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Edge-cloud collaborative architecture based multi-time scales rolling optimization of regional integrated electrical and natural gas energy system considering wind power uncertainty

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Abstract

With the serious energy crisis and speedy development of natural gas utilization, regional integrated electrical and gas energy system is an efficient way to improve energy potency. This paper studies the energy scheduling of integrated electrical and gas energy system with bi-directional energy conversion at distribution network level, considering wind power uncertainty. To realize independent autonomy of energy networks, meantime adjusting scheduling strategies of integrated energy system from system-level perspective, innovative edge-cloud collaborative operation architecture is proposed. In edge servers, electrical and gas networks are optimized severally for scheduling strategies. In cloud server, the uncertainty of wind power are processed with robust optimization method, strategies of energy conversion units are updated for re-optimization. Cooperated with edge-cloud architecture, a novel multi-time scales rolling optimization framework is proposed, electrical and gas networks are optimized under day-ahead time scale in corresponding edge servers, and electrical network is further adjusted under intraday time scale in electrical edge server. Case studies show that edge-cloud collaborative operation architecture can ensure the practical feasibility of optimization, which is more suitable for energy scheduling of integrated electrical and gas energy system. Multi-time scales rolling optimization framework have significant efficiency on reducing the impact of wind power uncertainty.

1 | INTRODUCTION

In recent years, as a low cost and high efficiency clean energy, natural gas has become the second largest energy resource around the world. In China, 4% power is provided by natural gas, and in United States and United Kingdom, this proportion rose to 39% and 32%, respectively [1]. Natural gas unit (NGU) has increased interdependence between electrical and natural gas network [2], particularly in distribution level. In addition, as a brand new energy conversion technology, power to gas (P2G) further intensified the coupling between two energy networks [3, 4]. A bi-directional energy conversion structure has constructed by NGU and P2G, which resulted in more flexible energy management [5]. On the other hand, energy crisis and environmental degradation have promoted the wide use of renewable energy. Its uncertainties brought difficulties to schedule energy between two energy systems [6]. According to above, under the condition of large-scale renewable energy access, in order to realize the efficient utilization of heterogeneous energy in regional integrated electrical and natural gas energy system (IEGES) at distribution network level, more feasible operation architecture and efficient optimization framework are desperately required to optimize the energy scheduling strategies.

One of the difficulties in obtaining the optimal energy scheduling strategies for IEGES containing heterogeneous energy is that, the closure and privacy of information in different energy networks require the system to own a practical and sensible information flow interactive architecture. Existing researches generally assumed that a vertically centralized cloud operator monitors and controls the entire IEGES, all the decisions were made within the cloud server, which would increase...
the computational complexity and the burden of data exchange. Faridpak et al. [7] proposed a multi-step strategy with surrogate Lagrange relaxation for co-optimization of IEGES, although relaxation method was utilized to consider the constraints of both networks at the same time, the optimization process was still conducted under a cloud architecture. Wang et al. [8] studied the optimal operation of IEGES with consideration of renewable energy uncertainties, also cloud architecture was assumed in the optimization and problem was constructed and solved as a mixed-integer linear programming (MILP) model. However in reality, two energy networks in IEGES are commonly managed by completely different operators, for instance in China and some other countries [9], cloud computing architecture is not practical for IEGES energy scheduling optimization. Under cloud architecture, electrical network and gas network need to share their respective parameters and information in the cloud to conduct centralized optimization. However, in reality, the sharing of information between different energy networks does not accord with the actual independently operating situation of both networks, nor conducive to protecting the data privacy of them. Moreover, with the expansion of the scale or quantity of the energy networks, a large amount of uplink data floods into the cloud operator, which is also highly likely to cause the computing capacity overload of the cloud server and affect the optimization efficiency of the integrated energy network. The scalability of the whole cloud optimization framework is poor due to this. And the transmission distance between the cloud and various energy networks is relatively long, and the transmission delay may lead to the difficulty in the unification of the optimization time scale among different energy networks. In order to ensure the independent operation of both networks and reduce the information interaction between them, edge-cloud collaborative operation architecture is considered to be suitable for IEGES. Edge computing can realize the migration of centralized computing from the cloud to each edge server, this separated and independent operation architecture perfectly accords with the particular operation model of electrical network and gas network in IEGES. Two energy networks can achieve optimal energy scheduling in their respective edge servers, which ensures the data security and privacy. Relatively, some shareable computing tasks can be migrated from the edge servers to the cloud, such as prediction of renewable energy generation, simulation of uncertainties, update of electricity and gas price. By this way, the computational burden of edge servers can be reduced and computing resources in the edge-cloud collaborative architecture can be rationally utilized. Using this hierarchical edge-cloud operation architecture, independent autonomy of the power grid and gas network can be realized in edge servers, system-level iteration and update of relevant scheduling parameters can be realized in cloud server. The feasibility of the entire operation architecture and also the effectiveness of energy scheduling strategies in IEGES can be ensured. From our known, the edge-cloud collaborative architecture is the first time to be applied to the optimization of energy scheduling strategies in IEGES.

On the other hand, in consideration of optimizing the energy scheduling strategies of IEGES under wind power uncertainty, efficient optimization framework is required to cooperate with the edge-cloud collaborative architecture. The optimization framework of IEGES has been studied in a lot of researches. Zhao et al. [10] proposed a stochastic optimization framework to optimize IEGES, the variability of gas supply and gas price were taken into consideration. Electricity and gas networks were coupled tightly by NGU, an unified probabilistic power and gas flow model was applied to consider the uncertainties of state variables in IEGES [11]. Chen et al. [12] constructed a probabilistic energy flow to benefit both energy systems, considering energy hubs in IEGES as coupling units. Sardou et al. [13] proposed a multi-objective framework for the coordinated operation of IEGES, considering the security constraints of both networks. Zhang et al. [14] considered the constraints of gas transmission in stochastic day-ahead optimization of IEGES, the effect of random outages of generating units and transmission lines were analyzed. Previous researches primarily focused on the transmission network, however, because of the increasing coupling of power and gas systems in distribution networks [15], the optimization of IEGES at distribution level also has great significance. To this end, the scheduling of IEGES in this paper is carried out in a distribution network.

With the rapid development of renewable energy, the uncertainty become one of the factors affecting the optimization of IEGES [16]. Several researches have studied the effect of uncertainty. Qiao et al. [17] constructed a comprehensive optimization model considering wind power uncertainty. Interval solutions were utilized to reduce the effect of uncertainty on IEGES. Liu et al. [18] proposed a day-ahead economic dispatch model of IEGES, reserve scheduling was utilized to handle renewable energy uncertainty. Alabdulwahab et al. [19] constructed a stochastic day-ahead optimization model for minimizing the expected operating costs of IEGES, the flexibility of NGU was utilized to reduce the effect of wind power uncertainty. Robust energy scheduling model was proposed to optimize the dispatching strategy of IEGES, NGU was used to adjust the energy considering wind uncertainty and natural gas network security [20].

Although lots of efforts have been made in optimizing IEGES with uncertainty, most of them have not considered bi-directional energy conversion structure. However, the emerging P2G technology which deepened the coupling of electrical grid and gas network should be incorporated into the optimization [21]. Moreover, it is common to process renewable energy under single time scale when analyzing the uncertainty. The characteristics of renewable energy is not considered, which is the errors would decrease when the prediction is close to real time [22, 23]. This could be further used to reduce the influence of renewable energy uncertainty [24]. Qu et al. [25] constructed robust multi-objective optimization framework for day-ahead optimization of IEGES, interval robust dispatch method was applied to handle wind power uncertainty. He et al. [26] used P2G to collaboratively optimize energy conversion between two energy networks, the uncertainty was handled by robust scheduling model. With the utilization of P2G and NGU, a bi-directional energy exchange framework was established [27], to analyze the day-ahead scheduling under steady-state condition. However, the
research only focused on the analysis of the impact of P2G on the quantity of energy exchanged with renewable energy accessed. There was no consideration of uncertainty. Guandalini et al. [28] constructed an IEGES containing P2G to optimize the dispatching of wind power. Although a statistical approach was utilized to present the uncertainty, still only day-ahead prediction errors were adopted to deal with wind power. Here, for the aim of utilizing the characteristics of wind power, which is that the prediction errors of wind speed would decrease as if the prediction interval approaches real time, robust optimization is combined with multi-time scales rolling optimization to use more accurate predicted wind power in the scheduling under the edge-cloud collaborative architecture.

In addition to the above necessary edge-cloud collaborative architecture and multi-time scales rolling optimization framework, in IEGES, the non-linear and non-convex characteristics of gas flow constraint which seriously affect the solution accuracy also need to be dealt with. Many approaches were used to convexify and linearize the constraint which is described as Weymouth equation. Borraz et al. [29] used an efficient relaxation method to convert the constraint in gas network into mixed-integer second-order cone (MISOCP) form, so as to ensure the optimality and feasibility of the solution of IEGES. Heuristic algorithms such as genetic algorithm and particle swarm optimization algorithm were used to handle the non-linearity of the Weymouth equation [30, 31]. Bao et al. [32] used piecewise linearization to divide the Weymouth equation into several segments. The calculation complexity and computation accuracy are compromised depending on how many linearized segments are divided. Although linearization methods are applied to convert the constraint, the results are not reliable enough because of the untight conditions in the relaxation process. In this paper, a penalty function based second-order cone (SOC) relaxation is employed in the conversion process of the gas flow constraint, so as to improve the tightness of the SOC programming.

To sum up, the main contribution of this paper can be summarized as follows.

1) Considering the independence of electrical energy network and natural gas energy network in IEGES, in order to ensure the practicality and feasibility of information flow architecture within the process of energy scheduling optimization, an edge-cloud collaborative operation architecture of IEGES is proposed here. In edge servers layer, private data of two energy networks are processed and stored in their respective servers, different energy systems can be optimized independently. The shareable parameters that require to be updated will be uploaded to the cloud for processing after the optimization in each edge servers completed, so as to realize the system-level interaction of energy networks in IEGES. In cloud server layer, some shareable data, computing tasks and historical data can be processed and saved, for instance the updating of operation parameters uploaded from edge servers, the historical data of renewable energy and the prediction of renewable energy generation. Through this edge-cloud collaborative operation architecture, the energy networks can be optimized independently with edge servers, meanwhile, the computing resources of cloud server can be rationally utilized.

2) In order to cooperate with the edge-cloud collaborative operation architecture and make the scheduling strategies more accurate under uncertainty condition of wind power, a novel multi-time scales rolling optimization framework is established for IEGES. Different from the other rolling optimization in power system, in integrated energy system, different energy networks are optimized under different time scales considering their deviation of response speed, also the error of predicted wind power is further dealt with under each time scale. Under day-ahead time scale, the entire IEGES is optimized to obtain the operation strategy of each energy network in respective edge servers. Day-ahead predicted wind power handled with prediction errors is utilized. Under intraday time scale, rolling optimization is applied to regulate the strategy of electrical network in electrical edge server, so as to further reduce the operating costs of IEGES. With this optimization framework, predicted wind power which close to real time can be used to reduce the impact of uncertainty on the optimization of IEGES.

