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Day-Ahead Scheduling of Distribution Level Integrated Electricity and Natural Gas System Based on Fast-ADMM With Restart Algorithm

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ABSTRACT Power generated by the natural gas (NG) is a promising option for solving the restrictions on the development of the power industry. Consequently, the high interdependence between NG network and electricity network should be considered in this integration. In this paper, a day-ahead scheduling framework of integrated electricity and NG system (IENG) is proposed at a distribution level based on the fast alternating direction multiplier method with restart algorithm considering demand side response and uncertainties. Within the proposed framework, the detailed model of the IENG system at a distribution level is established, where the NG flow equation is processed by incremental linearization method to improve the computational efficiency. The objective is to minimize the operation costs of the entire system. With consideration of the uncertainties of distributed generation and electricity load as well as the uncertainties from the NG load, a two-stage robust optimization model is introduced to obtain the worst case within the uncertainty set, which is solved by column and constraints generation algorithm. In addition, the demand-side response (DSR) model including the decentralized air conditioning (AC) load model and the centralized ice-storage AC load model is integrated into the scheduling framework. Finally, the proposed day-ahead scheduling framework is verified by numerical studies where the optimal scheduling schemes are obtained in different cases, both the effects of the uncertainties and the performance with introducing DSR to the system operation are analyzed.

INDEX TERMS Day-ahead scheduling, demand-side response (DSR), integrated electricity and natural gas system (IENG), natural gas (NG), uncertainty.

I. INTRODUCTION Environmental degradation and fossil energy depletion are the main factors which limit the development of the power industry. To solve these issues and sequentially promote the development of the power industry, the utilization of natural gas (NG) has been paid more and more attention due to its low-cost and high environmental benefits [1], [2]. Currently, the generation units utilizing NG like micro-turbine (MT) are becoming a top priority in electricity systems. Moreover, the large-scale configuration of MT is bound to result in the high interdependence between NG network and electricity network [3].

For an integrated energy system involving electricity and NG network, the view of ‘source-grid-load’ coordinated optimization is required to find the best scheduling scheme with the minimum overall cost in the whole system [4]. Due to the interdependence of electricity network and NG network, optimizing either of the system and neglecting the interaction between them may result in the increase of operation costs from the system point of view. Consequently, a joint optimization is more effective for IENG [5]–[7]. An IENG planning algorithm is proposed to enhance the power grid resilience in extreme conditions which is described by the proposed variable uncertainty set [8]; a multi-objective framework is proposed for the coordinated operation of the IENG, addressing the economic, dynamic security of electricity network, as well as the security of the NG network [9]. However, most previous investigations focus
on the issues of interactions between electricity and NG networks at a transmission level rather than at a distribution level [10]. With the large access of MT in distribution network, the interdependence of distribution network and NG network should be considered. Moreover, significant differences exist in the models of the IENG system regarding the distribution and transmission levels. Firstly, the network structure, parameters and power flow algorithm of the transmission network are different from those of the distribution network; secondly, the transmission network of NG have long distance pipelines and large amount of NG which lead to a large pressure loss of pipelines and compressors are required to compensate the loss of pressure [11], while the loss of pressure at a distributed level is much lower where compressors are not necessary. Due to these differences, it is essential to establish a detailed model of the IENG at a distribution level and to investigate the scheduling problem.

Besides, the IENG system is always formulated as a large-scale mixed integer nonlinear programming problem in which the nonlinearity of the NG flow equation is the key computational bottleneck. In [12], the pressure of pipeline is ignored during operation process. In order to expedite the solving process, the natural gas pipeline flow is represented as a variable constrained with pipeline capacity at each period in [13]. Reference [14] proposes the method of the IENG joint planning so that the gas turbines are reasonably connected to the distribution network, and the intelligent algorithm is used to solve this problem. However, the model which ignores the pressure of pipelines may result in that the planning results do not match the actual results. In the model of [14], intelligent algorithms are normally adopted to obtain the solutions, which cannot guarantee the optimal solution. Therefore, considering the accuracy and efficiency, the linearization is required to simplify the nonlinear flow equations which can effectively tackle the shortcomings of existing models within the tolerable range [15].

For the sources in the electricity system, the uncertainty of DG should be considered because of intermittent of renewable energy [16], [17]. Reference [18] proposes a robust co-optimization scheduling model to minimize the total costs of the electricity sub-system and NG sub-system considering power system uncertainty. Except the uncertainty of sources, the fluctuations of load (including gas turbines, MT, household load, etc.) also have a great impact on the operation of the entire system especially at a distribution level. In [19] and [20], the Monte Carlo simulation is applied to create multiple scenarios for representing the coordinated system uncertainties including the uncertainty of NG load. However, the scheduling schemes obtained by the scenarios approach may be infeasible in the extremely case. As a result, it is essential to consider the impact of NG load uncertainty and deal with it by robust methods.

