints were more consistent with empirical scheduling scenarios. Savari et al¹⁸ regarded P2G as an energy storage device to construct a dispatch model of a multisource energy storage microgrid with distributed power sources. Posada et al¹⁹ used the effect of P2G of “filling the valley” and the “peak-cutting” effect of gas turbines to develop an optimized scheduling model for an integrated gas–electricity energy system. Zhang et al²⁰ constructed a two-stage model of an optimized integrated gas–electricity energy system, and He et al²¹ studied the optimization of a combined gas and power system containing combined heat and power units, P2G, and other equipment. The target of optimization was the capacity of the P2G equipment. Chenghong et al²² constructed a multistage investment decision model for an integrated gas–electricity energy system to obtain the optimal levels of investment in different stages.

Researchers have mainly used transformations based on nonlinear models to solve models of energy systems. Xuan et al²³ solved the model for the multi-objective optimal configuration of a urban water supply network system by using chance constraint programming. Liu et al²⁴ constructed an operational model of a hybrid island power generation system to optimize the operating cost and used the particle swarm algorithm to solve the issue. Tan et al²⁵ used sensitivity analysis to determine the weight coefficients of different objective functions to convert the model into a mixed-integer single-objective model for integrated energy system. Dufo-López et al²⁶ systematically summarized the multi-objective algorithms used in integrated energy systems and noted that the genetic algorithm (GA) is a commonly used algorithm. Based on the work in Ref.,²⁶ Dufo-López et al²⁷ also used the GA to optimize the control strategy for a hybrid light-diesel-storage hydrogen system. Lee et al²⁸ studied the application of the GA to the optimization of hybrid photovoltaic–diesel systems, and Hakimi et al²⁹ proposed the application of particle swarm optimization to the configuration of complementary wind–solar systems that power time-sharing industrial users. Zhiqiang et al³⁰ have shown that the Rich semantics
algorithm is feasible for solving for the optimal configuration of joint entity and relation extraction with the goal of minimizing system cost. Yongming et al\textsuperscript{31} proposed an improved adaptive DEA cross-model algorithm to optimize a microgrid system that used complex chemical processes. They verified the effectiveness of the proposed algorithm. Yongming et al\textsuperscript{32} improved total factor productivity method based on slacks-based measure integrating data envelopment analysis. Peng et al\textsuperscript{33} proposed a novel Cuckoo variant, called Spark-based gaussian bare-bones cuckoo search with dynamic parameter selection, which can enhance the search ability of Cuckoo algorithm. He et al\textsuperscript{34} proposed a multistrategy serial Cuckoo algorithm to avoid getting trapped in the local optimum and enter the state of premature convergence.

1.2 | Motivation

This paper takes the operational structure of P2G in an integrated energy system of gas and power as research object. In case of uncertainty in the output of wind power, the authors clarify the role of P2G in the operation and the means of optimizing the integrated energy system by using a multi-objective model of collaborative optimization. The contributions of this paper are as follows:

1. A multi-objective optimization model of a P2G-integrated, interconnected gas–electricity energy system is constructed. Maximizing the rate of consumption of wind power by the natural gas system is set as an objective of optimization based on the conversion of electric energy of the P2G equipment into natural gas. Minimizing carbon emissions is set as another objective based on the effect of carbon capture of the P2G equipment. To reduce the likelihood of the optimal solution falling into a local optimum, the multi-objective optimal scheduling model is solved using the improved cuckoo algorithm.

2. The operating structure of the gas–electricity interconnection system is constructed in light of uncertainty in the output of wind power. CVaR theory is used to obtain typical scenarios of the output of a wind farm through the density-based clustering of the results of searches of historical data on wind speed. The uncertainty in the output of wind power is described as the risk of demand for the system’s reserves, and the cost of capacity reserve is designed in the multi-objective model to minimize the target.

1.3 | Organization of this paper

The remainder of this paper is organized as follows: Section 2 describes the logical relationship of the IEGES, and a multi-objective optimization model of it in case of uncertain output of the wind turbine is constructed. Indicators for operational evaluation are also introduced and are used to measure the efficiency of IEGES scheduling. Section 3 details the design of a fuzzy algorithm for solving the multi-objective optimization model by using the sigmoid function. In Section 4, we use a 10-node power system and a six-node natural gas system as examples of simulations to verify the proposed model. Section 5 summarizes the conclusions of this research.

2 | MULTI-OBJECTIVE OPTIMIZATION MODEL FOR INTERCONNECTED GAS–ELECTRICITY ENERGY SYSTEM

2.1 | Analyzing integrated gas–electricity energy system under uncertain wind power

The P2G equipment can flexibly realize the coupling of the interconnected gas–electricity energy system. Based on energy center model theory, wind turbines, coal-fired units, gas CHP units, and gas networks are considered in the input link. P2G is assumed to be at the center of the linked energy equipment, such as gas turbines, gas boilers, gas storage tanks, and pressurized stations. The energy-related needs are considered in the output link, including the demands for natural gas, heat, and electricity. Considering the uncertainty of integration of the interconnected gas–electricity energy system in the context of wind power, the operational structure of P2G in it is shown in Figure 1.

Figure 1 shows that the P2G equipment helps couple gas and electricity in the energy system. The effect of coupling by the P2G equipment involves splitting water into oxygen and hydrogen through electrolysis, converting electrical energy into artificial natural gas, and injecting the converted natural gas into natural gas pipelines and gas storage tanks for transportation or storage. Therefore, the P2G equipment enables the use of the two systems of gas and electricity as backups, which improves the flexibility of operation of the integrated energy system. The process of coupling of the P2G energy conversion equipment in the integrated gas–electricity energy system is shown in Figure 2.

Figures 1 and 2 show that the coupling performance of P2G is reflected in the unequal supply and demand of the power system. The power generated exceeds the demand for power, especially during the period of low night power load level and high output of wind power level, P2G electrolysis. The tank performs the electrolytic methanation reaction, converts electrical energy into artificial natural gas, and injects it into natural gas pipelines and gas storage tanks for transmission or storage. The P2G equipment is also a load point for the power system and thus can be used as a backup power source for shaving peaks and reducing congestion. It can also
be used as a source point for gas in natural gas systems for transmission.