3) To further ensure the accuracy of optimization strategies obtained under the proposed operation architecture and optimization framework, an additional concave constraint based penalty function is adopted to convert the optimization into mixed-integer second-order cone programming (MISOCP) form. Different case studies are simulated and compared from energy scheduling level and system architecture level, respectively. The role of P2G in improving the utilization of wind power is compared and verified in the case studies from energy scheduling level. The advantage of proposed edge-cloud collaborative optimization architecture is demonstrated from the comparison of system architecture level.

The paper is organized as follows. Section 2 constructs the edge-cloud collaborative operation architecture of IEGES. Section 3 presents the multi-time scales rolling optimization framework and formulates the mathematical models. The specific process of edge-cloud collaborative operation and SOC relaxation are described in Section 4. Finally, the case studies and conclusions are given in Sections 5 and 6, respectively.

# 2 EDGE-CLOUD COLLABORATIVE OPERATION ARCHITECTURE

The hierarchical edge-cloud collaborative operation architecture of IEGES is constructed as Figure 1. From bottom to top, three layers which are bottom energy layer, middle edge server layer and upper cloud server layer are contained in this architecture. Information flows between three layers depending on the functions and tasks of different servers, the specific work of each layer is elaborated as follows.

1) Bottom energy layer

In IEGES, energy layer contains renewable energy, electrical network and natural gas network as shown in the
The main work of this layer is to realize the adjustment of energy among energy networks according to the obtained energy scheduling strategies. In electrical network, power load, energy storage system (ESS), demand response program (DRP) and P2G are considered, renewable energy is also accessed into electrical network as uncertainty energy resource. ESS and DRP are considered as flexible energy resource to reduce the fluctuation caused by the uncertainties of renewable energy and electrical loads. P2G can be utilized to convert exceed electricity to natural gas for higher renewable energy utilization. In natural gas network, gas load, gas suppliers, gas storage system (GSS) and NGU are contained. GSS provides the necessary flexibility to adjust the balance of supply and demand in gas network, and NGU can realize the conversion of natural gas resource to electric energy, so as to improve the efficiency of comprehensive energy. In this layer, the uncertainty of wind power is one of the factors affecting the energy scheduling strategies, which need to be dealt with. Meanwhile, NGU and P2G construct bi-directional energy exchange between electrical network and gas network during the dispatching. These factors determine that in the optimization of IEGES, not only the independent operation of each energy network needs to be ensured, but also the energy conversion between them needs to be adjusted from system-level perspective. Therefore, the collaborative operation of middle edge server layer and upper cloud server layer becomes the key to the decision of energy scheduling strategies in bottom energy layer.

2) Middle edge layer
Two edge servers are contained in this layer, which are utilized to realize the independent operation of electrical network and gas network. In corresponding edge server of electrical network, the optimization process aims at minimizing the operating costs of power system, through collecting the network topology structure, power load demand, ESS state and other parameter information in the bottom electrical network, strategies such as utilization of wind power, charge and discharge amount of ESS, purchased electricity and converted energy of P2G can be decided. In gas network edge server, the objective is to minimize the operating costs of gas network by reducing the amount of purchased gas from suppliers, information like parameters of nodes and pipelines, gas load demand, GSS state are collected from bottom layer and used to adjust the strategies of purchased gas, operation of GSS and converted gas amount of NGU. After the independent optimization in each edge server is completed, the obtained amount of converted energy by P2G and NGU need to be adjusted from system-level perspective. They would be considered as edge-cloud cooperative factors and uploaded to the upper cloud server, after being updated in the cloud, they would be returned to corresponding edge servers for the re-optimization of energy scheduling strategies. Middle edge server layer and upper cloud server layer are connected by edge-cloud cooperative factors, the entire edge-cloud collaborative optimization is conducted in the form of iterative updates.

3) Upper cloud layer
In upper cloud layer, the cloud server collects and processes complex information uploaded by the edge servers. With the sufficient storage capacity and powerful computing capacity of cloud servers, system-level scheduling strategy adjustments can be performed in the cloud. As seen in the architecture, wind power is another edge-cloud cooperative factor in this paper, the information of wind power would processed in cloud server. Considering the limited storage capacity of edge server and the sufficient computing capacity of cloud server, large amount of wind power historical data and simulation of wind power uncertainty are processed in cloud server. Wind power in different time scales need to be predicted and robust optimization method is utilized to simulate the uncertainty of wind power. Therefore, cloud server is utilized to handle with the information of wind power and then download them to corresponding edge server. On the other hand, the converted energy of P2G and NGU are also updated in cloud server. After the amount of converted energy of each iteration is submitted to the cloud, in order to ensure the most optimal costs of the entire IEGES, scheduling strategies of P2G and NGU would be updated and returned to the middle edge servers for the next iteration optimization. Through updating of parameters and iteration optimization of scheduling strategies, the cloud can adjust the energy in IEGES from a macro perspective.

Taking advantage of this edge-cloud collaborative operation architecture, the optimization can ensure the independent operation of each energy network, and meanwhile realize the energy adjustment of system level in IEGES.
3 | MULTI-TIME SCALES ROLLING OPTIMIZATION FRAMEWORK AND MATHEMATICAL MODELLING

3.1 | Multi-time scales rolling optimization framework

Although the edge-cloud collaboration operation architecture can ensure the practical feasibility of the optimization, still efficient optimization framework is required to ensure the accuracy of energy scheduling strategies under uncertainty conditions. Wind power uncertainty brings great difficulties to the optimization of IEGES, it is necessary to adopt more accurate forecast wind power to weaken its impact. Considering that the prediction errors of wind speed increase with the extension of prediction time horizon, the closer to real time, the more precise predicted results are. Rolling optimization is one of the most effective approaches to utilize this characteristics. Taking advantage of serialization time windows, more near real-time and accurate wind power can be used.

Multi-time scales rolling optimization framework is described in this section, day-ahead scheduling and intraday scheduling are contained as shown in Figure 2. This optimization framework is implemented in the edge servers corresponding to two energy networks in IEGES, day-ahead optimization is conducted in both edge servers, which means the entire IEGES is optimized to obtain the scheduling strategies for both networks. Day-ahead forecast wind power is obtained from the cloud server in the optimization. Intraday optimization is embedded in electrical network edge server, by using sliding time window of rolling optimization, more precise predicted wind power is obtained from the cloud server and applied in the edge servers during dispatching.

Different time scales are adopted during the complete optimization process, correspondingly, the fluctuations of the wind speed are not the same in different optimization stages. For optimization under day-ahead time scale, the energy scheduling strategies in both energy networks are optimized. In this process, because the wind power generation can only be predicted under day-ahead time scales, therefore in the first optimization stage of proposed multi-time scales rolling optimization framework, the fluctuations of wind speed are still assumed as 20%. Meanwhile, in this optimization stage, ESS and DRP are not taken into consideration. It is mainly because that, for the ESS, the relatively fast charge and discharge speed enables it to be used in the second optimization stage, which requires quick response of scheduling component. For the DRP, users need to change their consumption behaviour of energy to achieve flexible utilization of demand response load. Although incentive policies will be adopted, frequent changes in both optimization stage still would reduce their satisfaction. Considering these, the scheduling of ESS and DRP are optimized under intraday time scale. In the second optimization stage of proposed multi-time scales rolling optimization framework, only energy scheduling strategies in power grid are optimized in this process, because the gas network cannot be ensured to reach steady state again...
after each time optimization under this time scale. Rolling horizon optimization mechanism is adopted during the optimization, as a result, the fluctuations of wind speed are much smaller than that under day-ahead time scale, in this article, the fluctuations are assumed as 5% in this optimization stage. During the optimization in this stage, the strategies related to the gas network, such as the production of gas wells, the energy scheduling strategies of GSS and the converted gas from P2G facility, are still maintained as the results of the first stage. Besides, ESS and DRP are regarded as adjustable energy in this stage to reduce the impact of wind power uncertainty.

This multi-time scales optimization framework can effectively cooperate with the edge-cloud collaborative operation architecture, which not only makes efficient use of computing resources in the architecture, but also ensures the accuracy of predicted wind energy used in the optimization.

### 3.2 Mathematical modelling of IEGES

Most of the existing literatures on IEGES only considered NGU as coupling unit and optimized under the day-ahead time scale. However, P2G is a promising technology that can convert excessive power into natural gas, which intensifies the energy exchange in IEGES as another coupling unit. Meanwhile, when rolling horizon optimization is adopted for IEGES, the response speed of different networks should be considered to make appropriate adjustments.

In this section, the specific mathematical models of IEGES are presented. In order to consider the uncertainty of wind power and electrical loads, robust uncertain sets are adopted in the multi-time scales rolling optimization framework as follows.

#### 3.2.1 Uncertain sets of wind power and electrical loads

Because of the fluctuations of wind power and electrical loads in the IEGES, if the predicted values are directly used for scheduling without considering the uncertainties, the safe operation of IEGES may be affected. Therefore, according to robust optimization method, through adding corresponding prediction errors to the predicted values of wind power and electrical loads, robust uncertain sets are constructed to present the interval of these variables. During the optimization, by optimizing the scheduling strategies under the worst case in the robust uncertain sets, the results can be ensured to satisfy all the operating environments of IEGES. The specific uncertain sets of wind power and electrical loads are shown below:

\[
\begin{align*}
    \mathbf{u} &= [u^{WT}(t), u^{L}(t)]' \in \mathbb{R}^{2x2}, t = 1, 2, ..., T \\
    \mathbf{U} &= \begin{cases} 
    [u^{WT}(t), u^{L}(t)]' \in \mathbb{R}^{2x2}, t = 1, 2, ..., T \\
    u^{WT}(t) \in [\bar{u}^{WT}(t) - \Delta u^{WT}(t), \bar{u}^{WT}(t) + \Delta u^{WT}(t)] \\
    u^{L}(t) \in [\bar{u}^{L}(t) - \Delta u^{L}(t), \bar{u}^{L}(t) + \Delta u^{L}(t)]
    \end{cases}
\end{align*}
\]

in which, \(u^{WT}(t), u^{L}(t)\) are the uncertain variables of wind power and electrical loads. \(\Delta u^{WT}(t), \Delta u^{L}(t)\) are the prediction errors, which are distinguished in different time scales. It should be pointed out that the power factor of the wind turbine is assumed to be 1 here, therefore only the active power produced by the wind turbine is considered for scheduling [33]. According to the obtained robust uncertain sets, the scheduling strategies under the worst case can be obtained to ensure the safety and stability of IEGES.