In addition to the uncertainty of load, DSR can offer an effective option to reduce system operation costs and stabilize the power fluctuations [21], [22]. Currently, the proportion of air conditioning (AC) load in the total load has been gradually increasing which even reach 30%–40% in the summer [23], and a number of control methods create the conditions for participation of AC in the DSR. As an important DSR resource, the AC load can respond quickly to the power dispatching through the reasonable regulation, which can effectively alleviate the contradiction between power supply and demand and reduce the system peaking difficulty and operation cost. Reference [24] proposes a microgrid optimization scheduling model considering the centralized ice-storage AC load, which reduces the operation cost of the system by utilizing the shifting characteristics of ice-storage AC load. The periodic suspension control strategy of decentralized AC load is proposed in [25], and the indoor temperature is controlled within a certain range according to the heat storage characteristics of the building. Centralized AC load is generally concentrated in the daytime when scheduling potential is high, but the scheduling potential at night is very low. Decentralized AC load peak load generally appears in the evening, and valley load appears in the morning, so that decentralized AC load have higher scheduling potential in peak period than that in valley period. Since the scheduling potentials of the two AC loads vary in different periods, considering the two kinds of AC loads can play a complementary role, which is rarely concerned with the current researches. To further reduce the system operation costs and power fluctuations, it is worth to note the complementary effect of the different AC loads.

To realize an integrated management of the IENG at a distribution level, a detailed IENG model at a distribution level is established in the paper. Firstly, the electricity network model is described by simplified Dist-flow equations, and an incremental linearization method is used to simplify the NG flow equation. Secondly, the uncertainties of DG are considered because of the intermittent of renewable energy. Furthermore, the uncertainties of load are considered including both electricity load and NG load, and a two-stage robust optimization model (TSRO) model is introduced where the worst case is obtained by C&CG algorithm. In addition, hourly demand response of AC load is considered. According to different control methods, decentralized AC load model and centralized ice-storage AC load model are proposed, respectively. Finally, an optimization framework of the IENG is proposed based on fast-ADMM with restart algorithm which tackles the information barriers between the different operators. The main contributions of this paper can be summarized as follows: (1) The impacts of uncertainties including NG load uncertainty on the system are considered, which is formulated as a TSRO problem and solved by C&CG algorithm; (2) The DSR model of decentralized AC load and centralized ice-storage AC load is established; (3) The model of IENG at a distribution level based on fast-ADMM with restart algorithm is established which offers higher convergence accuracy within limited iteration times.

The paper is organized as follows. Section II describes the mathematical model of the system. Section III introduces the formulation of uncertainty. Section IV formulates the optimization problem. Finally, optimization results of case
study and conclusions are presented in Section V and VI, respectively.

II. MODEL OF IENG AT A DISTRIBUTION LEVEL

In this section, the detailed models of IENG are proposed, including the economic model and the operation model.

A. ECONOMIC MODEL OF IENG

The objective function describes the economic costs of the entire system, including the electricity system costs $\text{Cost}_{\text{grid}}^d$, the startup/shutdown costs of MT $\text{C}_{\text{MT}}$ and the NG system costs $\text{Cost}_{\text{gas}}^d$. Among them, the cost of electricity system includes the purchase costs from main grid, electricity sales revenue to main grid; and NG system costs include NG production costs and NG storage costs.

$$\text{MinCost}_{\text{grid}}^d + \text{Cost}_{\text{gas}}^d + \text{C}_{\text{MT}}$$

(1)

$$\text{Cost}_{\text{grid}}^d = \sum_{t=1}^{T} [P_{\text{in}} (t) C_{\text{ele.purchase}} (t) - P_{\text{out}} (t) C_{\text{ele.sell}} (t)]$$

(2)

$$\text{Cost}_{\text{gas}}^d = \sum_{t=1}^{T} [F_{\text{supply}} (t) C_{\text{gas.supply}} (t) + F_{\text{in}} (t) C_{\text{gas.inject}} (t)]$$

(3)

where $T$ is the day-ahead scheduling period; $t$ represents the time; $P_{\text{in}}$ is the power transferred from main grid to distribution network; $P_{\text{out}}$ is the power transferred from distribution network to main grid; $F_{\text{supply}}$ is the gas supplied by transmission network; $F_{\text{in}}$ is the gas injection amount of the gas storage tank; $C_{\text{ele.purchase}}$ is the price purchasing from main grid; $C_{\text{ele.sell}}$ is the price selling to main grid; $C_{\text{gas.supply}}$ is the price purchasing from transmission network; $C_{\text{gas.inject}}$ is the storage price of gas storage.