2.2 | Multi-objective optimization model

2.2.1 | Objective functions

1. Minimizing operating costs

In the context of the operating cost of the integrated gas–electricity energy system, this paper considers the cost of power generation of the coal-fired unit, the cost of gas supply from the source of natural gas, and the operating costs of the gas storage tank and the P2G equipment. In addition, it is assumed that the operating costs of the wind turbine and other equipment of the system is zero. The mathematical model of the operating cost of the integrated gas–electricity energy system is as follows:

\[
\min C_{\text{total}} = C_{\text{coal}} + C_{\text{gas}} + C_{\text{tank}} + C_{\text{P2G}}
\]  

\[
C_{\text{coal}} = s \Omega^{x} \in \sum_{i=1}^{T} q_{i} \Omega_{i}^{x} \in \sum (a_{i} + \beta_{i} P_{i,t}^{\text{coal}} + \gamma_{i} P_{i,t}^{\text{coal}^{2}})
\]  

\[
C_{\text{gas}} = s \Omega^{x} \in \sum_{i=1}^{T} q_{i} \Omega_{i}^{x} \in \sum c_{i}^{\text{gas}} q_{i,t}^{\text{in}}
\]
C_{tank}^{s} = \sum_{t=1}^{n} q_{s}^{m} \in \sum_{t=1}^{T} (c_{t}^{in} q_{s, t}^{in} + c_{t}^{out} q_{s, t}^{out}) \quad (4)

C_{P2G}^{s} = \sum_{t=1}^{n} q_{s}^{P2G} \in \sum_{t=1}^{T} c_{t}^{P2G} p_{P2G, t} \quad (5)

In the above formula, \(C_{total}^{s}, C_{coal}^{s}, C_{gas}^{s}, C_{tank}^{s}, \) and \(C_{P2G}^{s}\) are the total operating cost of the integrated energy system, the cost of power generation of the coal-fired unit, the cost of the source of the natural gas generated, and the operating costs of the gas storage tank and the P2G equipment, respectively; \(\Omega_{s}, \Omega_{t}^{u}, \Omega_{t}^{y}, \Omega_{t}^{m}, \) and \(\Omega_{t}^{P2G}\) are scenario sets for the nodes representing the coal-fired unit, source of natural gas, gas storage tank, and the coupling grid for P2G equipment, respectively. \(T\) is a dispatch cycle, \(q_{s}\) is the probability of occurrence of a given scenario, \(\alpha_{t}, \beta_{t}, \) and \(\gamma_{t}\) are the cost functions of the coal-fired unit of the first node, a constant term, and the primary and the term coefficients, respectively. \(p_{coal}^{s, t}\) and \(p_{P2G}^{s, t}\) are the output of the coal-fired unit at the first node and the rate of gas flow of the P2G equipment, respectively, \(c_{i, t}^{gas}, c_{i, t}^{in}, c_{i, t}^{out}, \) and \(c_{i, t}^{P2G}\) are the price of the source of natural gas of the first node, intake of the gas tank, gas output, flow price, and operating cost per unit gas flow of the P2G equipment, respectively, and \(Q_{i, t}^{source}, Q_{i, t}^{in}, \) and \(Q_{i, t}^{out}\) are the output of the source of natural, inlet of the gas tank, and outlet gas flow, respectively, at the first node under scenario \(S,\) respectively.

2. Maximizing rate of consumption of wind power of natural gas system

This paper builds an optimized model of a P2G-integrated gas–electricity interconnection energy system that has aims different from that of traditional models—maximizing the rate of consumption of wind power. The proposed model can be used to measure the consumption of wind power by the P2G equipment participating in operation scheduling and can make full use of its coupling characteristics to improve the overall benefit to the gas–electricity interconnection energy system. The mathematical model of the rate of consumption of wind power of the natural gas system is as follows:

\[
\frac{\partial}{\partial t} = \frac{P_{total \_wind}^{P2G, t} - \sum_{t=1}^{T} \sum_{j=1}^{T} p_{P2G, t, j}}{P_{total \_wind}^{P2G}}
\]

In the above formula, \(P_{total \_wind}^{P2G}\) is the total output of the wind turbine, \(P_{P2G}\) is the active power of P2G, and \(\Omega_{P2G}\) is the collection of the P2G equipment.

3. Minimizing total carbon emissions

This paper builds an optimization model for an integrated gas–electricity energy system, in which the P2G participates, that is different from traditional models used to reduce carbon emissions. We design a goal that can be used to measure the contribution of the P2G equipment to reducing carbon emissions. In this way, the effect of carbon capture of the P2G equipment can be fully utilized to improve the environmental benefits of the system. The mathematical model of the total reduction in carbon emissions by the system is as follows:

\[
\max \Delta E = E_{C} - (E_{T} - E_{CO2})
\]

In the formula, \(E_{C}\) represents the total carbon emissions of the system without P2G, \(E_{T}\) is the total carbon emissions of the system with P2G, and \(E_{CO2}\) is the mass of carbon dioxide absorbed during the dispatch period \(T.\) \(c_{C, t}\) and \(c_{T, t}\) are, respectively, the consumption of coal and natural gas by the \(i\)-th generating unit in the dispatch period when the P2G was connected and when it was not, \(f_{E}\) represents carbon emissions generated by the complete combustion of standard coal or natural gas per unit, and \(v\) is the coefficient of carbon capture that represents the total amount of carbon dioxide that can be captured by the unit output of the P2G equipment.

4. Minimizing the cost of spare capacity

Uncertainty in the output of wind turbines leads to the provision of reserve capacity when the interconnected gas–electricity energy system is optimally dispatched. The P2G equipment has a short response time, and the cost of providing backup capacity is lower than that in conventional units. Once it has been connected to the interconnected gas–electricity energy system, P2G can replace conventional units to provide system backup services.