#### 3.2.2 Objective function under day-ahead time scale

Day-ahead uncertain sets of wind power and electrical loads are used in this time scale. Since there is enough time for the gas network to reach steady state in this stage, the optimization is performed for the entire IEGES, the specific model is presented as Equation (2):

\[
C^{DA} = \min \sum_{t \in T} \left[ c_f(t) P_f(t) + \sum_{m \in \mathbb{M}} (c_w(P_w(t) - u^{WT}(t)) + c_{om} P_w(t)) \right] + \sum_{m \in \mathbb{M}_{gas}} \epsilon_{gas} Q_{gas}^{om}(t),
\]

where, the first term in Equation (2) is the cost of energy exchange between the distribution network and the main grid, \(c_f(t)\) and \(P_f(t)\) is the price and amount of exchanged power with main grid. The second term represents the punishment cost of wind power deviation, \(P_w(t)\) is scheduled wind power and \(u^{WT}(t)\) is forecast wind power in day-ahead time scale, \(c_w\) is the penalty price of the deviation of wind power, \(c_{om}\) is the operating and maintenance costs of wind turbines [34]. The third term is gas production cost of gas wells, which incurred in natural gas network. \(\epsilon_{gas}\) is the price of natural gas and \(Q_{gas}^{om}(t)\) is the amount of gas demand from the gas wells.

#### 3.2.3 Objective function under intraday time scale

Under this time scale, rolling horizon optimization mechanism is adopted to obtain more economical strategies. Since the gas network cannot be ensured to reach steady state again after each time optimization, therefore, only power grid participates in this optimization. The strategies related to the gas network, such as the production of gas wells, the strategy of gas storage and the converted gas from P2G facility, still maintain the results of the first stage. Besides, ESS and DRP are regarded as adjustable energy in this stage to reduce the impact of wind power uncertainty. The specific objective function is presented as
Equation (3).

\[ C^{INT} = \min_{t \in T} \left[ c_v(t) F_v(t) + \sum_{n \in \Omega_n} \left( c_w(F_w(t) - n_{tot}^{WT}) + c_{sw} F_s(t) \right) \right. \\
\left. + \sum_{d \in \Omega_{DR}} c_{DR} F_d^{DR}(t) + \sum_{g \in \Omega_{ESS}} c_{ESS}^{in} F_g^{ESS}(t) \right]. \]

The difference between Equations (2) and (3) is that, because of the sliding time window in this stage, the prediction errors used under this time scale are near real-time prediction errors, which are more accurate than the day-ahead forecast wind power adopted in the first stage. After each time rolling optimization, only the scheduling strategies of next 4 h [35, 36] would be submitted as the strategies to be executed by the operators. The first term in Equation (3) is still the cost of power exchange between the distribution network and the main grid. \( F_v(t) \) means the transferred power in this stage. The second term is also the penalty cost of wind power deviation, \( F_s(t) \) and \( n_{tot}^{WT} \) are scheduled wind power and forecast wind power in intraday time scale. The last term is the cost of implementing DRP in this stage. \( c_{DR} \) is the penalty cost of scheduled DR load and \( F_d^{DR}(t) \) is the scheduled DR load. \( c_{ESS}^{in} \) is the operating and maintenance costs of scheduled ESS and \( F_g^{ESS}(t) \) is the scheduled energy of ESS [34].

Taking advantage of the rolling horizon optimization to realize the collaborative scheduling of different time scales, the operating cost of the IEGES can be further reduced. In the process of optimization, the operational constraints of both networks must be met to ensure the safety and stability of the whole IEGES.

### 3.2.4 Constraints of electrical network

Traditional radial distribution network is adopted in this paper. Dist-Flow method [37] is utilized to deal with the power distribution flows as follows.

\[ P_{n+1}(t) = P_n(t) - \frac{r_n(P_n^2(t) + Q_n^2(t))}{V_n^2(t)} - u_{n+1}(t) + P_{s+1}(t), \]

\[ Q_{n+1}(t) = Q_n(t) - \frac{x_n(P_n^2(t) + Q_n^2(t))}{V_n^2(t)} - u_{n+1}(t) + Q_{s+1}(t), \]

\[ V_{n+1}^2(t) = V_n^2(t) - 2(r_n P_n(t) + x_n Q_n(t)) + \frac{(r_n^2 + x_n^2)(P_n^2(t) + Q_n^2(t))}{V_n^2(t)}, \]

where \( P_n(t) \) and \( Q_n(t) \) are the active and reactive power flowing from node \( n \) to the next node \( n + 1 \). \( r_n \) and \( x_n \) are resistance and reactance between node \( n \) and \( n + 1 \). \( V_n(t) \) represents the voltage of node \( n \). \( n_{tot}^{WT}(t) \) and \( Q_n(t) \) are the load demand of active and reactive. \( P_{s+1}(t), Q_{s+1}(t) \) are active and reactive power generation injected into node \( n \).

Linearized transformation of the Dist-Flow equations above is adopted to simplify the calculation [38–40] and the node voltage is limited to a safe range as follows:

\[ P_{n+1}(t) = P_n(t) - u_{n+1}(t) + P_{s+1}(t) - \text{char}^{ESS}(t) \eta F_g^{ESS, in}(t) \]

\[ + \text{dischar}^{ESS}(t) \frac{F_g^{ESS, out}(t)}{\eta}, \]

\[ Q_{n+1}(t) = Q_n(t) - Q_{s+1}(t) + Q_{s+1}(t), \]

\[ V_{n+1}(t) = V_n(t) - \frac{r_n P_n(t) + x_n Q_n(t)}{V_n^2(t)} \]

\[ \frac{r_n^2 + x_n^2}{V_n^2(t)} \]

\[ V_n^\text{min} \leq V_n(t) \leq V_n^\text{max}, \]

where \( \text{char}^{ESS}(t), \text{dischar}^{ESS}(t) \) are binary variables presented the operating state of ESS. \( \eta \) is the efficiency factor. \( F_g^{ESS, in}(t), F_g^{ESS, out}(t) \) are the scheduled energy of ESS. \( V_n^\text{min}, V_n^\text{max} \) limit the allowable range of node voltage during optimization.

\[ E_g^{ESS}(t) = E_g^{ESS}(t-1) + \text{char}^{ESS}(t) \eta F_g^{ESS, in}(t) \]

\[ - \text{dischar}^{ESS}(t) \frac{F_g^{ESS, out}(t)}{\eta}, \]

\[ 0 \leq \text{char}^{ESS}(t) + \text{dischar}^{ESS}(t) \leq 1, \]

\[ F_g^{ESS, min} \leq E_g^{ESS}(t) \leq F_g^{ESS, max}, \]

\[ F_g^{ESS, in, min} \leq F_g^{ESS, in}(t) \leq F_g^{ESS, in, max}, \]

\[ F_g^{ESS, out, min} \leq F_g^{ESS, out}(t) \leq F_g^{ESS, out, max}, \]

where \( E_g^{ESS}(t) \) is the amount of power retained in the ESS, \( F_g^{ESS, min}, F_g^{ESS, max} \) limit the bound of this amount. Equation (12) makes sure that the ESS cannot charge and discharge at the same time. The amount of each charge and discharge are constrained in Equations (14) and (15).

### 3.2.5 Constraints of natural gas network

Natural gas network is one of the most complex non-linear systems. Gas production wells, pipelines, gas consumers and GSS are contained in this network. Here, the steady-state natural gas flow is described with the Weymouth equation (16), which is widely adopted to construct the relationship between the
The widely use of NGU and P2G further intensifies the coupling between electrical network and natural gas network. In gas network, NGU is considered as gas loads, and its gas consumption is determined by the needed power in electrical network. Here, the startup and shutdown cost of NGU are also considered as part of the gas fuel cost and quantified by the amount of consumed gas. Thus, the model of NGU can be described with Equation (25). Similarly for the P2G facility, it is regarded as gas producer in the gas network, while consuming power in the electrical network. It can be modelled as Equation (26).

\[ Q^{\text{NGU}}_a(t) = \left[ F_v(t) + S_{\text{in}}^{\text{NGU}}(t) + S_{\text{out}}^{\text{NGU}}(t) \right] / HHV, \]  

(25)

\[ Q^{\text{P2G}}_a(t) = \phi P_{\text{NGS}}^{\text{P2G}}(t) \eta_{\text{P2G}}^{\text{NGS}} / HHV, \]  

(26)

where \( HHV \) and \( \phi \) are 1.026 MBtu/kcf and 3.4 MBtu/MWh, which presents the high heating value (HHV) of natural gas and magnitude conversion factor of P2G, respectively. \( F_v(\cdot) \) is the consumed fuel of NGU, which always considered as a quadratic function. \( S_{\text{in}}^{\text{NGU}}(t) \) and \( S_{\text{out}}^{\text{NGU}}(t) \) are the startup and shutdown cost of NGU. \( \eta_{\text{P2G}}^{\text{NGS}} \) is the efficiency of P2G facility.

### 4. OPERATION PROCESS OF EDGE-CLOUD COLLABORATIVE ARCHITECTURE

During the optimization of the whole IEGES, the amount of converted energy by P2G and NGU are considered as edge-cloud cooperative factors, they need to be uploaded to the cloud server after the optimization in each edge serve is completed. In the cloud server, they would be updated and then returned to the edge servers for next iteration. In order to realize the information interaction between edge servers and cloud server, auxiliary variables \( (\zeta_1, \zeta_2) \) are introduced to represent the scheduled energy of NGU and P2G in both networks, as shown in Equations (27)–(30). Through submitting these auxiliary variables to the cloud server, it can be ensured that there is no direct information exchange between electrical network and gas network in this architecture. Meanwhile, edge-cloud collaborative operation architecture can also be realized. The specific operating process of edge-cloud collaborative architecture can be seen in Figure 3.

\[ P_{\text{NGS}}^{\text{NGS}}(t, k) - \zeta_1(t, k) = 0, \]  

(27)

\[ P_{\text{NGS}}^{\text{P2G}}(t, k) - \zeta_2(t, k) = 0, \]  

(28)

\[ P_{\text{NGS}}^{\text{EN}}(t, k) - \zeta_1(t, k) = 0, \]  

(29)

\[ P_{\text{NGS}}^{\text{GN}}(t, k) - \zeta_2(t, k) = 0, \]  

(30)
in where, \(k\) is the iteration time of edge-cloud information updating, \(r, n\) are the index of NGU and P2G, respectively. Using variables \(\gamma_v\), the energy produced by NGU in electrical network and natural gas network are decoupled and represented as \(Q^{\text{rng,EN}}(t, k), Q^{\text{rng,GN}}(t, k)\) in Equations (27) and (28). Similarly, the consumed energy of P2G are also decoupled and expressed as \(P^{\text{PG,EN}}(t, k), P^{\text{PG,GN}}(t, k)\) in Equations (29) and (30).

\[
Q^{\text{rng,EN}}(t, k) = \left[ F^v_t (Q^{\text{rng,EN}}(t, k)) + S_{\text{rng}}^v(t, k) \right] / HHV, \\
Q^{\text{rng,GN}}(t, k) = \left[ F^v_t (Q^{\text{rng,GN}}(t, k)) + S_{\text{rng}}^v(t, k) \right] / HHV,
\]

\[
P^{\text{PG,EN}}(t, k) = \phi P^{\text{PG,EN}}(t, k) \eta_{\text{PG}} / HHV, \\
P^{\text{PG,GN}}(t, k) = \phi P^{\text{PG,GN}}(t, k) \eta_{\text{PG}} / HHV.
\]

According to Equations (25) and (26), \(Q^{\text{rng,GN}}(t, k)\) and \(Q^{\text{PG,GN}}(t, k)\) are the gas consumption of NGU \(v\) and the gas output of P2G \(u\) in the gas network. Similarly, \(Q^{\text{rng,EN}}(t, k)\) and \(Q^{\text{PG,EN}}(t, k)\) are the duplicated variables utilized in the electrical network. \((\gamma_v, \gamma_u)\) ensure the variables of NGU and P2G used in both networks are equal to each other.