B. OPERATION MODEL OF IENG

1) MODEL OF ELECTRICITY NETWORK

In this paper, traditional radial distributed network is considered which is shown in Figure 1, and Dist-Flow [26] is used to describe the complex power flow:

$$P_{l+1}(t) = P_{l}(t) - \frac{r_l (P_{l}^2(t) + Q_{l}^2(t))}{V_{l}^2(t)} - p_{l+1,l}(t) + p_{l+1,g}(t)$$

(4)

$$Q_{l+1}(t) = Q_{l}(t) - \frac{x_l (P_{l}^2(t) + Q_{l}^2(t))}{V_{l}^2(t)} - q_{l+1,l}(t) + q_{l+1,g}(t)$$

(5)

$$V_{l+1}^2(t) = V_{l}^2(t) - 2(r_l P_{l}(t) + x_l Q_{l}(t)) + (r_l^2 + x_l^2)(P_{l}^2(t) + Q_{l}^2(t))$$

(6)

where $l$ represents the node in the distribution network; $P_l$, $Q_l$ are the active and reactive power of line from node $i$ to $i + 1$, respectively; $p_{l,g}, q_{l,g}$ are active and reactive power of generation of node $i$; $p_{l,g}, q_{l,g}$ are active and reactive load of node $i$, respectively; $r_l$, $x_l$ are resistance and reactance between node $i$ and $i + 1$, respectively; $V_l$ is the voltage of node $i$.

The Dist-Flow equations can be simplified using linearization. The linearized power flow equations have been extensively used and justified in both traditional distribution systems and MGs [27]–[29]. In addition, the voltage level at each node is within the permissible range.

$$P_{l+1}(t) = P_{l}(t) - p_{l+1,l}(t) + p_{l+1,g}(t)$$

(7)

$$Q_{l+1}(t) = Q_{l}(t) - q_{l+1,l}(t) + q_{l+1,g}(t)$$

(8)

$$V_{l+1}^2(t) = V_{l}^2(t) - [r_l P_{l}(t) + x_l Q_{l}(t)]/V_0$$

(9)

$$V_{l+1}^2(t) \leq V_{l}^2(t) \leq V_{l}^2_{\text{max}}$$

(10)

2) MODEL OF NG NETWORK

NG network constraints [9] are shown in the following equations. The Weymouth equation is employed to describe the relationship between the pressure loss and the natural gas flow in the pipelines as shown in Eq. (11). The flow and node pressure is within certain range due to the physical characteristic of pipelines as shown in Eq. (12)–(13). Besides, the node demand-supply balance is described by Eq. (14).

$$\text{sign} \cdot (f_{pq}(t))^2 = \varphi(q_{m}^2(t) - \pi_{m}^2(t))$$

(11)

$$\text{sign} = \begin{cases} 1, & \pi_{m} \geq \pi_{n} \\ -1, & \pi_{m} < \pi_{n} \end{cases}$$

$$F_{q}^\text{min} \leq f_{pq}(t) \leq F_{q}^\text{max}$$

(12)

$$\pi_{m}^\text{min} \leq \pi_{m}^2(t) \leq \pi_{m}^\text{max}$$

(13)

$$\sum_{q \in S_m} f_{pq}(t) + F_{m,s}(t) - F_{m,l}(t) = 0$$

(14)

where $q$ represents the number of pipelines; $m$ or $n$ is the node of NG network; sign is the variable representing the direction of gas flow $f_{pq}$ is NG flow of pipe $q$; $\varphi$ is NG pipeline parameters; $\pi_{m}$, $\pi_{n}$ are the pressure of node $m$ and $n$, respectively; $F_{q}^\text{min}$ and $F_{q}^\text{max}$ are the lower and upper limits of NG flow in the pipeline $q$; $\pi_{m}^\text{min}$ and $\pi_{m}^\text{max}$ are the lower and upper limits of pressure in node $m$; $S_m$ is the set of pipelines which is attached to node $m$; $F_{m,s}$ is the gas supply of node $m$; $F_{m,l}$ is the gas load of node $m$.

To reduce the computational difficulty, the nonlinear constraints are linearized by the incremental linearization method [15], [30]. The nonlinearity of the square terms of NG
pipeline pressure, \(\pi^2\), can be eliminated by a new variable \(p_{sm} = \pi^2m\). In this case, the nonlinear term turns to be the square term of the NG flow, \(fp^2\), then the flow equations are linearized by introducing variables \(\delta_{q,k}\) and \(\eta_{q,k}\), where \(\eta_{q,k}\) are binary variables. The specific linearization process is shown in the following:

1) Balance the linearization accuracy and the calculation amount, then determine appropriate number of linear segments, \(NP\), and calculate the reference point \(fp_q\), \(fp_{q,1}\) by Eq. (15);
2) Describe \(fp_1, fp_2, \ldots, fp_{NP}\) by variables \(\delta_{q,k}\) and constants \(F_{q,max}, F_{q,min}\) and \(NP\) in Eq. (16);
3) Find \(fp^2_q\) values corresponding to each discrete point by the reference point and variables \(\delta_{q,k}\) in Eq. (17);
4) Ancillary variables \(\delta_{q,k}\) and \(\eta_{q,k}\) subjected to constraints Eq. (18)–(19) are added.