In accordance with the above, this paper uses the power of wind turbines connected to the grid as a benchmark to quantify error in forecasts of the output of wind power, that is, the system’s reserve demand:

\[
\begin{align*}
\Delta q_{s}^{e} & = \max [\Delta t, \Omega_{s} \in \sum_{i, j, t} P_{L, i, j} + j \Omega_{P2G} + \sum_{i, j, t} P_{P2G, i, j} - k \Omega_{W} \in \sum_{i, j, t} P_{w, f, k, l} (1 + e) - m \Omega_{gen} \in \sum_{i, j, t} P_{gen, m, t} 0] \\
\Delta q_{i}^{e} & = \max [\Omega_{s} \in \sum_{i, j, t} P_{L, i, j} + j \Omega_{P2G} + \sum_{i, j, t} P_{P2G, i, j} - k \Omega_{W} \in \sum_{i, j, t} P_{w, f, k, l} (1 + e) - m \Omega_{gen} \in \sum_{i, j, t} P_{gen, m, t} 0]
\end{align*}
\]
In the formula, $\Delta q^+_i$ and $\Delta q^-_i$ are the overestimated and underestimated system reserve requirements for wind power, respectively. $P_{t,u,t}$, $P_{w,u,k,t}$, and $P_{gen,m,t}$ are, respectively, the electrical load, output of, and output of the conventional unit, and $e$ is the percentage of error in the forecasted wind power, which is a random variable. When $e$ is less than zero, this represents an overestimated output of wind power. $i, j, k, m$ are the numbers of electrical loads, items of P2G equipment, wind turbines, and conventional units, respectively, and $\Omega_L, \Omega_W, \Omega_{gen}$ are the collections of electrical loads, wind turbines, and conventional units, respectively.

And are the probabilities of not exceeding a certain threshold, the specific mathematical model, namely:

$$
\begin{align*}
\varphi(\Delta q^+_i, \delta_1) &= \Delta q_i e \delta_1 \leq p(e)de \\
\varphi(\Delta q^-_i, \delta_2) &= \Delta q_i e \delta_2 \leq p(e)de
\end{align*}
$$

(9)

where $p(e)$ is the probability density function of the percentage of error $e$ in the forecasted wind power.

Conditional value at risk (CVaR) can overcome the shortcomings of value at risk (VaR). It can describe the distribution of risk outside the given confidence level and quantify loss under uncertainty. Let the loss functions $f_k(x, \xi) \in \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$ related to the decision variables $x \in X \subset \mathbb{R}^n$ be continuous functions, and let $\xi$ be a continuous random variable that represents random factors that may affect the loss function. If there is a probability density function $p(z)$, the distribution function, $f_k(x, \xi)$, is

$$
k(x, y_k) = P[f_k(x, \xi) \leq y_k | f_k(x, z) \leq p(z)dz]
$$

(10)

The weight of each loss function is defined as $\tau$, and the loss function $f_k(x, y_k)$ is introduced; then, the VaR loss value of the decision variable $x$ based on the weight at confidence level is:

$$
\phi(x, y^*(x, \tau)) = \sum_{i=1}^n \tau_i \phi_{\beta_i}(x, y^*(x, \tau))
$$

(11)

where $\beta_i$ is the confidence level for different loss functions.

CVaR theory is used to describe the uncertainty in wind power as a risk of demand for the system’s reserves. According to it, under given confidence levels $\beta_1, \beta_2 (\beta_1, \beta_2 \in [0, 1])$, the risks of demand for reserves $\Delta q^{+, \text{CVaR}}_{\beta_1,t}$ and $\Delta q^{-, \text{CVaR}}_{\beta_1,t}$ are overestimated or underestimated:

$$
\begin{align*}
\Delta q^{+, \text{CVaR}}_{\beta_1,t} &= \Delta q^{+, \text{VaR}}_{\beta_1,t} + \frac{1}{1-\beta_1} \Delta q^+_t e \Delta q^{+, \text{VaR}}_{\beta_1,t} + \int \Delta q^+_t e p(e)de \\
\Delta q^{-, \text{CVaR}}_{\beta_1,t} &= \Delta q^{-, \text{VaR}}_{\beta_1,t} + \frac{1}{1-\beta_2} \Delta q^-_t e \Delta q^{-, \text{VaR}}_{\beta_2,t} - \int \Delta q^-_t e p(e)de
\end{align*}
$$

(12)

Combined with the quick density clustering-based search algorithm to simulate scenarios for the output of wind power, discrete CVaR is used because it is convenient for optimization-related calculations. $\Delta q^{+, \text{CVaR}}_{\beta_1,t}$ and $\Delta q^{-, \text{CVaR}}_{\beta_1,t}$ can then be given as:

$$
\begin{align*}
\Delta q^{+, \text{CVaR}}_{\beta_1,t} &= \Delta q^{+, \text{VaR}}_{\beta_1,t} + \frac{1}{1-\beta_1} \sum_{i=1}^T \max(\Delta q^+_t(e') - q^+_\text{VaR}, 0) \\
\Delta q^{-, \text{CVaR}}_{\beta_1,t} &= \Delta q^{-, \text{VaR}}_{\beta_1,t} + \frac{1}{1-\beta_2} \sum_{i=1}^T \max(\Delta q^-_t(e') - q^-_{\text{VaR}}, 0)
\end{align*}
$$

(13)

In the formula, $\psi$ is the number of scenarios, and $e'$ is the percentage of error in the wind power in random scenario $I$ generated by sampling by using the Cauchy distribution proposed in Ref.\textsuperscript{23}

This paper considers uncertainty in the system’s wind power generation, utilizes the low cost of P2G to provide services for backup capacity, and quantifies the cost of the system's backup capacity:

$$
\begin{align*}
\min C^{\text{capacity}} &= \sum_{i=1}^T (m\Omega \in \sum \rho_{\text{re,gen,m}} (\Delta P_{\text{gen,m},i}^+ + \Delta P_{\text{gen,m},i}^-) + \beta P_{\text{P2G}} \in \sum \rho_{\text{re,P2G,m}} \Delta P_{\text{P2G,m},i})
\end{align*}
$$

(15)

In the formula, $\rho_{\text{re,gen,m}}$ is the cost of the capacity coefficient of a conventional unit.