By leveraging the auxiliary variables, edge-cloud collaborative architecture can be implemented and the integrated objective function can be formulated as Equation (35). In turn, the optimization can be naturally decomposed into a electrical network subproblem Equation (36) and a natural gas network subproblem Equation (37), which can be solved in corresponding edge servers, respectively.

1) Integrated objective function:

\[
\text{Cost} = \min \sum_{t \in T} \left[ c^v_t (P^v_t) + \sum_{u \in \Omega} c^u_r (P^u_r - \eta_{\text{PG}} (\hat{w}_t^u)) \right] + \sum_{u \in \Omega} \gamma_u \left( Q^{\text{PG,EN}}(t) - \gamma_u^t \right) + \rho_a / 2 (Q^{\text{PG,GN}}(t) - \gamma_u^t)^2
\]

2) Electrical network subproblem:

\[
\text{Cost}^{\text{EN}} = \min \sum_{t \in T} \left[ c^v_t (P^v_t) + \sum_{u \in \Omega} c^u_r (P^u_r - \hat{w}_t^u) \right] + \sum_{u \in \Omega} \gamma_u \left( Q^{\text{PG,EN}}(t) - \gamma_u^t \right) + \rho_a / 2 (Q^{\text{PG,GN}}(t) - \gamma_u^t)^2
\]

3) Natural gas network subproblem:

\[
\text{Cost}^{\text{GN}} = \min \sum_{t \in T} \left[ \sum_{u \in \Omega} \gamma_u \left( Q^u(t) - \gamma_u(t) \right) + \rho_a / 2 (Q^u(t) - \gamma_u(t))^2 \right]
\]

Through the iteration, variables \(P^v_t, P^u_r, P^{\text{PG,EN}}(t, k + 1)\) and \(P^{\text{PG,GN}}(t, k + 1)\) can be optimized.

4) Cooperating process:

Cloud server is responsible for updating the constraints related to auxiliary variables. After receiving the duplicated...
variables of NGU and P2G ($P^{\text{ngu},\text{EN}}_a(t, k + 1)$, $P^{\text{ngu},\text{GN}}_a(t, k + 1)$, $P^{\text{pg2e},\text{EN}}_a(t, k + 1)$, $P^{\text{pg2e},\text{GN}}_a(t, k + 1)$) from edge servers, cloud server checks the convergence criteria of iterative optimization. If not satisfied, cloud server would update the auxiliary variables and related multipliers with Equations (38)–(43) for the next iteration.

$$z_u(t, k + 1) = \frac{1}{2}(P^{\text{ngu},\text{EN}}_a(t, k + 1) + P^{\text{ngu},\text{GN}}_a(t, k + 1)),$$

(38)

$$z_v(t, k + 1) = \frac{1}{2}(P^{\text{pg2e},\text{EN}}_a(t, k + 1) + P^{\text{pg2e},\text{GN}}_a(t, k + 1)),$$

(39)

$$\lambda^{\text{EN}}_u(t, k + 1) = \lambda^{\text{EN}}_u(t, k) + \rho_u(P^{\text{pg2e},\text{EN}}_a(t, k + 1) - z_u(t, k + 1)),$$

(40)

$$\lambda^{\text{GN}}_u(t, k + 1) = \lambda^{\text{GN}}_u(t, k) + \rho_u(P^{\text{pg2e},\text{GN}}_a(t, k + 1) - z_u(t, k + 1)),$$

(41)

$$\lambda^{\text{EN}}_v(t, k + 1) = \lambda^{\text{EN}}_v(t, k) + \rho_v(P^{\text{ngu},\text{EN}}_a(t, k + 1) - z_v(t, k + 1)),$$

(42)

$$\lambda^{\text{GN}}_v(t, k + 1) = \lambda^{\text{GN}}_v(t, k) + \rho_v(P^{\text{ngu},\text{GN}}_a(t, k + 1) - z_v(t, k + 1)).$$

(43)

These updated variables and multipliers would be sent back to corresponding edge servers of electrical network and gas network for the next iteration until the convergence criteria is satisfied.

5) Process of algorithm:
In the studied problem of IEGES in this article, convergence thresholds usually depend on the desired proximity of the scheduled energy amount of energy conversion devices, which are choices based on experience. Here, considering the base power of electrical network is 10 MVA, the convergence thresholds are selected as 0.02, which means the allowable gap between scheduled amount of NGU and P2G is 2 kW [26]. The specific process of edge-cloud collaborative operation architecture is explained in Appendix A.2 as Algorithm 1.

4.1 Conversion of non-linear gas network constraints
Due to the highly non-linearity of constraints (16) and (25), the subproblem of natural gas network is non-convex and hard to solve with commercial solvers. In order to make the problem convexity, SOC relaxation is adopted to these constraints, and an additional concave constraint based penalty function method is introduced to guarantee the tightness of relaxation.

Specifically, constraints (25) can be converted to SOC form directly, as shown in Equation (44), it is always tight in this subproblem, because the minimization of objective would eliminate unnecessary gas consumption of NGU.

$$Q^{\text{ngu}}_a(t) \geq \frac{1}{HHV} [F^{\text{EN}}_a(P^{\text{ngu},\text{EN}}_a(t)) + SL^{\text{ngu}}_a + SD^{\text{ngu}}_a(t)].$$

(44)

By adding binary auxiliary variables $I^+_a, I^-_a$ to represent the gas flow directions in the gas pipeline, the highly non-linear steady-state gas flow constraints (16) can be reformulated as a mixed-integrated non-linear program (MINLP) form shown in Equations (45)– (48), considering that the squared of node pressure $\pi_a$ can be seen as constant, therefore $\omega_a$ is adopted to replace the squared of $\pi_a$.

$$((I^+_a(t) - I^-_a(t))(\omega_a(t) - \omega_b(t)) = \left(\frac{1}{C_{ab}}\right)^2 GF^2_{ab}(t),$$

(45)

$$I^+_a(t) + I^-_a(t) = 1, $$

(46)

$$\omega_{a \min} \leq \omega_a(t) \leq \omega_{a \max},$$

(47)

$$-1 - I^+_a(t)GF_{ab \max} \leq GF_{ab}(t) \leq -1 - I^-_a(t)GF_{ab \max}. $$

(48)

Furthermore, by replacing Equation (45) with Equations (49)– (53), mixed-integrated second-order cone program (MISOCP) form of constraints can be obtained:

$$\Psi_{a \ b}(t) \geq \left(\frac{1}{C_{ab}}\right)^2 GF^2_{ab}(t), $$

(49)

$$\Psi_{ab}(t) \geq \omega_a(t) - \omega_b(t) + (I^+_a(t) - I^-_a(t) + 1)(\omega_{a \min} - \omega_{b \max}),$$

(50)

$$\Psi_{ab}(t) \geq \omega_a(t) - \omega_b(t) + (I^+_a(t) - I^-_a(t) - 1)(\omega_{a \max} - \omega_{b \min}),$$

(51)

$$\Psi_{ab}(t) \leq \omega_b(t) - \omega_a(t) + (I^+_a(t) - I^-_a(t) + 1)(\omega_{a \max} - \omega_{b \min}),$$

(52)

$$\Psi_{ab}(t) \leq \omega_a(t) - \omega_b(t) + (I^+_a(t) - I^-_a(t) - 1)(\omega_{a \min} - \omega_{b \max}).$$

(53)

Equations (49)– (53) are McCormick envelope [43, 44] used to limit $\Psi_{a b}$. When constraints (49) is tight, SOC constraints (49)–(53) can be used to replace constraint (45). However, unforeseeable relaxation gap of SOC may occur during optimization, which would lead the obtained solution infeasible to the original problem. For this reason, an additional concave constraint based penalty function method is adopted to drive constraint (49) tight when solving the subproblem of natural gas network, the concave constraint is shown as
Figure 4: The structure of IEGES

Equation (54):

\[ \psi_{ab}(t) - \left( \frac{1}{c_{ab}} \right)^2 GF^2_{ab}(t) \leq 0. \]  

After introducing constraint (54), the problem is converted to an MISOCP with concave constraint. In order to solve it, constraint (54) is approximated by a first-order Taylor expansion as follows:

\[ \psi_{ab}(t) - \left( \frac{1}{c_{ab}} \right)^2 GF^2_{ab}(t, k - 1) + 2GF_{ab}(t, k - 1)(GF_{ab}(t, k) - GF_{ab}(t, k - 1)) \leq \alpha_{ab}(t, k), \]  

\( \alpha_{ab} \) is a non-negative slack variable and used as a penalty term in subproblem as described in Equation (56). \( \xi(t, k - 1) \) is a gradually increasing penalty factor which is used to drive the \( \alpha_{ab} \) to zero. When the convergence criteria (57), (58) are satisfied, constraint (54) can be tightly represented by (55). Otherwise, the penalty factor \( \xi(t, k - 1) \) would be updated by Equation (59). \( \gamma_g \) is set as 10 and \( \gamma_\alpha \) is set as 1, they are used to limit the allowable gap.

5 CASE STUDIES

Here, an IEGES consisting of an IEEE 33-bus radiation distribution network and a Belgian 20-node natural gas network is utilized to analyze the effectiveness and validity of the proposed edge-cloud collaborative operation architecture and multi-time scales rolling optimization framework. The numerical simulations are operated on Matlab R2016b platform with a Core I7-6700, 3.40 GHz, 16 GB RAM personal computer, the proposed MISOCP problem is solved by CPLEX 12.6.

Figure 4 shows the structure of IEGES which contains a wind turbine (WT) with capacity of 6 MW, an electrical storage system (ESS) of 1 MW, a NGU and a P2G facility with capacity of 1.5 MW, a GSS with capacity of 60 kcf and two gas wells (GWs). The reference voltage of electrical network is 12.66 kV and each node is allowed a \( \pm 5\% \) pu fluctuation, the base power is 10 MVA. DR loads are considered in bus 2, 7, 22, which take in 30%, 40%, and 30% of the load in these bus. Time of use...
(TOU) electricity price is adopted to incent the DR loads to participate in scheduling, the uncertainty of electricity price is not the main concern in this article. With this structure, a bi-directional energy exchange system is realized. For the compactness of the article, some important parameters in the optimization is given in the Appendix A.4.

In this section, first, the results of multi-time scales rolling optimization are compared with day-ahead optimization. Then, the effect of P2G on reducing the penalty of wind power uncertainty is studied. At last, the optimization results with edge-cloud collaborative operation architecture is compared with that of centralized cloud optimization and fully decentralized optimization.