\[
fp_q = F_{q,min}^{\prime} + \sum_{k=1}^{NP-1} \left( F_{q,max}^{\prime} - F_{q,min}^{\prime} \right) / (NP-1) \delta_{q,k}(t)
\]

\[
fp^2_q = fp^2_{q,1}^{\prime} + \sum_{k=1}^{NP-1} \left[ fp^2_{q,k+1}(t) - fp^2_{q,k}(t) \right] \delta_{q,k}(t)
\]

\[
\delta_{q,k+1}(t) \leq \eta_{q,k} \cdot \eta_{q,k}(t) 
\leq \delta_{q,k}(t), \quad k = 1, 2, \ldots, NP - 2
\]

\[
1 \leq \delta_{q,k}(t) \leq 0, \quad k = 1, 2, \ldots, NP - 1
\]

3) MODEL OF MT

The annual fuel costs of the MT \(C_{\text{gas, fuel}}\) can be calculated from the power of MT, \(P_{mt}^p\), by the power consumption function [31]:

\[
C_{\text{gas, fuel}} = \sum_{t=1}^{T} \alpha + \beta P_{mt}^p(t) + \gamma \left[ P_{mt}^p(t) \right]^2
\]

where \(p\) is the numbers of MT; the parameters, \(\alpha, \beta, \gamma\) of the consumption function can be chosen from the fuel consumption curve of the MT [32]. The MT also should be subject to the on and off constraints:

\[
U_p(t) P_{mt}^{\text{min}} \leq P_{mt}^p(t) \leq U_p(t) P_{mt}^{\text{max}}
\]

\[
I_p(t) + M_p(t) \leq 1
\]

\[
U_p(t - 1) - U_p(t) + I_p(t) - M_p(t) = 0
\]

where \(U_p\) is a binary variable describing the state of MT; \(I_p\) and \(M_p\) are binary variables representing on and off states of MT, respectively; \(P_{mt}^{\text{min}}, P_{mt}^{\text{max}}\) are the lower and upper power limits of MT, respectively.

4) MODEL OF DSR

Owing to the DSR characteristics of AC load, power dispatch can achieve quick response with reasonable control method, which alleviates the contradiction between power supply and demand and reduces operation costs. Due to the distinctive characteristics of the AC load, the control methods are also variant. The AC load considered in this paper includes decentralized AC load and centralized ice-storage AC load.

For decentralized AC, controlling the state of AC can maintain the indoor temperature within a certain range according to the thermal hysteresis effect of the room. As shown in Figure 2, the on time \(t_0\) and the off time \(t_1\) can be obtained by thermal parameter model, where the time of a control cycle is \(\tau_c\). The AC are divided into \(\tau_c\) groups and each group has \(\tau_c\) states. Consequently, when entering the next control cycle, there is always a group of AC to be off, and another group of AC to be on, which guarantee that only \(t_1\) groups of AC are on for every minute [33].

The specified control method is shown as follows. Assuming the control period of the AC is 10 min, the on time is 3 min, the off time is 7 min. Then every group has 10 states \((a_0, b_0, c_0, d_0, e_0, f_0, g_0, h_0, i_0, j_0)\) as shown in Figure 2. The state distribution of the 10 groups of AC in the two control cycles is shown in Figure 3, where the horizontal axis represents the number of AC groups, and the vertical axis represents the time interval. For every group, the AC are on for 7 min (the states of \(a_0, b_0, c_0, d_0, e_0, f_0, g_0\)) and off for 3 min (the states of \(h_0, i_0, j_0\)), which ensure the temperature to be maintained in a certain range in each control cycle. Furthermore, for every minute, there are only 3 groups to be on. Therefore, the load of decentralized AC after reduction can be calculated as follows:

\[
P_{de}(t) = P_{de0}(t) \frac{t_1}{(t_0 + t_1)} = P_{de0}(t) a
\]

where the \(P_{de0}\) represents the original decentralized AC load of corresponding nodes, which is a part of total electric load, \(p_{l,i}\); \(P_{de}\) represents the AC load after DSR; \(a\) is the cut coefficient.