2.2.2 Constraints on power system

As shown in the operating structure in Figure 1, the power system includes thermal power units, gas CHP, gas turbines, and electrical load users. It needs to meet system constraints during operation as follows:

1. Constraints on power balance

The generated power and electric power in the integrated gas–electricity energy system need to be instantaneously balanced:

$$
P_{\text{load}} = P_{\text{t,u,t}} + P_{\text{wind,t}} + P_{\text{gu,t}} + P_{\text{chp,t}} + P_{\text{msp,t}} - P_{\text{P2G,t}}
$$

(16)

In the formula, $P_{\text{load}}$ is the demand of the system for electrical energy, $P_{\text{t,u,t}}$, $P_{\text{wind,t}}$, $P_{\text{gu,t}}$, $P_{\text{chp,t}}$, and $P_{\text{P2G,t}}$ are, respectively, the real-time powers of the coal-fired unit, wind turbine, gas turbine, P2G equipment, and gas CHP unit of the system, and $P_{\text{msp,t}}$ is the demand for electric power that the system cannot satisfy.
2. Constraints on unit output

The output of the units is limited by the relevant maximum and minimum parameters:

\[
\begin{align*}
P_{emin} & \leq P_e \leq P_{emax}, \quad \forall e \in \Omega^{iu}, \Omega^{gu} \\
P_{wind} & = \begin{cases} 
0, & v < v_{in}, \quad v > v_{out} \\
\frac{P_{rated}}{v_{rated}} (v^3 - v_{in}^3) - \frac{P_{rated}}{v_{rated}} (v_{out}^3 - v_{in}^3), & v_{in} \leq v \leq v_{rated} \\
\frac{P_{rated}}{v_{rated}} (v_{rated}^3 - v_{out}^3), & v_{rated} \leq v \leq v_{out}
\end{cases}
\end{align*}
\]  

(17)

(18)

In the formula, \(\Omega^{iu}\) and \(\Omega^{gu}\) are the coal-fired unit set and the gas turbine unit set, respectively. \(P_{emin}\) and \(P_{emax}\) are the upper and lower limits of the unit’s active output, respectively. \(P_{rated}\) the rated output power of the fan, \(v_{in}\) is its cut-in wind speed, \(v_{out}\) is its cut-out wind speed, and \(v_{rated}\) is its rated wind speed.

3. Unit climbing constraint

The climbing of the unit is limited by its maximum and minimum speeds during the climbing process:

\[ -R_{e}^{down} \Delta t \leq P_{e,t} - P_{e,t-1} \leq R_{e}^{up} \Delta t, \quad \forall e \in \Omega^{gu}, \Omega^{iu} \]  

(19)

\(R_{e}^{down}\) and \(R_{e}^{up}\) are the upward and downward climbing rates of the unit, respectively.

4. Constraints on reserve capacity

The constraints on the reserve capacity of the power system at any time are as follows:

\[
\begin{align*}
\sum_{i} P_{CHP,i}^{max} + \sum_{i} P_{wind,i}^{max} + \sum_{i} P_{tu,i}^{max} & \geq L_{i}^{max} + S_{i}
\end{align*}
\]  

(20)

\(L_{i}^{max}\) represents the maximum electrical load of the system at moment \(i\), \(S_{i}\) represents the system's backup capacity, which is usually proportional to, represents the maximum installed capacity of the CHP unit associated with the energy center, \(P_{wind,i}^{max}\) represents the maximum installed capacity of the wind turbine; and represent the maximum installed capacity of the conventional unit.

2.2.3 Constraints on natural gas system

As shown in the operational structure in Figure 1, the natural gas system includes a gas source, a pressurized station, and a gas storage tank. It needs to meet the system constraints during operation as follows:

1. Constraints on power balance

The natural gas system of the interconnected gas–electricity energy system needs to maintain a balance between the demand for and supply of gas:

\[
wk \in \sum q_{well}^{out} + k \in \sum (q_{well}^{out} - q_{well}^{in}) = q_{load}^{out} + gk \in \sum q_{gu}^{out} + ck \in \sum q_{chp}^{out}
\]  

(21)

\(q_{load}^{out}\) is the demand for natural gas, \(q_{gu}^{out}\) is the consumption of natural gas by the gas unit, \(q_{chp}^{out}\) is the consumption of natural gas by the gas CHP unit, \(q_{well}^{out}\) is the output flow rate of gas at source \(w\) source at time \(t\), and \(q_{well}^{in}\) and \(q_{chp}^{in}\) are the gas flow rates at the outlet and inlet of the pipeline, respectively.

2. Constraints on output of gas source

The output of the gas source is restricted by the upper and lower output limits:

\[
qu_{w, min} \leq q_{well}^{out} \leq qu_{w, max}
\]  

(22)

In the formula, \(q_{w, min}\) is the output flow rate of source \(w\) at time \(t\); and \(q_{w, min}^{out}\) and \(q_{w, max}^{out}\) are the upper and lower output limits of \(w\), respectively.

3. Constraints on node pressure

The pressure of nodes of the natural gas is limited by the upper and lower limits of pressure that can be withstood:

\[
p_{k, min} \leq p_{k,t} \leq p_{k, max}
\]  

(23)

\(p_{k,t}\) is the pressure of node \(k\) of natural gas at time \(t\), and \(p_{k, min}\) and \(p_{k, max}\) are the upper and lower limits of pressure at \(k\), respectively.

4. Pressurization station

During the transmission of gas in pipelines, a certain loss in transmission occurs due to the friction of the wall and changes in the terrain. We consider only the relationship of an increase in pressure between the inlet and outlet, and the capacity of the pressurization station:

\[
p_{tl} \leq \xi \times p_{k,t}
\]  

(24)

In the formula, \(\xi > 1\) is the compression constant used to ensure that natural gas flows from the low-pressure node to the high-pressure node.
5. Gas storage tank

The gas storage tank is limited by its own storage capacity as well as the gas intake and output at each moment. The constraints on the gas storage tank within a dispatch cycle are as follows:

\[
E_t^i = E_{s,j-1} + Q_{s,j}^{in} - Q_{s,j}^{out} \\
E_{s,min}^i \leq E_t^i \leq E_{s,max}^i \\
Q_{s,min}^{in} \leq Q_{s,j}^{in} \leq Q_{s,max}^{max} \\
Q_{s,min}^{out} \leq Q_{s,j}^{out} \leq Q_{s,max}^{max}
\]  

(25)

In the formula, \(E_{s,j}^i\) is the storage capacity of the natural gas storage tank at time \(t\), \(E_{s,min}^i\) and \(E_{s,max}^i\) are the minimum and maximum gas storage capacities, respectively, of \(s\), and \(Q_{s,min}^{in}\) and \(Q_{s,max}^{max}\) are the maximum and minimum limits on gas flow, respectively, of \(s\).