5.1 The worst case of wind power and electrical loads

Robust optimization method is one of the common methods to solve optimization problems involving uncertain random variables, which has low computational complexity and can great simulate the uncertainty of renewable energy. During the optimization process, the uncertain sets are used to describe the fluctuation interval of the random variables, within this interval, get the worst case for the objective function and optimize the scheduling strategies under this scenario. By this method, the optimized scheduling strategies are robust to various fluctuation cases. Here, the uncertainties of wind power and electrical loads are handled with robust optimization method in the cloud server.

The optimization goal is to minimize operating costs at each stage, so the worst cases of wind power and electrical loads are the scenarios that take the most operating costs. According to previous researches [45], when the wind power is at the lower limit of the fluctuation range and the electrical loads are at the upper limit, the system operation costs is the highest, this scenario is the worst case in the uncertain sets. As the uncertain sets of wind power in optimization of two time scales are different, the worst cases are also not the same, which are shown below:

1) Day-ahead time scale

In Figure 5, the worst cases of wind power and electrical loads are shown. Under this time scale, it is assumed that the fluctuations of wind speed and electrical loads are 20%. When the costs of buying electricity is high, generation of wind power and demand of electrical loads are the lowest and highest, respectively.

2) Intraday time scale

Under this time scale, more accurate predicted wind power is utilized. In each rolling optimization, the fluctuations of wind speed are assumed to be 5%. On the other hand, since the forecast errors of electrical loads is relatively stable, it is still considered as 20% in the optimization. The worst cases are shown in Figure 6. After each optimization, the scheduling strategies of the following 4 h are considered to be the required operating strategies of IEGES.

5.2 Effectiveness of multi-time scales rolling optimization framework

In order to illustrate the effectiveness of multi-time scales rolling optimization framework, the results are compared with that of single time scale day-ahead optimization which is widely used in many researches before. Under day-ahead time scale, the cases of wind power and electrical loads in Figure 5 are utilized. NGU and P2G are operated as the coupling units of two energy networks, so as to obtain the optimal cost of the whole IEGES.
With the utilization of edge-cloud collaborative operation architecture, the power produced by NGU and consumed by P2G can be obtained and listed in Table 1. The negative values in the table represent the consumed power by P2G facility in electrical network. It can be seen from Table 1 that, because of the fluctuations of wind power, the demand and supply of power cannot be satisfied all the time depending on the wind power. In order to save the operating costs of IEGES as much as possible, when wind power cannot meet the demand of electrical loads, NGU would operated to supply energy for the distribution network, and when the wind power supply exceeds the electrical demand in some periods, P2G is adopted to convert exceeded wind power to natural gas for storing. By this bi-directional energy conversion approach, the utilization of wind power can be improved and the total operating costs of integrated energy system can be saved.

In natural gas network, the gas flow of each pipeline and the pressure of each node can be obtained after day-ahead optimization, in this article, the capacity of each gas pipeline is limited as 50 kcf, and the pressure boundaries of each node are also limited and given in the Appendix A.3. It can be seen in Tables 2 and 3 that they are all constrained by the operation conditions of natural gas network. The transferred natural gas from two gas wells are also shown in Figure 7.

After the optimization under day-ahead time scale is completed, the operating cost of IEGES can be obtained and listed in Table 4. As shown in the table, the total cost is 90,725.29 RMB, the operating cost of electrical network is 23,971.26 RMB and the cost of natural gas network is 60,779.40 RMB, The deviation amount of wind power is 11.47 MW in this stage, which led to 4015.75 RMB penalty costs.

In order to further reduce the operating cost of IEGES, as described in Section 2, rolling horizon mechanism is utilized under intraday time scale to further dispatch the energy in

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**TABLE 1** Scheduled energy of NGU and P2G

| Time interval | Produced power of NGU (MW) | Consumed power of P2G (MW) |
|---------------|---------------------------|----------------------------|
| 1             | 0                         | -0.137                     |
| 2             | 0                         | -0.108                     |
| 3             | 0.940                     | 0                          |
| 4             | 0                         | -0.194                     |
| 5             | 0.948                     | 0                          |
| 6             | 0                         | -0.185                     |
| 7             | 0.933                     | 0                          |
| 8             | 0                         | -0.067                     |
| 9             | 0.980                     | 0                          |
| 10            | 0.966                     | 0                          |
| 11            | 0.997                     | 0                          |
| 12            | 0.998                     | -0.077                     |
| 13            | 0                         | -0.077                     |
| 14            | 0.989                     | 0                          |
| 15            | 0                         | -0.074                     |
| 16            | 0                         | -0.126                     |
| 17            | 0.970                     | 0                          |
| 18            | 0.955                     | 0                          |
| 19            | 0.935                     | 0                          |
| 20            | 0.991                     | 0                          |
| 21            | 0.963                     | 0                          |
| 22            | 0.960                     | 0                          |
| 23            | 0.983                     | 0                          |
| 24            | 0.981                     | 0                          |
TABLE 2  Gas flow in pipelines

| Pipeline     | 1-2 | 2-3 | 3-4 | 4-5 | 5-6 | 6-7 | 8-9 | 9-10 | 10-11 | 11-12 | 12-13 | 13-14 | 14-15 | 15-16 | 16-17 | 17-18 |
|--------------|-----|-----|-----|-----|-----|-----|-----|-----|-------|-------|-------|-------|-------|-------|-------|-------|
| Gas flow (kcf)| 14.54 | 11.07 | 5.61 | 3.20 | 25.69 | 25.23 | 19.77 | 6.32 | 3.10 | 10.81 | 7.87 | 4.54 | 9.83 | 5.64 | 2.36 | 3.99 |

TABLE 3  Pressure of nodes

| Node     | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Pressure (Bar) | 30.00 | 22.64 | 20.22 | 18.93 | 17.76 | 13.97 | 15.30 | 13.45 | 12.38 | 11.91 | 11.15 | 10.24 | 10.50 | 13.14 | 13.70 | 11.84 | 11.02 |

Under this time scale, DR loads and ESS are dispatched in the rolling horizon optimization, TOU electricity price is used as incentive for the DR loads and ESS. In Figure 8, the scheduled power of DR loads and ESS are presented. From the results of DR loads scheduling strategies, it can be seen that the dispatched power of DR loads in different buses are not the same, it is mainly because that in distribution network, each bus is constrained by factors such as power and voltage of other buses to obtain the optimal power flow. From the perspective of the combination of DR loads and ESS, the conclusion can be obtained that large amounts of electricity discharging appears at times of high electricity price, such as 11:00 and 20:00. In these periods, DR loads in different buses and ESS in bus 4 released lots of power to suffice the demand of electrical network.

In distribution network with large amount of wind power accessed, the deviation between scheduled wind power obtained after optimization and actual wind power would be penalized. In rolling horizon optimization, with the sliding of time window, more accurate predicted wind power can be utilized. In Figure 9, the optimal scheduled wind power obtained after multi-time scales rolling optimization is compared with the result of day-ahead optimization. From this figure, it is clear that, although under day-ahead time scale, electrical network and natural gas network can coordinate with each other to optimize the operating cost of IEGES, however, the predicted wind power with relatively large errors and the constraints of their respective networks still lead to a large deviation of wind power. By contrast, in proposed multi-time scales rolling optimization framework, taking advantage of more precise predicted wind power, DRP and ESS can be used to further smooth the fluctuations of wind.

TABLE 4  Costs comparison of multi-time scales rolling optimization and day-ahead optimization

| Optimization framework | Electrical network costs | Gas network costs | Wind power deviation penalty | Wind turbine operating costs | ESS operating costs | DRP costs | Total operating costs |
|------------------------|--------------------------|-------------------|-----------------------------|----------------------------|-------------------|-----------|----------------------|
| Day-ahead optimization  | 23,971.26                | 60,779.40         | 4015.75                     | 1664.90                    | 159.60            | 134.38    | 90,725.29            |
| [14]                   |                          |                   |                             |                            |                   |           |                      |
| Multi-time scales rolling optimization (proposed) | 23,850.40                | 60,777.40         | 1213.62                     | 1767.59                    | 155.36            | 133.80    | 87,902.41            |
Here, the actual wind power is considered as the intraday predicted wind power without error handling. As a result, it can be seen from Figure 9 that, the optimal scheduled wind power obtained in proposed optimization framework is much closer to the actual wind power than that of day-ahead optimization. The penalty costs of wind power deviation is listed in Table 4, it can be concluded more directly that multi-time scales rolling optimization framework can effectively reduce the penalty costs caused by wind power uncertainty, so as to optimize the total operating costs.

The transferred power and voltage deviations of point of common coupling (PCC) node obtained in both optimization frameworks are compared in Figure 10. It can be seen that, with single time scale day-ahead optimization framework, the obtained transferred power at PCC node is clearly larger than that obtained with multi-time scales rolling optimization. This situation will lead to unstable quality of electricity injected into the distribution network, which will also increase the corresponding adjustment burden of power lines and energy units. In contrast, with the proposed multi-time scales rolling optimization framework, the obtained transferred power at PCC node is lower, the influence to the electricity quality in it is relatively small, the fluctuations of power in the power lines and energy units can be kept at a low degree. From Figure 10b, it can be seen that the deviations of voltage in day-ahead optimization is higher than that in multi-time scales optimization, which means that less fluctuations would happen when optimizing the energy scheduling strategies in distribution network with the proposed framework, the electricity quality can be further ensured during the optimization. Therefore, from the perspective of electrical network, the stability of the proposed optimization framework is much better than single time scale optimization framework.

It can be concluded from the total operating costs of IEGES in Table 4 that, utilizing rolling horizon mechanism of multi-time scales optimization, the penalty costs of wind power deviation would be reduced to 1213.62 RMB, which is about 69.8% less than that obtained in day-ahead optimization. Although more utilized wind power causes the increasing of wind turbine operating costs, still the total operating costs is reduced with the proposed multi-time scales rolling optimization.
5.3 The effect of P2G facility

Here, P2G is considered as energy conversion unit in the IEGES together with NGU, which form the bi-directional energy exchange structure. In order to better illustrate the effect of P2G in reducing the effect of wind power uncertainty, in this section, the optimization is conducted without P2G. The obtained costs is compared with that in last section, which are shown in Table 5. It can be seen that, due to the lack of P2G, more costs of purchasing natural gas and wind power deviations are produced, although the operating costs of wind turbines in system with P2G is a little higher, still the saved penalty of wind power deviations reduces the total operating costs significantly.

In Figure 11, the scheduled wind power and the deviation without P2G are compared with the results of IEGES contained P2G. It is clearly that, with the utilizing of P2G, the deviation of wind power can be significantly reduced, which demonstrated that the P2G facility can effectively reduce the impact of wind power fluctuations.

5.4 The advantage of edge-cloud collaborative operation architecture

In order to better illustrate the mathematical stability of proposed edge-cloud collaborative operation architecture, the specific description of the convergence of proposed edge-cloud operation architecture is added in the Appendix A.1, and the simulation results of convergence process are given to further illustrate the mathematical stability of the proposed architecture in this section.