As shown in Figure 4, the ice-storage AC generally includes the chiller unit, ice-storage tank, pumps and other auxiliary equipment and the ice is used as storage medium. Centralized ice-storage AC makes and stores ice in the ice storage tank (ice-making mode) in the evening when the electricity price is low. The ice is melted (ice-melting mode)
in the daytime when the electricity price is high, and the chiller operates (cooling-making mode) at the same time to joint supply the cooling load. The system operation costs are reduced in which the load is shifted from high price period to the low price period [34], [35]. Centralized ice-storage AC has two modes of operation: the chiller provides the base load or the ice-storage tank provides the base load. The later makes full use of the ice-storage tank, which results in more benefits than the chiller priority mode. Centralized ice-storage AC load model is as follows: the cooling load supply-demand balance is shown in Eq. (25); the calculation of ice column of ice storage tank is shown in Eq. (26); the relationship between the power consumption of chiller and cooling power is described by Eq. (27); the cooling power of chiller in ice-making mode or cooling-making mode should be in certain range as shown in Eq. (28)~(29), and the ice-making mode or cooling-making mode cannot operate at the same time in Eq. (30).

\[
\begin{align*}
Q_{\text{load}} (t) &= Q_a (t) + Q_d (t) \\
E_{\text{red}} (t) &= (1 - \theta_1) Q_a (t) + \theta_2 Q_d (t) \Delta t - Q_d (t) \Delta t \\
P_a (t) &= Q_a (t) / \text{COP}, P_c (t) = Q_c (t) / \text{COP} \\
\end{align*}
\]

where \( Q_{\text{load}} \) is the cooling load; \( E_{\text{red}} \) is the cooling power stored in ice storage tank; \( P_a \) represents the electric power of chiller in cooling-making mode; \( P_c \) represents the electric power of chiller in ice-making mode; \( Q_a \) and \( Q_c \) are the cooling power corresponding to the electric power \( P_a \) and \( P_c \), respectively; \( Q_d \) is the cooling power by melting ice; \( I_a \) and \( I_c \) are the state variables of cooling-making mode and ice-making mode; \( Q_{a\text{-min}} \) and \( Q_{a\text{-max}} \) are lower and upper cooling power of chiller; \( \theta_1 \) is the dissipation coefficient of stored cooling, which is chosen to be 0.02. \( \theta_2 \) is refrigeration coefficient, equaling to be 0.67. COP is coefficient of refrigeration of chiller [36].

5) MODEL OF NG STORAGE TANK
The NG load may exceed the capacity of pipelines, but it is not economical to build new NG pipelines. Accordingly, the NG storage facilities serve as adjustable supply or demand entities when the network security or load cannot be guaranteed [37]. The capacity of the storage should be kept at a certain level to ensure an enough pressure of gas storage tank:

\[
F_{s,\text{min}} \leq F_s (t) \leq F_{s,\text{max}} 
\]

The gas withdrawal and injection amount are also subject to in-flow and out-flow limit [37]:

\[
\begin{align*}
F_{\text{w,\text{min}}} &\leq F_{\text{w}} (t) \leq F_{\text{w,\text{max}}} \\
F_{\text{in,\text{min}}} &\leq F_{\text{in}} (t) \leq F_{\text{in,\text{max}}} 
\end{align*}
\]

Besides, storage capacity is calculated as Eq. (34) at each time step [38].

\[
F_s (t + 1) = F_s (t) - F_w (t) + F_{\text{in}} (t)
\]

where \( F_s \) is the gas column in gas storage tank; \( F_w \) is gas withdrawal amount of gas storage tank; \( F_{s,\text{min}}, F_{s,\text{max}} \) are lower and upper limit of gas storage tank, respectively; \( F_{\text{w,\text{min}}}, F_{\text{w,\text{max}}} \) are lower and upper limit of gas withdrawal amount, respectively; \( F_{\text{in,\text{min}}}, F_{\text{in,\text{max}}} \) are lower and upper limit of gas injection amount, respectively.

III. FORMULATION OF UNCERTAINTY

To obtain the robust solution of the system with consideration of uncertainties, a TSRO model is introduced and C&CG algorithm is utilized to solve this problem.

A. TWO-STAGE ROBUST OPTIMIZATION MODEL
In the robust optimization model, uncertainty is grouped as a set, and the uncertainty variables are obtained to represent the worst case. In the worst case, the uncertainty variables are fixed, and the optimal solution obtained in this scenario is the robust solution under uncertainty.
The TSRO model can be formulated as follows in a matrix form:

\[
\begin{align*}
\min & \quad c^Tx + \max \min d^Ty \\
\text{s.t.} & \quad Ax \geq b, \quad Bx = e, \quad Dy \geq f, \quad Ey = g, \\
& \quad Fy \geq -Gx, \quad Jy \leq w, \quad Ky \leq pv, \quad My = l
\end{align*}
\]