2.2.4 | Constraints on thermal system

As shown in the operating structure in Figure 1, the components of the thermal energy system include the heat source of the CHP unit and the gas boiler. The thermal energy system needs to meet the following system constraints during operation:

1. Constraints on power balance

The thermal energy system needs to maintain a balance between the demand for and supply of the heat load:

\[
c\Omega_{chp} \in \sum H_{c,j}^{chp} + H_{t}^{nh} = H_{t}^{load}
\]  

(26)

In the formula, \(H_t^{load}\) is the demand of the system for heat energy, \(H_{t}^{nh}\) is the unsatisfied power of the system, and \(H_{c,j}^{chp}\) is the output of thermal power of the CHP unit at time \(t\).

2. Constraints on CHP output

The output of the CHP is limited by the upper and lower parameters of output:

\[
H_{c,j}^{chp} = cm_{c}^{chp}(T_r^{c} - T_{c,j}^{e})
\]  

(27)

In the formula, \(c\) is the specific heat capacity of water; \(m_{c}^{chp}\), \(T_r^{c}\), and \(T_{c,j}^{e}\) are the flow of hot water, temperature of the water supplied, and the return water temperature at the outlet of the CHP unit, respectively.

3. Constraints on gas boiler

The thermal power of the gas boiler is limited as:

\[
0 \leq P_{gu}\leq P_{max}\leq P_{max,gu}
\]  

(28)

\(P_{max}\) is the upper limit of the output of the thermal power of the gas boiler.

2.2.5 | Constraints on coupling elements

Components in the proposed system that can help with coupling include the P2G equipment, gas turbines, and CHP units. When the interconnected gas–electricity energy system is operating, the coupling constraints must be met as follows:

1. Constraints on P2G power

\[
0 \leq P_{P2G}\leq P_{P2G,max}
\]  

(29)

In the formula, \(P_{P2G,max}\) is the upper limit of the electric power of the P2G device.

2. Constraints on P2G conversion

During P2G conversion, the efficiency of energy conversion is constrained as follows:

\[
P_{P2G} = \frac{Q_{P2G} \times \eta_{P2G}}{GHV}
\]  

(30)

\(P_{P2G}\) is active power consumed by the P2G equipment, \(Q_{P2G}\) is natural gas flow generated by it, \(\eta_{P2G}\) is the efficiency of conversion of the P2G equipment, and \(GHV\) is the calorific value of natural gas.

3. Constraints on CHP unit conversion

The electrical and thermal outputs of the CHP unit must satisfy the following:

\[
P_{c,j}^{chp} = k_{c,j}^{chp} H_{c,j}^{chp}
\]  

(31)

In the formula, \(k_{c,j}^{chp}\) is the electric heat ratio of the unit.

The consumption of the CHP unit is constrained by the efficiency of conversion:

\[
ck \in \sum q_{c,j}^{chp} = \sum (P_{c,j}^{chp} + H_{c,j}^{chp})/\eta_{c,j}^{chp}/H_{GV}
\]  

(32)

\(\eta_{c,j}^{chp}\) is the efficiency of conversion of the CHP, and \(H_{GV}\) is the high heating value of natural gas, which was 39 MJ/m³.

4. Constraints on gas turbine conversion

The gas turbine needs to meet the following constraint in case of gas-to-electricity conversion:

\[
gk \in \sum q_{g,j}^{gu} = gk \in \sum p_{g,j}^{gu}/\eta_{gu}/H_{GV}
\]  

(33)
\( \eta_{gt} \) is the efficiency of conversion of the gas turbine.

# 3 | ALGORITHM FOR SOLVING OPTIMIZATION MODEL

## 3.1 | Standard multi-object cuckoo algorithm

The multi-object cuckoo algorithm was proposed by Yang Xinsh\textsuperscript{e} in Cambridge University in 2013. The algorithm has been widely used for optimization owing to its simple structure and highly efficient search. In the standard multi-object cuckoo algorithm, the formulae for the cuckoo search path and position update are as follows:

\[
x_{i}^{t+1} = x_{i}^{t} + \alpha \odot \text{levy}(\beta) \\
\alpha = a_{0}(x_{i}^{t} - x_{j}^{t})
\]

\( x_{i}^{t} \) is the position of birdhouse in generation of birdhouses, \( \alpha \) is the step size used to control the search range of the algorithm, \( \odot \) is point-to-point multiplication, and \( a_{0} \) is a constant, often taken as 0.01. The flight \( \text{levy} \) provides a random walk that obeys the following distribution:

\[\text{levy} \sim u = t^{-1-\beta}(0 < \beta \leq 2)\]

In the optimization algorithm, the complete \( \text{levy} \) distribution, used to make full use of the local optimal solution, is as follows:

\[
a_{0}(x_{j}^{t} - x_{i}^{t}) \odot \text{levy}(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}}(x_{j}^{t} - x_{i}^{t})
\]

\( u \) and \( v \) both obey the normal distribution, and \( \Gamma \) is the standard chi-squared distribution:

\[
\delta_{u} = \left\{ \frac{\Gamma(1+\beta)\sin(\pi \beta/2)}{\Gamma(1+\beta/2)\beta \times 2^{\beta-1/2}} \right\}^{1/\beta}
\]

\( \delta_{\gamma} = 1 \)

## 3.2 | Improved cuckoo algorithm

In the standard multi-object cuckoo algorithm, the magnitude of flight step control is fixed. The original population is updated after random walk in which it loses poor individuals with the probability of discovery “pa,” and randomly generates a new solution. This does not guarantee the convergence and accuracy of optimization of the algorithm in case of few iterations. In light of the shortcomings of the standard algorithm, the improved multi-objective cuckoo search algorithm (IMOCS) is proposed here by considering the selection of the leader, updates to the location of the bird nest, maintenance of the external archives, and the elite learning strategy.