As shown in Figure 12, in order to more intuitively explain the mathematical stability of the edge-cloud collaborative operation architecture proposed in this article, the convergence process of studied optimization problem is given, and for the same optimization problem, the obtained result for the optimization process without adding penalty factor to the SOC relaxation is considered as contrast simulation in this figure.

During the optimization, once the maximum value of original residual and dual residuals is below the convergence threshold, it means that all the original residuals and dual residuals can meet the convergence criteria, therefore, with the maximum value of them, the convergence condition of the optimization process can be judged. From the comparison of optimization with and without adding penalty factor to SOC relaxation in Figure 12, it can be concluded that, with the driving effect of penalty factor, the convergence process of edge-cloud collaborative operation architecture adopted in this article is much faster than that without penalty factor, the optimization without penalty factor converges at the 70th iteration and the optimization with penalty factor converges at the 35th iteration. Therefore, it can be known that the proposed edge-cloud collaborative operation architecture can effective solve the optimization of IEGES.

On the other hand, for illustrating the advantage of collaborative optimization between edge servers and cloud server in solving the scheduling problem of IEGES, in this section, centralized cloud architecture, fully decentralized architecture and edge-cloud collaborative architecture are utilized to solve the optimization, respectively.

The operating costs are compared in Table 6, it can be seen that, the costs of centralized cloud architecture is better than
the other two optimization architectures, the total operating costs is 87,180.09 RMB. This is mainly because that, in centralized cloud optimization, the optimization objective and related constraints of natural gas network was incorporated into the optimization of electrical network energy scheduling subproblem, so as to solve and obtain the optimal energy scheduling strategies of the whole integrated energy system in a centralized manner. Because of the joint optimization of electrical network and natural gas network, the information of all parameter variables in both energy networks can be completely shared and adopted in the optimization process, which ensured that the obtained results are the global optimal solutions of the optimization process. In contrast, the fully decentralized architecture has not consider the connection between two networks, but only takes the minimum operating costs of each network as the target of optimization. However, due to the interactions and constraints between two networks are not taken into consideration, different kinds of energy cannot efficiently utilized through bi-directional conversion, because of that, the operating costs in both energy networks are higher than that obtained in the other two optimization architectures, and the total operating costs of integrated energy system is the highest as 92,505.21 RMB. Although the results of centralized cloud optimization is the best, in this kind of centralized cloud architecture, all relevant parameters of both energy networks have to be acquired, interacted and utilized, which does not fit with the actual operating architecture of IEGES. In reality, two energy networks are commonly managed by their respective energy operators, which means it is impractical to require complete information interaction between them. The centralized cloud architecture cannot guarantee their independent operation and protect the information privacy of operators. But in the proposed edge-cloud collaborative optimization architecture, the energy networks can be optimized independently with edge servers, meanwhile, the computing resources of cloud server can be rational utilized. It can be seen from Table 6 that, with the proposed optimization framework, the operating costs in both electrical network and gas network are close to the optimal results obtained in centralized cloud optimization, it means that with the proposed edge-cloud operation architecture, the optimization objective in each energy network can be satisfied as much as possible. Also it has great performance in ensuring the utilization of wind

| Operation architecture       | Electrical network costs | Gas network costs | Wind power deviation penalty | Wind turbine operating costs | ESS operating costs | DRP costs | Total operating costs |
|------------------------------|--------------------------|------------------|-------------------------------|-----------------------------|--------------------|-----------|-----------------------|
| Centralized cloud [7]        | 23,776.23                | 60,770.53        | 485.04                        | 1850.24                     | 164.18             | 133.87    | 87,180.09             |
| Fully decentralized [46]     | 24,017.34                | 64,360.11        | 2132.85                       | 1689.85                     | 168.29             | 136.77    | 92,505.21             |
| Edge-cloud collaborative     | 23,850.40                | 60,777.40        | 1213.62                       | 1767.59                     | 155.36             | 133.80    | 87,902.41             |

FIGURE 11 Scheduled wind power and deviations with and without P2G facility

FIGURE 12 The comparison of convergence process
power, the wind power deviation penalty is smaller than that in decentralized optimization. The operating costs of ESS and DRP obtained in proposed operation architecture is close to the optimal solutions in centralized optimization, but still less than the optimal results. It means that although the performance of the proposed operation architecture is close to obtain the optimal results, still the dispatchable energy units have not been fully utilized, which leads to the difference in the total optimization costs between these two operation architectures. The total operating costs of IEGES is close to the optimal solution, which is 87,902.41 RMB. Here, the slightly deviation of total operating costs is considered as allowable, therefore edge-cloud collaborative architecture also has great effect for the optimization of IEGES, meanwhile ensuring the independent operation of each energy network. Consequently, in this paper, edge-cloud collaborative architecture is considered to be the most appropriate architecture to solve the optimization of IEGES.

5.5 | Results comparison with scenario generation stochastic optimization

Here, in order to better verify the performance of the proposed optimization framework under uncertainty conditions, scenario generation method which is the most widely used stochastic optimization method is also adopted to solve the optimization of IEGES, and the results are compared with that of the proposed optimization framework.

Scenario generation method is an effective method to solve stochastic problems, according to the known probability distribution of random variables, Monte Carlo simulation is used to generate the possible scenarios, so as to transform the uncertainties in the model into multiple deterministic scenarios. After a large number of scenarios are generated, in order to reduce the burden of calculation and maintain credibility, the scenario reduction method is used to reduce the number of generated scenarios. Through combining the scenarios with the smallest probability distance in the original scenario set, an approximate subset of the original set and the probability of each scenario in it are obtained until the required number of scenarios are achieved.

In this section, scenario generation method is used to simulate the uncertainty of wind power and electrical loads. 1000 scenarios are generated to form the original set, and then scenario reduction method is adopted to the original set until 5 scenarios are kept at last as approximate subset. As the probability distribution of wind speed prediction errors in two optimization stages are different, the obtained scenario set are also not the same, which are shown below:

1) Day-ahead time scale

In Figure 13, the scenarios of wind power generation and electrical loads utilized under day-ahead time scale are presented separately. In this optimization stage, it is assumed that the predicted error of wind power and electrical loads are 20%, which is adopted in the MCS to generate scenarios. After obtaining the original sets of wind power and electrical loads, scenario reduce method is used to curtail the number of scenarios, and the probability of each scenario can be obtained after the scenario reduction and listed in Table 7.

2) Intraday time scale

Under this time scale, considering the characteristics of wind speed prediction that, more closer to real-time prediction,
more accurate the predicted wind speed is. In each rolling optimization process, the prediction errors of wind speed in the first 4 h of time window is assumed to be 5%, the errors in the other time intervals still maintained as 20%. On the other hand, since the forecast errors of electrical loads is relatively stable, it is still considered that the fluctuation of electrical loads is 20%, which is kept as the same with that adopted in the proposed robust uncertain set. Therefore, in order to more obviously reflect the impact of the change of wind power scenarios, the electrical loads scenarios utilized under this time scale is as the same as the ones in day-ahead optimization. The scenarios of wind power generation and electrical loads under intraday time scale are shown in Figure 14, respectively. After each time rolling horizon optimization, the scheduling strategies of the next 4 h are considered to be the required optimal strategies of IEGES. The probability of scenarios in this stage are listed in Table 8.

According to the obtained scenarios of wind power and electrical loads under different time scales, multi-time scales rolling optimization based on scenario generation method is adopted to the studied IEGES, and the results are compared with that in Section 5.2. In Figure 15, the scheduled wind power after optimization of scenario generation method is shown and compared. It can be seen that, with the optimization based on scenario generation method, the obtained scheduled wind power is close to the results in previous section. The deviations of wind power after both optimization method are also shown in Figure 15b, which is 4.45 MW of scenario generation method and 3.47 MW of robust optimization method.

It means that for the optimization of studied IEGES, scenario generation method does not have better performance than robust optimization method. Furthermore, from the perspective of system safety and stability, robust optimization method...
is better than scenario generation method, because the optimization of scenario generation method is mainly based on probability, only those scenarios with higher probabilities can be selected as the typical scenarios and adopted in the optimization. By this way, some possible extreme scenarios cannot be considered, such as the boundary scenarios presented in robust uncertain set. In contrast, in robust optimization of this article, the optimization is conducted under the worst case in the uncertain set, the results have already considered all the possible extreme scenarios during the optimization, therefore, the safety and stability of the obtained results are better than that obtained by scenario generation method, especially for the IEGES with more complex structure and energy conversion relationships.

In Table 9, the obtained operating costs of both optimization method are compared, it can be seen that the obtained total operating costs of two optimization methods are very close, both of them can be adopted to solve the optimization problem in this article. The results of robust optimization method is slightly more than the costs of scenario generation method, this is because that robust optimization method is more conservative than scenario generation method, the optimization is conducted under the worst case in the uncertain set, it makes a certain loss in the economics of the results, but it also makes the results much safe and stable for the studied IEGES, which is considered as an important aspect of the IEGES. More conservative results can ensure their effectiveness during the operation of IEGES under complex and changeable energy conversion situations. Therefore, for the studied optimization problem of IEGES, robust optimization method is better than scenario generation method.

### 6 CONCLUSION

Here, an IEGES in distribution level with high penetration of wind power is studied, in order to reduce the impact of wind power and electrical uncertainties and obtain the optimal operating costs of system, meanwhile, ensuring the practical feasibility of optimization. Innovative edge-cloud collaborative operation architecture and multi-time scales rolling optimization framework are proposed, they cooperate with each other to optimize the energy scheduling strategies of IEGES.

With the utilization of edge-cloud collaborative operation architecture, electrical network and gas network can achieve independent autonomy, meanwhile, different computing resources of edge and cloud server can be reasonably utilized, although the investment costs of edge servers may increase, more efficient and independent operating mode is still suitable for the operation of IEGES. With the utilization of multi-time scales rolling optimization framework, the uncertainty of wind power under different time scales is considered, more accuracy predicted wind power can be utilized to adjust the energy scheduling strategies in IEGES.

Simulations show that the proposed multi-time scales rolling optimization framework can effectively reduce the impact of wind power and electrical loads uncertainties, compared with single time scale day-ahead optimization framework, the total operating costs can be saved more than 3%, and the penalty of wind power deviations can be reduced more than 50%. P2G is also demonstrated to have a significant effect on reducing the impact of wind power uncertainty and smoothing the transferred power between main grid and IEGES, with the using of P2G facility, the costs of wind power deviation can be saved more than 60% during the optimization. Besides that, the edge-cloud collaborative operation architecture can reduce the information exchange between two energy networks, so as to protect the privacy in IEGES. The obtained operating costs of edge-cloud collaborative architecture is compared with the result of centralized cloud architecture and fully decentralized architecture, the comparison shows that the edge-cloud collaborative architecture is the most appropriate approach to solve the optimization of IEGES.

This work is meaningful to obtain the optimal operating strategies of IEGES in distribution level, the edge-cloud collaborative operation architecture and multi-time scales rolling optimization framework can be referred to. However, as more renewable energy accessed and the number of power conversion devices increases, more studies on the coordination optimization of IEGES still need to be completed. The future work is to study the optimization of energy scheduling strategies in multiple IEGESs, and more kinds of renewable energy resource may be considered in the energy system, which means more efficient methods need to be utilized to handle with the uncertainties of renewable energy, also the fluctuations of electricity price, gas price and gas load would further considered in future optimization, which makes the proposed optimization method much more practical.