where \( x \) is the first-stage variable as well as the binary vector representing the state variables of MT; \( u \) is uncertainty variable set including uncertainty variables \( w, pv \) and \( l \); \( y \) is the second-stage variable including \( P_{w0}, P_{w0}, Q_v, V_i, f_P, f_{in}, F_w, \pi_m, P_w, P_pv, P_{load}, F_{load} \) are actual wind power, photovoltaic power, electricity load and NG load; \( c^T x \) represents the startup/shutdown costs of MT, \( C_{MT} ; d^T y \) represents the costs including Cost'_grid and Cost'_gas; \( A \) and \( B, C \) are the corresponding matrix representing the inequality and equality constraints about variables \( x \), respectively. \( D \) and \( f \), \( E \) and \( g \) are the corresponding matrix representing the inequality and equality constraints about variables \( y \). \( F \) and \( G \) are the corresponding matrix representing the inequality constraints about variables \( x \) and \( y \). \( J, K, M \) are the corresponding matrix representing the inequality constraints about variables \( y \) and uncertain variables \( w, pv, l \). In the TSRO problem shown in Eq. (35), the first ‘min’ aims to minimize the first-stage costs by optimizing the first-stage variable \( x \). The ‘max’ is to find the worst case under the uncertainty set \( u \) by maximizing the minimization of the second stage costs. The second ‘min’ is to minimize the second stage costs by optimizing the second-stage variable \( y \). The uncertainty sets of wind power, photovoltaic power, electricity load and NG load is described as follow:

\[
\begin{align*}
U_w &= \{ w : P_w(t) = P_{w0}(t) + \mu_+ (t) P_{w+}(t) \\
&\quad - \mu_-(t) P_{w-}(t) \} \\
U_{pv} &= \{ pv : P_{pv}(t) = P_{pv0}(t) + \beta_+ (t) P_{pv+}(t) \\
&\quad - \beta_-(t) P_{pv-}(t) \} \\
U_{load} &= \{ l : F_{load}(t) = F_{l0}(t) + \theta_+ (t) P_{l+}(t) \\
&\quad - \theta_-(t) P_{l-}(t) \} \\
U_{g, load} &= \{ l : F_{load}(t) = F_{l0}(t) + \sigma_+ (t) P_{l+}(t) \\
&\quad - \sigma_-(t) P_{l-}(t) \}
\end{align*}
\]

where \( U_w, U_{pv}, U_{load} \) and \( U_{g, load} \) are uncertainty set of forecast data; \( P_{w0}, P_{pv0}, P_{l0} \) and \( F_{l0} \) are forecast data, and \( P_{w+}, P_{w-}, P_{pv+}, P_{pv-}, P_{l+}, P_{l-}, F_{l+}, F_{l-} \) represent the positive and negative deviation of forecast data, and \( \mu_+, \beta_+, \theta_+, \sigma_+, \mu_-, \beta_-, \theta_-, \sigma_- \) represent the binary variables of deviation. Because of information privacy of different operators, the entire problem is decomposed into two sub-problems according to two different system. Based on above form and variables, the TSRO problems are organized as follow including electricity sub-problem and NG sub-problem.

\[
\min \quad C_{MT} + \text{Cost'}_{grid} \\
\text{s.t. constraints (7) \sim (10) , (20) \sim (30), (36) \sim (38)
\]

\[
\min \max \quad \text{Cost'}_{gas} \\
\text{s.t. constraints (12) \sim (19), (31) \sim (34), (39)
\]

B. COLUMN AND CONSTRAINTS GENERATION (C&CG)

For TSRO problem, Benders decomposition and C&CG are widely used. According to [40], the convergence speed and iteration times of C&CG are better than Benders decomposition, and C&CG is selected to solve this problem. In the C&CG algorithm, the TSRO problem (35) is decomposed into the main problem (42) and the slave problem (43).

\[
\begin{align*}
\min & \quad C_{MT} + \delta \\
\text{s.t.} & \quad Ax \geq b, \quad Bx = e, \quad d^T y \geq \lambda \\
& \quad \max \min d^T y \\
\text{s.t.} & \quad Dy \geq f, \quad Ey = g, \quad Fy \geq -Gx, \\
& \quad Jy \leq w, \quad Ky \leq pv, \quad My = l
\end{align*}
\]

According to above form, the TSRO problem of electricity sub-problem in this paper is organized as follows, which includes the main problem (44) and the slave problem (45).

\[
\begin{align*}
\min & \quad C_{MT} + \lambda \\
\text{s.t.} & \quad (21) \sim (23), \quad \text{Cost'}_{grid} \geq \lambda \\
& \quad \max \min \quad \text{Cost'}_{grid} \\
\text{s.t.} & \quad (7) \sim (10), (20), (24) \sim (30)
\end{align*}
\]

For the ‘max-min’ slave problem (43), it can be transformed into a ‘max’ problem by introducing the dual variables which is a bilinear maximization problem and the dual problem can be described as follow [41]:

\[
\begin{align*}
\max & \quad \alpha' \beta' \gamma' \psi' \\
& \quad \delta_+(t) \mu_+(t)
\end{align*}
\]

\[
\begin{align*}
\text{s.t.} & \quad \alpha' \beta' \gamma' \psi' \\
& \quad \gamma' (t) = \gamma' (t) \mu_+(t) + \mu_+(t) \mu_- (t) - \gamma' (t) \mu_-(t) \mu_+ (t)
\end{align*}
\]

where \( \alpha', \beta', \gamma', \psi', \mu' \) are the dual variables of \( y \). However, \( \gamma' w, \psi' pv \) and \( \mu' l \) are bilinear term which is difficult to solve. Therefore, big-M method is used to handle this bilinear problem [42]. The bilinear term, \( \gamma' w \), is linearized as following:

\[
\begin{align*}
\gamma' w &= \gamma' (t) P_{w0}(t) + \gamma' (t) \mu_+(t) P_{w+}(t) - \gamma' (t) \mu_-(t) P_{w-}(t) \\
\delta_+(t) &= \gamma' (t) \mu_+(t) \\
\delta_-(t) &= \gamma' (t) \mu_-(t)
\end{align*}
\]