### 3.2.1 | Choice of leader

The choice of leader includes the local and global optima. When the population is selected, the local optimum is the best position of the bird’s nest identified at the time, that is, the optimal set of values in the multi-objective optimization-based control of the variable representing sewage treatment. The relationship of Pareto dominance is used to determine the local optimum. If the new solution following an update in the location of the bird’s nest dominates the old one, the latter replaces the former; otherwise, the new solution does not replace the old one.

The global optimal is the best position of the bird’s nest discovered by all individuals in the initial field of nest positions and guides the direction of evolution of the population. For multi-objective optimization problems, the global optimum is a set of Pareto solutions, and an optimal solution needs to be selected for each position of the bird’s nest. In the standard optimization algorithm, the global optimal solution is chosen from within the population after discarding the probability of discovery and generating a new solution, which leads to insufficient diversity in the population. In light of this, the authors use non-dominant sorting plus the elite learning strategy to select the global optimal solution to enhance population diversity and the range of search of the optimal solution.

### 3.2.2 | Updating location of bird nest (Pareto distribution)

In the standard multi-object cuckoo optimization algorithm, the position of the bird’s nest is updated using Pareto distribution. When this is used to solve multi-object optimization problems, its speed of convergence and accuracy decrease. Because the Pareto distribution has the advantages of a faster convergence and more accurate optimization than the \( \text{levy} \) distribution, Cauchy distribution, and Gaussian distribution, it is more suitable for complex optimization problems. Based on the Pareto distribution, the global walk is defined as:

\[
x_{i}^{t+1} = x_{i}^{t} + \alpha \ast \text{rand}_{1} \ast x_{i}^{\text{new}}
\]

where \( \alpha \) is the magnitude of step control, and,

\[
x_{i}^{\text{new}} = \frac{1}{\sqrt{1 - \text{rand}_{2}}} \ast (x_{i}^{t} - x_{i}^{t})
\]
In the above, \( rand_1 \) and \( rand_2 \) are random numbers, which is often set to 0.01. However, in the initial stage of optimization, the multi-object cuckoo optimization algorithm needs to ensure a larger step size to obtain a wider search range to avoid falling into a local optimum. However, as the number of iterations increases, the process of optimization requires a smaller step size to enable the process of convergence to gradually approach the global optimum. Therefore, the magnitude of constant step control reduces the speed of convergence and, thus, degrades the effect of optimization. After several simulations, the basic Pareto distribution \( \alpha \ast rand_1 \) was adjusted and replaced with Formula (41). The adaptive control of step size helps optimize the position of the bird’s nest, enabling it to converge more quickly and making it less likely for it to fall into the local optimum:

\[
\alpha \ast rand_1 = e^{-\rho \ast \left( \frac{\text{iter}}{\text{max iter}} \right)^p}
\]  

(41)

where \( \rho \) is 30.

### 3.2.3 Maintenance of external archives

Choosing the crowded distance method can help maintain the diversity of solutions. Based on the standard multi-object cuckoo optimization algorithm, the degree of crowding is calculated and sorted, first according to the level and then according to the size of the crowding distance at the same level. Individuals at lower levels are first selected. If two individuals are at the same level, the one with higher levels of crowding is selected. After sorting, the first \( n \) rows of elements equal to the size of the population are selected to form a new population, which is used to initialize the population in the next iteration.

### 3.2.4 Elite learning strategies

In the standard MOCS, the probability of discovery is used to discard and randomly generate new solutions. However, for complex multi-objective optimization problems in practice, it is difficult to avoid the local optimum when relying only on the mutation operation of the population. Based on this, the authors propose a process of evolution of elite learning strategies to obtain non-dominant solutions. We combine the population updated by the Pareto distribution and that updated by discarding the worst solution with the probability of discovery, and then select the non-inferior solution set equivalent to the size of the population.

To verify the performance of the algorithm, the authors used typical test functions of the ZDT and SCH series in MATLAB2014a to conduct numerical experiments. The test function is shown in Appendix A, Table A1.

### 3.3 Steps of the algorithm

The main task of the IEGES multi-objective optimal dispatch model is to minimize operating cost, maximize the rate of consumption of natural gas for wind power, minimize total carbon emissions, and minimize the cost of spare capacity. The various types of units are scheduled for 24 hours. The internal force value is used as a control variable to find the optimal solution to the optimization problem and deal with multiple, conflicting objective functions. This helps make the best possible use of P2G’s functional characteristics under the premise of minimizing operating costs and improving the system’s rate of consumption of wind power. The detailed steps are as follows:

Step 1: Initialize the parameters, set the population size to, optimize the upper and lower limits of the set values
lb and, respectively, and initialize the maximum number of iterations to \( m_{\text{iter}} \) and the size of the external file to.

Step 2: Initialize nest 1 and find its objective function; select the non-dominant solution through non-dominant sorting; and output the result as the Pareto solution.

Step 3: If the number of iterations is less than or equal to the maximum number of iterations, go to step 4; otherwise, go to step 7.

Step 4: Use formulae (39)-(41) to update the position and state of the bird's nest, and find the value of its target function. Record the updated population as nest 2, discard the worst position of the bird's nest with the largest probability of discovery, and update the generation substitute solution nest 3.

Step 5: Merge parent nest 2 with child nest 3, select the first \( n \) rows of the non-dominant solutions through non-dominant sorting and store them in the external file set, and use the crowded distance method to maintain the external file set.

Step 6: Iterate, \( t = t + 1 \), and go to step 3.

Step 7: Output the global optimal position, that is, the optimal solution of the output of each unit in the dispatch cycle.

4 | SIMULATION EXAMPLE

4.1 | Basic data

Consider an interconnected gas–electricity energy system consisting of a 10-node power system and a six-node natural gas system. The schematic diagram of the operational structure of the system is shown in Figure 3.