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APPENDIX A
A.1 Convergence description of edge-cloud collaborative operation architecture

For the proposed edge-cloud collaborative operation architecture in this article, the optimization process is conducted in an iterative way and finally converges to the optimal solution, this iterative optimization process combining edge and cloud architecture mainly refers to the decomposability of the dual ascent method and the upper bound convergence of the multiplier method. Here, the optimization problem can be presented as a form of electrical network subproblem and gas network subproblem, which is shown as follow:

\[
\begin{align*}
\min_{P_{\text{EN}}, P_{\text{GN}}, P_{\text{EN}}, P_{\text{GN}}} & \quad f(P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}) + g(P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}), \\
\text{s.t.} & \quad P_{\text{EN}} - \zeta_{\text{EN}} = 0, \\
& \quad P_{\text{GN}} - \zeta_{\text{GN}} = 0, \\
& \quad P_{\text{EN}} - \zeta_{\text{EN}} = 0, \\
& \quad P_{\text{GN}} - \zeta_{\text{GN}} = 0,
\end{align*}
\]

(A1)

where, the objective functions \(f(P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}), g(P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}})\) are the objective functions in electrical network and gas network, respectively. The optimization variables in electrical network are \(P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}\), and the optimization variables in gas network are \(P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}\). The optimization target of objective function (A1) is to minimize the sum of both functions, then for (A1), the optimal solution \(p^*\) must satisfy:

\[
p^* = \inf_p \left\{ f(P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}) + g(P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}) \right\}.
\]

(A3)

The introduced auxiliary variables \((\zeta_{\text{EN}}, \zeta_{\text{GN}})\) have already decoupled the objective functions of electrical network \(f(P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}})\) and gas network \(g(P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}})\), therefore the objective function (A1) can be reformulated and separated as two independent objective functions (A4) and (A5), which are shown as follow: According to this and referring to multiplier method, the optimization problem of function (A1) can be constructed as the form of augmented Lagrangian function, which is as below:

\[
\begin{align*}
\min_{P_{\text{EN}}, P_{\text{GN}}, P_{\text{EN}}, P_{\text{GN}}} & \quad f(P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}, P_{\text{EN}}), \\
\min_{P_{\text{EN}}, P_{\text{GN}}, P_{\text{EN}}, P_{\text{GN}}} & \quad g(P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}, P_{\text{GN}}),
\end{align*}
\]

(A4)

(A5)

The optimization processes of both objective functions are the same, taking the objective function (A4) as an example to illustrate the optimization process, referring to multiplier method, the optimization problem of function (A4) can be constructed as the form of augmented Lagrangian function, which is as below:

\[
\begin{align*}
L_{\rho}(P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}, \zeta_{\rho}, \zeta_{\rho}, \lambda_{\rho}, \lambda_{\rho}) &= f(P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}) \\
&+ \lambda_{\rho}(P_{\rho_{\text{EN}}} - \zeta_{\rho}) + \frac{\rho}{2} \| P_{\rho_{\text{EN}}} - \zeta_{\rho} \|^2, \\
&+ \lambda_{\rho}(P_{\rho_{\text{EN}}} - \zeta_{\rho}) + \frac{\rho}{2} \| P_{\rho_{\text{EN}}} - \zeta_{\rho} \|^2,
\end{align*}
\]

(A6)

where, \(\lambda_{\rho}, \lambda_{\rho}\) are the Lagrangian multipliers and \(\rho, \rho\) are the augmented Lagrangian penalty factors. The solution process obtains the optimal solution of this augmented Lagrangian function in an iterative way:

\[
P_{\rho_{\text{EN}}}^{(k+1)} = \arg \min_{P_{\rho_{\text{EN}}}} L_{\rho}(P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}, \zeta_{\rho}(k), \zeta_{\rho}(k)), \\
\lambda_{\rho}(k), \lambda_{\rho}(k),
\]

(A7)

\[
P_{\rho_{\text{EN}}}^{(k+1)} = \arg \min_{P_{\rho_{\text{EN}}}} L_{\rho}(P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}, P_{\rho_{\text{EN}}}, \zeta_{\rho}(k), \zeta_{\rho}(k)), \\
\lambda_{\rho}(k), \lambda_{\rho}(k),
\]

(A8)

\[
\lambda_{\rho}(k+1) = \lambda_{\rho}(k) + \rho(P_{\rho_{\text{EN}}}^{(k+1)} - \zeta_{\rho}(k+1)),
\]

(A9)
\[ \lambda_{EN}^{(k+1)} = \lambda_{EN}^{(k)} + \rho_s (P_s^{EN} (k+1) - \xi (k+1)). \]  
(A10)

It can be seen from the optimization process that, in each iteration, not only the optimization variables are updated, the Lagrangian multipliers are also updated and replaced.

Then assuming solution \((P_{\nu}^{EN}(\ast), P_s^{EN}(\ast), \xi(\ast), \lambda_s(\ast), \lambda_{EN}(\ast))\) is one feasible solution of constructed objective function (A6), if it is the optimal solution of the problem, it must satisfy the original feasibility equations and the dual feasibility equations:

\[ P_{\nu}^{EN}(\ast) - \xi(\ast) = 0, \]  
(A11)

\[ P_s^{EN}(\ast) - \xi(\ast) = 0, \]  
(A12)

\[ 0 \in \partial f (P_{\nu}^{EN}(\ast)) + \lambda_{EN}(\ast), \]  
(A13)

\[ 0 \in \partial f (P_s^{EN}(\ast)) + \lambda_s(\ast). \]  
(A14)

Then use \(Pr_{\nu}^{EN}(k+1), Pr_s^{EN}(k+1)\) to represent the original residuals of the optimization problem (A6) in the \(k+1\) iteration, which are:

\[ Pr_{\nu}^{EN}(k+1) = P_{\nu}^{EN}(k+1) - \xi(k+1), \]  
(A15)

\[ Pr_s^{EN}(k+1) = P_s^{EN}(k+1) - \xi(k+1). \]  
(A16)

According to the solutions after iterations in Equations (A7)–(A10), it can be known that \(P_{\nu}^{EN}(k+1), P_s^{EN}(k+1)\) can minimize the results of (A7) and (A8), therefore the following equations can be obtained:

\[ 0 \in \partial f (P_{\nu}^{EN}(k+1)) + \lambda_{EN}(k) + \rho_s (P_{\nu}^{EN}(k+1) - \xi(k)) \]

\[ = \partial f (P_{\nu}^{EN}(k+1)) + \lambda_{EN}(k) + \rho_s Pr_{\nu}^{EN}(k+1) \]

\[ + \rho_s (\xi(k+1) - \xi(k)) \]

\[ = \partial f (P_{\nu}^{EN}(k+1)) + \lambda_{EN}(k+1) + \rho_s (\xi(k+1) - \xi(k)), \]  
(A17)

\[ 0 \in \partial f (P_s^{EN}(k+1)) + \lambda_s(\ast) \]

\[ + \rho_s (P_s^{EN}(k+1) - \xi(k)) \]

\[ = \partial f (P_s^{EN}(k+1)) + \lambda_s(k) + \rho_s Pr_s^{EN}(k+1) \]

\[ + \rho_s (\xi(k+1) - \xi(k)) \]

\[ = \partial f (P_s^{EN}(k+1)) + \lambda_s(\ast) \]  
(A18)

which also can be presented as follow:

\[ -\rho_s(\xi(k+1) - \xi(k)) \in \partial f (P_{\nu}^{EN}(k+1)) + \lambda_s(\ast), \]

(A19)

\[ -\rho_s(\xi(k+1) - \xi(k)) \in \partial f (P_s^{EN}(k+1)) + \lambda_s(\ast), \]

(A20)

where, the left side of these equations can be considered as the residuals of the dual feasibility Equations (A13) and (A14) in the \(k+1\) iteration, which are called dual residuals and represented by \(D_{\nu,\ast}^{EN}(k+1), D_{s,\ast}^{EN}(k+1)\) as follows.

\[ D_{\nu,\ast}^{EN}(k+1) = -\rho_s(\xi(k+1) - \xi(k)), \]  
(A21)

\[ D_{s,\ast}^{EN}(k+1) = -\rho_s(\xi(k+1) - \xi(k)). \]  
(A22)

Summarizing all these descriptions above, it can be known that the constraints to ensure that the obtained solution is the optimal solution for the problem are the original feasibility Equations (A11), (A12) and the dual feasibility Equations (A13) and (A14). For the obtained solution \((P_{\nu}^{EN}(k+1), P_s^{EN}(k+1), \xi(k+1), \lambda_s(k+1), \lambda_{EN}(k+1))\) according to Equations (A7)–(A10), the residuals of the original feasibility Equations (A11), (A12) and the dual feasibility Equations (A13), (A14) can be presented as \(Pr_{\nu}^{EN}(k+1), Pr_s^{EN}(k+1)\) and \(D_{\nu,\ast}^{EN}(k+1), D_{s,\ast}^{EN}(k+1)\), respectively. If both original residuals and dual residuals are 0, it can be ensured that the original feasibility equations and dual feasibility equations are satisfied. According to this, it can be concluded that during the optimization process of natural gas network subproblem, with the increasing of iteration number, the residuals \(Pr_{\nu}^{EN}(k+1), Pr_s^{EN}(k+1)\) and \(D_{\nu,\ast}^{EN}(k+1), D_{s,\ast}^{EN}(k+1)\) should converge to 0 to ensure the optimality of the obtained solution. In the practical application, such as the optimization of IEGES studied in this article, when the residuals \(Pr_{\nu}^{EN}(k+1), Pr_s^{EN}(k+1)\) and \(D_{\nu,\ast}^{EN}(k+1), D_{s,\ast}^{EN}(k+1)\) converge to the acceptable degree, the whole optimization process can be considered convergent. The convergence criterions are expressed as follows:

\[ \|Pr_{\nu}^{EN}(k+1)\|_2 \leq \varepsilon_{\nu}, \]

\[ \|Pr_s^{EN}(k+1)\|_2 \leq \varepsilon_{\nu}, \]  
(A23)

\[ \|D_{\nu,\ast}^{EN}(k+1)\|_2 \leq \varepsilon_{D_{\ast}}, \]

\[ \|D_{s,\ast}^{EN}(k+1)\|_2 \leq \varepsilon_{D_{\ast}}, \]

where, \(\varepsilon_{\nu}, \varepsilon_{D_{\ast}}\) represents the specific convergence threshold of optimization problem.