(47) (48) (49)

where \( \gamma', \beta', \gamma', \psi', \mu' \) are the dual variables of \( y \). However, \( \gamma' w, \psi' pv \) and \( \mu' l \) are bilinear term which is difficult to solve. Therefore, big-M method is used to handle this bilinear problem [42]. The bilinear term, \( \gamma' w \), is linearized as following:

\[
\begin{align*}
\gamma' w &= \gamma' (t) P_{w0}(t) + \gamma' (t) \mu_+(t) P_{w+}(t) - \gamma' (t) \mu_-(t) P_{w-}(t) \\
\delta_+(t) &= \gamma' (t) \mu_+(t) \\
\delta_-(t) &= \gamma' (t) \mu_-(t)
\end{align*}
\]
where $M'$ is a large enough constant; $\delta_-(t)$, $\delta_+(t)$ are the auxiliary variables. By Eq. (47)-(51), the bilinear term is transferred to linear constraints, and $\psi^T p v$ and $\mu^T 1$ can also be handled in the same method.

The specific flowchart is shown in Figure 5:

Step 1: Initialize lower bound (LB), upper bound (UB). Set $x = x_0$, iteration times $\rho = 0$, initialize $w_0$, $p_0$, $l_0$;

Step 2: $x_{\rho+1}$ and $\lambda_{\rho+1}$ are obtained by solved (44) based on $w_\rho$, $p_\rho$ and $l_\rho$, then LB is updated;

Step 3: $w_{\rho+1}$, $p_{\rho+1}$ and $l_{\rho+1}$ is obtained by solved (46) based on $x_{\rho+1}$, then $w_{\rho+1}$, $p_{\rho+1}$ and $l_{\rho+1}$ is brought in (45) to obtained $y_{\rho+1}$; Update UB=min(UB, $c^T y_{\rho+1} + d^T y_{\rho+1}$)

Step 4: If thresholds, Gap, are small enough, the optimal solution is obtained. Otherwise, turn to Step 2.

IV. FORMULATION OF OPTIMIZATION PROBLEM

In this section, an optimal day-ahead scheduling framework for the IENG system at a distributed level is formulated based on the fast-ADMM with restart algorithm. Distributed algorithm is used to guarantee the privacy of their information for operators of electricity and NG systems and adopt distinct models and algorithms to solve their individual systems. The ADMM is well suited to distributed optimization, and in particular to large-scale problems [43]. And the fast-ADMM with restart algorithm use a restart rule can improve the stability of convergence rate [44].

A. OPTIMAL DAY-AHEAD SCHEDULING MODEL BASED ON FAST-ADMM WITH RESTART ALGORITHM

The IENG system includes the electricity network and the NG network, but it is difficult to carry out the optimization over the whole system directly because of the opacity of the information between the two operators. To obtain the optimal solution, the fast-ADMM with restart algorithm is utilized where the entire system is decomposed into an electricity sub-problem and a NG sub-problem, which are iteratively solved. According to the fast-ADMM with restart algorithm, the NG consumption of MT, $F_{r,grid}$ and $F_{r, gas}$ are the local variables in the sub-problems corresponding to the global variable $F_{r, couple}$.

(1) Electricity Sub-problem

$$Cost_{grid} = Cost'_{grid} + C_{MT}$$

$$+ \sum_{t=1}^{T} \sum_{p} \left\{ \lambda_{t,p} (t) [F_{t, grid}(t) - F_{t, couple}(t)] \right\}$$

$$s.t. \text{ constraints (7)} \sim (10), (20) \sim (30), (36) \sim (38)$$

(52)

(2) NG Sub-problem

$$Cost_{gas} = Cost'_{gas}$$

$$+ \sum_{t=1}^{T} \sum_{p} \left\{ \lambda_{t,p} (t) [F_{t, gas}(t) - F_{t, grid}(t)] \right\}$$

$$s.t. \text{ constraints (12)} \sim (19), (31) \sim (34), (39)$$

(53)
Step 1: Initialize global variable $F_{p,0,couple}$, $F_{p,0,\text{gas}}$, $\lambda^*_p$, $\lambda_{p,0}$, penalty factors $\tau$ and $c_p$. Set iteration index $r = 1$. Set the convergence thresholds $\varepsilon$. Set $\alpha_1 = 1$;