In the six-node natural gas system, node 1 was connected to the P2G equipment and node 3 was connected to a gas unit. The maximum gas supply of each source of gas in the natural gas system was 10 Mm³/h. The relevant parameters of the source point of gas and the gas storage tank are shown in Table 1.

In the 10-node power system, the coal-fired units were located at nodes 3, 6, 7, 8, and 9, the wind turbines and P2G equipment were located at node 5, and the gas units were located at node 10. The parameters of each generator set are shown in Table 2.

Table 3 shows the parameters of the P2G device.

The P2G equipment and gas units had dual roles in the power system and the natural gas system. P2G could be used as a power load or source of natural gas at the same time, and the gas unit could be used as a source of power or a natural gas load simultaneously. Therefore, to better study the role of P2G technology in promoting the optimal operation of the integrated gas–electricity energy system, we defined the integrated electrical load and gas load and analyzed the efficiency of optimization due to the participation of P2G in the system’s scheduling operation:
1. Comprehensive electrical load: This is the difference between the electrical load, the sum of the power used by P2G equipment, and the output of the gas unit.
2. Comprehensive gas load: This is the difference between the gas load, the sum of the gas flow of the gas unit, and the gas flow of the P2G equipment.

In addition, parameters of the output of the wind turbine are, and, the shape parameter and the scale parameter and. Using the method to simulate scenarios of wind power proposed in Ref.,36 50 groups of outputs of such scenarios were randomly sampled. Then, using the scene reduction technology proposed in Ref.,37 10 groups of typical simulation scenarios for wind power were screened out. Fast search-based density clustering was used to obtain typical scenes of six sequences of outputs of wind power as well as the probability of occurrence of each scene, as shown in Figure 4.

As shown in Figure 5, there were many typical outputs of the wind power scenarios considered, and the probability of occurrence of each was not considerably different from that of another. Scenario 1 had the highest probability of occurrence, its output was high, and peak-valley differences were small. Therefore, scenario 1 was selected as an example of the simulation to predict wind power.

Forecasts of the electric load, gas load, and output of wind power of the integrated gas–electricity energy system in this paper are shown in Figure 5.

### Table 2: Genset parameters

| Node | Unit type | Rated power/GW | Minimum output/GW | Climbing rate/MW min⁻¹ | Capacity spare cost/$ MW⁻¹ |
|------|-----------|----------------|-------------------|------------------------|--------------------------|
| 3    | Coal fired| 0.500          | 0.100             | 1.000                  | 2.500                    |
| 6    | Coal fired| 0.900          | 0.050             | 1.300                  | 2.770                    |
| 7    | Coal fired| 0.600          | 0.110             | 0.970                  | 2.420                    |
| 8    | Coal fired| 0.500          | 0.100             | 1.000                  | 2.890                    |
| 9    | Coal fired| 0.500          | 0.100             | 1.000                  | 1.500                    |
| 5    | Wind turbine| 1.500        | 0.000             | -                      | 0.000                    |
| 10   | Gas       | 1.000          | 0.000             | 5.500                  | 0.400                    |

### Table 3: Parameters of P2G device

| Parameter | Value |
|-----------|-------|
| $c_{P2G}/($ $MW⁻¹$) | 20.000 |
| $P_{P2G,max}/MW$ | 1.270 |
| $η_{G2P}/%$ | 40.000 |
| $η_{P2G}/%$ | 60.000 |
| $ρ_{P2G}/($ $MW⁻¹$) | 1.190 |
| $T$ | 24.000 |

### 4.2 Scenario setting

Using the integrated gas–electricity energy system composed of a 10-node power system and a six-node natural gas system, this study set-up three scenarios. The system structures of these scenarios are shown in Table 4.

The percentage of error in the forecasted wind power followed the Cauchy distribution. The price of the source of gas, increase in gas load, capacity of the P2G equipment, and confidence level are shown in Table 5.

### 4.3 Results of simulations of different scenarios

Following the optimization of the system schedule, 1 day was equivalent to one scheduling cycle, and the interval was 1 hour. Unit schedules under different scenarios are shown in Figure 6.

Based on the resultant angle of the target of operation, the results of different scenarios are shown in Table 6.

The system could be roughly divided into two operating states, at night (1-6 hours, 23-24 hours) and in the daytime (7 hours–22 hours). At night, the demand for various types of power loads was low. When the gas turbines were running at low output, the output of the wind turbine was at its peak. This is the reverse peaking characteristic of wind power. Therefore, nighttime was the peak period of wind curtailment. When P2G was not connected, the system could not apply the effect of carbon capture, and the total reduction in carbon emissions was zero. The high output of wind turbines at night was not absorbed by the natural gas system, because of which its rate of wind power absorption was zero. Because the system's capacity reserve due to the output of wind power at night was provided by the gas CHP unit at night, the capacity reserve of scenario 1 was the highest.

Because there was a large surplus in wind power at night and its output during the day was lower, P2G was used only at night. Compared with the results of scheduling of scenario 1, those of scenario 2 were superior. The operating costs and cost
In addition, due to the use of P2G equipment, the effects of wind power absorption and carbon capture were evident, and the rate of consumption of wind power by the natural gas system and its reduction of total carbon emissions improved, showing that the P2G equipment could optimize the results of scheduling of the integrated gas–electricity energy system.

**TABLE 4** Scenario settings of the optimization model

| Scenario | Coal fired | Wind turbine | CHP | Gas unit | P2G | P2G provides spare capacity |
|----------|------------|--------------|-----|----------|-----|-----------------------------|
| 1        | ✓          | ✓            | ✓   | ✓        | ×   | ×                           |
| 2        | ✓          | ✓            | ✓   | ✓        | ✓   | ×                           |
| 3        | ✓          | ✓            | ✓   | ✓        | ✓   | ✓                           |

*Note:* The symbol ✓ represents participation in the operation of system optimization, and the symbol × denotes a lack of such participation.