For the subproblem of gas network, the optimization process is similar. Therefore, the convergence criterions can also be
obtained and shown as follows:

\[
\begin{align*}
&\| P_{\text{EN}}(k+1) - P_{\text{y}}(k+1) \|_2 \leq \varepsilon_{\text{Pri}}, \\
&\| P_{\text{Co}}(k+1) - P_{\text{y}}(k+1) \|_2 \leq \varepsilon_{\text{Pri}}, \\
&\| D_{\text{EN}}(k+1) - P_{\text{y}}(k+1) \|_2 \leq \varepsilon_{\text{Dua}}, \\
&\| D_{\text{Co}}(k+1) - P_{\text{y}}(k+1) \|_2 \leq \varepsilon_{\text{Dua}}.
\end{align*}
\]  (A24)

For the original residuals in (A23) and (A24), since the auxiliary variables $z_v, z_u$ equals $P_{\text{y}}(k+1), P_{\text{y}}(k+1)$ and $P_{\text{Co}}(k+1), P_{\text{Co}}(k+1)$ in each network, respectively. Therefore, when checking the original and dual residuals in cloud server, the auxiliary variables can be replaced and the integrated convergence criterions can be presented as follow:

\[
\begin{align*}
&\| P_{\text{EN}}(k+1) - P_{\text{y}}(k+1) \|_2 \leq \varepsilon_{\text{Pri}}, \\
&\| P_{\text{Co}}(k+1) - P_{\text{y}}(k+1) \|_2 \leq \varepsilon_{\text{Pri}}, \\
&\| P_{\text{y}}(k+1) - P_{\text{Co}}(k+1) \|_2 \leq \varepsilon_{\text{Dua}}, \\
&\| P_{\text{y}}(k+1) - P_{\text{Co}}(k+1) \|_2 \leq \varepsilon_{\text{Dua}}.
\end{align*}
\]  (A25)

where, in the studied problem of IEGES in this article, are usually dependent on the desired proximity of the scheduled energy amount of energy conversion devices, which are choices based on experience. Here, considering the base power of the electrical network is 10 MVA, the convergence thresholds are selected as 0.02, which means the allowable gap between scheduled amount of NGU and P2G is 2 kW.

A.2 The specific process of edge-cloud collaborative operation architecture

**Algorithm 1 Process of edge-cloud collaborative operation architecture**

1. The upper cloud server initializes $\lambda^{\text{EN}}, \lambda^{\text{Co}}, \lambda^{\text{Co}}, \lambda^{\text{Co}}$ and $z_v, z_u$ for NGU and P2G, and sends them to the middle edge servers.

2. The edge servers solve their corresponding optimization subproblems $P_{\text{EN}}, P_{\text{Co}}$, so as to obtain the produced power of NGU $P_{\text{EN}}(k+1)$ and consumed power of P2G $P_{\text{Co}}(k+1)$. Then the obtained $P_{\text{EN}}(k+1)$ and $P_{\text{Co}}(k+1)$ are sent back to the cloud server.

3. As soon as the calculated results from edge servers are received, the cloud server checks if the original and dual residuals are within tolerances:

\[
\begin{align*}
&\| P_{\text{EN}}(k+1) - P_{\text{y}}(k+1) \|_2 \leq \varepsilon_{\text{Pri}}, \\
&\| P_{\text{Co}}(k+1) - P_{\text{y}}(k+1) \|_2 \leq \varepsilon_{\text{Pri}}, \\
&\| P_{\text{y}}(k+1) - P_{\text{Co}}(k+1) \|_2 \leq \varepsilon_{\text{Dua}}, \\
&\| P_{\text{y}}(k+1) - P_{\text{Co}}(k+1) \|_2 \leq \varepsilon_{\text{Dua}}.
\end{align*}
\]

$\varepsilon_{\text{Pri}}, \varepsilon_{\text{Dua}}$ are both 0.02. If yes, the iteration ends. Otherwise, the cloud server updates the auxiliary variables and multipliers via Equations (38)–(43).

4. The algorithm repeats steps 2, 3 until the criteria are satisfied.

A.3 The limitation of pressure boundaries at each gas node

**TABLE A1** Pressure boundaries of gas node

| Gas node | Minimum pressure (bar) | Maximum pressure (bar) |
|----------|------------------------|------------------------|
| 1        | 15                     | 30                     |
| 2        | 15                     | 30                     |
| 3        | 10                     | 25                     |
| 4        | 10                     | 25                     |
| 5        | 10                     | 20                     |
| 6        | 10                     | 20                     |
| 7        | 10                     | 20                     |
| 8        | 15                     | 30                     |
| 9        | 15                     | 30                     |
| 10       | 15                     | 30                     |
| 11       | 10                     | 20                     |
| 12       | 10                     | 15                     |
| 13       | 10                     | 15                     |
| 14       | 10                     | 15                     |
| 15       | 10                     | 15                     |
| 16       | 10                     | 15                     |
| 17       | 10                     | 20                     |
| 18       | 10                     | 20                     |
| 19       | 10                     | 20                     |
| 20       | 10                     | 20                     |

A.4 Important parameters adopted in the optimization
TABLE A2 Price in the optimization

| Electricity (Valley) | Electricity (Regular) | Electricity (Peak) | DRP compensation | ESS operating | Wind turbine maintenance | Wind power penalty | Gas price |
|---------------------|-----------------------|--------------------|------------------|---------------|--------------------------|--------------------|-----------|
| 336 RMB/MWh         | 532 RMB/MWh           | 728 RMB/MWh        | 60 RMB/MWh       | 65 RMB/MWh    | 29.6 RMB/MWh             | 350                | 49.5 RMB/kcf |

TABLE A3 Operating parameters of ESS

| ESS capacity | Initial capacity | Minimum allowable capacity | Maximum allowable capacity | Charging/discharging rate | Charging/discharging efficiency |
|--------------|------------------|----------------------------|----------------------------|---------------------------|-------------------------------|
| 1 MWh        | 60 %             | 20 %                       | 80 %                       | 0.2 MW                    | 95 %                          |

TABLE A4 Operating parameters of GSS

| GSS capacity | Initial capacity | Minimum allowable capacity | Maximum allowable capacity | Charging/discharging rate | Charging/discharging efficiency |
|--------------|------------------|----------------------------|----------------------------|---------------------------|-------------------------------|
| 60 kcf       | 50 %             | 10 %                       | 90 %                       | 5 kcf                     | 90 %                          |

TABLE A5 Operating parameters of edge-cloud collaborative architecture

| Initial $\alpha$ | Initial $\xi$ | $\xi_{max}$ | $\gamma_{E}$ | $\gamma_{P}$ | $\epsilon_1$ | $\epsilon_2$ | $\epsilon_{DR}$ | $\epsilon_{in}$ | $\epsilon_{out}$ | $\epsilon_{ESS}$ | $\epsilon_{GSS}$ | $\epsilon_{DR,\text{in}}$ | $\epsilon_{DR,\text{out}}$ | $\epsilon_{GSS,\text{in}}$ | $\epsilon_{GSS,\text{out}}$ | $\epsilon_{ESS,\text{in}}$ | $\epsilon_{ESS,\text{out}}$ | $\epsilon_{GSS,\text{in}}$ | $\epsilon_{GSS,\text{out}}$ |
|------------------|---------------|-------------|--------------|--------------|--------------|--------------|-----------------|-----------------|-----------------|----------------|----------------|------------------------|--------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| 5                | 1             | 100         | 10           | 1            | 0.02         | 0.02         |                 |                 |                 |                 |                 | Compensate costs of adjusted DR loads |                 |                 |                 |                 |                 |                 |                 |

A.5 The list of parameters

Nomenclature

Sets

- $\Omega_w$ Set of wind turbines
- $\Omega_{well}$ Set of gas wells
- $\Omega_{DR}$ Set of DR loads
- $\Omega_{ESS}$ Set of ESS
- $\Omega_{pipe}$ Set of gas pipelines
- $\Omega_{ngu}$ Set of natural gas unit
- $\Omega_{p2g}$ Set of power to gas unit

Symbols

- $C_{EMS}$ Operating costs under day-ahead time scale
- $C_{INT}$ Operating costs under intraday time scale
- $C_{ab}$ Weymouth constant of pipeline from node $a$ to node $b$
- $C_{IT}$ Integrated operating costs in cloud server
- $C_{EN}$ Electrical network operating costs in edge server
- $C_{GSS}$ Gas network operating costs in edge server
- $\zeta(t)$ Electricity price in interval $t$
- $\xi_E$ Penalty costs of abandoned wind power
- $\xi_P$ Operating costs of wind turbines

Compensate costs of adjusted DR loads
Operating costs of ESS
Charge state of ESS in interval $t$
Absorb state of GSS in interval $t$
Discharge state of ESS in interval $t$
Release state of GSS in interval $t$
Stored electricity of ESS in interval $t$
Minimum allowable capacity of ESS
Maximum allowable capacity of ESS
Stored gas of GSS in interval $t$
Minimum allowable capacity of GSS
Maximum allowable capacity of GSS
Purchased electricity under intraday time scale in interval $t$
Scheduled wind power under intraday time scale in interval $t$
Scheduled DR loads under intraday time scale in interval $t$
Scheduled electricity of ESS under intraday time scale in interval $t$
Charged electricity of ESS under intraday time scale in interval $t$
Discharged electricity of ESS under intraday time scale in interval $t$
Minimum allowable charge amount of ESS under intraday time scale in interval $t$
Maximum allowable charge amount of ESS under intraday time scale in interval $t$
Minimum allowable discharge amount of ESS under intraday time scale in interval $t$
Maximum allowable discharge amount of ESS under intraday time scale in interval $t$

Gas flow in pipeline from node $a$ to node $b$ in interval $t$

Maximum allowable amount of gas flow in pipeline $ab$

Gas supply of node $a$ in interval $t$

Gas demand of node $a$ in interval $t$

Gas network operating costs of $k$th iteration

High heating value of natural gas

Binary variables of gas flow directions in pipeline $ab$

Purchased electricity under day-ahead time scale in interval $t$

Scheduled wind power under day-ahead time scale in interval $t$

Active power of bus $n$ in interval $t$

Generated power of bus $n$ in interval $t$

Generated power by NGU in interval $t$

Generated power by NGU in electrical network edge server in interval $t$

Generated power by NGU in gas network edge server in interval $t$

Consumed power by P2G in interval $t$

Consumed power by P2G in electrical network edge server in interval $t$

Consumed power by P2G in gas network edge server in interval $t$

Reactive power of bus $n$ in interval $t$

Reactive load demand of bus $n$ in interval $t$

Generated reactive power of bus $n$ in interval $t$

Purchased gas from gas wells in interval $t$

Absorbed gas of GSS in interval $t$

Maximum allowable absorbed gas of GSS

Minimum allowable absorbed gas of GSS

Maximum allowable absorbed gas of GSS

Released gas of GSS in interval $t$

Minimum allowable released gas of GSS

Maximum allowable released gas of GSS

Consumed gas by NGU in interval $t$

Consumed gas by NGU in electrical network edge server in interval $t$

Consumed gas by NGU in gas network edge server in interval $t$

Generated gas by P2G in interval $t$

Generated gas by P2G in electrical network edge server in interval $t$

Generated gas by P2G in gas network edge server in interval $t$

Resistance between bus $n$ and bus $n+1$

Startup costs of NGU in interval $t$

Shutdown costs of NGU in interval $t$