**TABLE 5** Parameter settings for the scenarios

| Parameter                               | Value |
|-----------------------------------------|-------|
| Gas source 1 price                      | 0.11  |
| Gas source 2 price                      | 0.14  |
| P2G equipment conversion capacity (GW)  | 0.003 |
| Confidence level $\beta$                | 0.2   |

of capacity reserve fell by 19.56% and 15.21%, respectively. In addition, due to the use of P2G equipment, the effects of wind power absorption and carbon capture were evident, and the rate of consumption of wind power by the natural gas system and its reduction of total carbon emissions improved, showing that the P2G equipment could optimize the results of scheduling of the integrated gas–electricity energy system.
Compared with scenario 2, the operating cost and cost of capacity reserve in scenario 3 were further reduced by 17.80% and 64.72%, respectively. The decrease in capacity cost occurred because P2G equipment can provide cheaper backup services. In addition, the system reduce carbon emissions by more. Compared with scenario 2, the reduction in carbon emissions in scenario 3 was higher by 145.52 tons. This was due to the provision of backup capacity services by P2G, which contributed to the reduction in the output of conventional units. However, due to the capacity backup service provided by the P2G equipment, the rate of consumption of wind power by natural gas system decreased by 0.85% in scenario 3 compared with scenario 2.

### 4.4 | Analysis of results

To assess the role and efficiency of the P2G equipment in the system, we compared the difference between the integrated electrical load and the simple electrical load in scenarios 1 and 3. This helped clarify the optimal efficiency of the P2G equipment in the power system, as shown in Figure 7.

Figure 7 shows that during periods of peak electric load, the combined electrical loads of scenarios 1 and 3 were higher than the simple electrical load because the gas generator was used to shave the peak in this period to reduce the electric load. As the price of the source of natural gas decreased, the intensity of "peak-cutting" of the electric load increased. In the period with low electric load, the difference between the integrated electric load of scenario 1 and the electric load was small. Scenario 3 had a higher integrated electrical load than simple electrical load because the P2G equipment converted excess electrical energy in the power system into artificial natural gas and sent it to the natural gas system, thereby "filling the valley" of the electrical load. Therefore, the P2G equipment can be combined with gas turbines to attain "peak load" and "fill valleys" in the electric load in the power system.

Once the P2G equipment provided the backup service, the negative backup of the conventional unit was provided by it. At a confidence level of 0.2, the risk of abandonment of the wind turbine and demand for output power in scenarios 2 and 3 are shown in Figure 8.

As is shown in Figure 8, if the P2G equipment in the interconnected gas–electricity energy system provided backup services, most load from conventional units was transferred to it. In scenario 3, the rate of transfer of negative reserve of conventional units was 59.03%. This reduced pressure on the conventional unit to provide negative backup and ensured that it could operate at a lower pressure limit during the period of generation of a large magnitude of wind power, such as between points 1 and 7. This was conducive to promoting the consumption of wind power by the integrated energy system.

Because P2G equipment can increase the reserve capacity of the system, it can reduce the risk of a reduction in the output power of the wind turbine in case of uncertain wind power. At a confidence level of 0.2, we compared scenarios 1 and 2 with scenario 3, the rate of system abandonment of which was significantly lower, by 6.88% and 0.64%, respectively.

In summary, the P2G equipment significantly optimized the power system by reducing the rate of abandonment of the wind turbine, cutting the peak and filling the valley of the electric load, and reducing total carbon emissions and the cost of spare capacity.

### 5 | CONCLUSIONS

This study constructed a multi-objective optimization model of an integrated gas–electricity energy system under uncertain access to wind power. To verify the effectiveness of the model, we used a 10-node power system and a six-node natural gas system as examples in simulations. The following conclusions can be drawn:

1. The overall efficiency of optimization of the system showed that once P2G equipment had been connected to it, it reduced the total operating cost and increased the rate of consumption of wind power by the natural gas system regardless of whether it provided backup.
services. Its effect of carbon capture also helped reduce carbon emissions by the system. The provision of capacity reserve by the P2G equipment reduced its rate of utilization. Compared with scenario 2 in the examples considered, the rate of utilization of the P2G equipment in scenario 3 decreased by 6.84%.

2. The results of optimization of the power system show that the P2G equipment can be combined with gas-fired CHP units to "cut peaks and fill valleys" in electrical loads. In scenario 3, when the P2G equipment provided backup services, the rate of negative reserve transfer of conventional units was 59.03%, which reduced pressure on them to provide negative backup.

This paper focused on the problem of multi-objective energy scheduling for an integrated gas–electricity energy system and considered only the logical relationship between the center of energy conversion and each energy system. In future research, it is important to consider the uncertainty brought about by system operation, and to formulate a demand response mechanism to improve the economics of the system.
CONFLICT OF INTEREST
No conflicts.

ORCID
Bowen Yang https://orcid.org/0000-0003-3480-3349

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## APPENDIX A

### TABLE A1 Standard test functions

| Name | Objective function | Optimal solution | Performance         |
|------|--------------------|------------------|---------------------|
| SCH  | $f_1(x) = x^2$     | $x \in [0, 2]$  | Convergent          |
|      | $f_2(x) = (x - 2)^2$ |                  |                     |
| ZDT1 | $f_1(x) = x_1$     | $x_1 \in [0, 1]$| Convergent          |
|      | $f_2(x) = g(x)[1 - \sqrt{x_1/g(x)}]$ | $x_1 = 0$     |                     |
|      | $g(x) = 1 + 9\left(\sum_{i=2}^{n} x_i/(n-1)\right)$ | $i = 2, \ldots, n$ |                     |
| ZTD2 | $f_1(x) = x_1$     | $x_1 \in [0, 1]$| Not convergent      |
|      | $f_2(x) = g(x)[1 - (x_1/g(x))^2]x$ | $x_1 = 0$     |                     |
|      | $g(x) = 1 + 9\left(\sum_{i=2}^{n} x_i/(n-1)\right)$ | $i = 2, \ldots, n$ |                     |
| ZTD3 | $f_1(x) = x_1$     | $x_1 \in [0, 1]$| Convergent but discrete |
|      | $f_2(x) = g(x)[1 - \sqrt{x_1/g(x)} - \frac{x_1}{g(x)}\sin(10\pi x_1)]$ | $x_1 = 0$     |                     |
|      | $g(x) = 1 + 9\left(\sum_{i=2}^{n} x_i/(n-1)\right)$ | $i = 2, \ldots, n$ |  |