Step 2: Solve (52) with given $F_{p,r,couple}$ and obtain the optimal solution $F_{p,r,\text{grid}}$;

Step 3: Solve (53) with given $F_{p,r,\text{grid}}$ and obtain the optimal solution $F_{p,r,\text{gas}}$;

Step 4: Calculate the Lagrange multipliers $\lambda_{p,r}$ by $\lambda^r_{p,r}$, $F_{p,r,\text{grid}}$ and $F_{p,r,\text{gas}}$ in (55), and $c_p$ is obtained by $\tau$, $\lambda_{p,r}$, $\lambda^r_{p,r}$, $F_{p,r,\text{grid}}$ and $F_{p,r,\text{gas}}$ in (56);

Step 5: If $c_{p,r} < \sigma \ast c_{p,r-1}$, update $\alpha_{r+1}$, $F_{p,r+1,couple}$, $\lambda^r_{p,r+1}$ by Eq. (57), Eq. (58), Eq. (59), otherwise, set $\alpha_{r+1} = 1$, $F_{p,r+1,couple} = F_{p,r-1,\text{gas}}$, $\lambda^r_{p,r+1} = \lambda_{p,r-1}$, $c_{p,r} = 1/\sigma$ *$c_{p,r-1}$;

Step 6: If thresholds are met in Eq. (54), the final optimal solution is obtained; Otherwise, go to Step 2.

$$\text{Gap} = \max \{F_{p,r,\text{grid}} - F_{p,r,\text{gas}}, F_{p,r,\text{gas}} - F_{p,r,couple}\}$$

$$\lambda_{p,r} (t) = \lambda^r_{p,r} (t) + \tau[F_{p,r,\text{grid}} (t) - F_{p,r,\text{gas}} (t)]$$

$$c_{p,r} (t) = \frac{[\lambda^r_{p,r} (t) - \lambda_{p,r} (t)]^2}{\tau} + \tau[F_{p,r,\text{gas}} (t) - F_{p,r,couple} (t)]^2$$

$$\alpha_{r+1} = [1 + \sqrt{1 + \alpha_r^2}] / 2$$

$$F_{p,r+1,couple} (t) = F_{p,r,\text{gas}} (t) + \frac{\alpha_r - 1}{\alpha_{r+1}} [F_{p,r,\text{gas}} (t) - F_{p,r-1,\text{gas}} (t)]$$

$$\lambda^r_{p,r+1} (t) = \lambda_{p,r} (t) + \frac{\alpha_r - 1}{\alpha_{r+1}} [\lambda_{p,r} (t) - \lambda_{p,r-1} (t)]$$

V. CASE STUDY

In this section, numerical studies are conducted for analyzing the performance of our proposed model, and the effects of the uncertainties and DSM are investigated. The performance of fast-ADMM with restart algorithm is also investigated compared with standard ADMM [18]. In this paper, as shown in Figure 7, the example system includes the IEEE33 node radiation distribution network and a 7-node NG network, which is implemented in YALMIP and solved by Gurobi 7.0.2. The voltage of the balanced node is 12.66kV, and the voltage range of each node is 0.95 p.u~1.05 p.u. The nodes 14, 16, 31 are connected to three wind turbines (WTs), and the nodes 19, 27, 32 are connected to three photovoltaic (PV) arrays. The hourly forecasted hourly power of PV arrays and WTs are shown in Figure 8 and Figure 9, respectively. The 3, 4, 6, 7 nodes of the NG network are connected to the power network nodes 8, 13, 16, 33 by MT [45]. Besides, the load in node 8, 14, 33 include decentralized AC load taking in 30%, 30% and 40% of total load. For node 24, centralized ice-storage AC is configured to meet the cooling load. The chiller power of centralized ice-storage AC is 250kW, and the capacity of ice-storage tank is 1800kWh. The peak load of centralized ice-storage AC is 500kW, and the total load
is 4020kWh. The total load per hour is shown in Figure 10. The uncertain bounds of DG, electricity load and the NG load forecast data is 10%.

A. OPTIMAL SCHEDULING OF IENG CONSIDERING DSR AND UNCERTAINTY

To verify the proposed model, four cases are considered:
Case1: without considering uncertainty and DSR;
Case2: with only considering uncertainty;
Case3: with only considering DSR;
Case4: with considering uncertainty and DSR.

1) THE EFFECT OF UNCERTAINTIES

The operation costs of four cases are shown in Table 1, and Figure 11 shows the NG consumption of MT. The NG consumption variations in Case2 compared to Case1 are shown in Figure 12 and Figure 13 shows the column variation of NG storage tank where the NG is stored in low electricity price period especially from 0:00 to 8:00, and released in high electricity price period, 12:00-15:00 and 18:00-23:00. Compared to Case 1 and Case 2 in Figure 11 and Figure 13, in which the uncertainty is considered, MT and the NG storage tank are required to absorb more NG to balance the supply and demand. It can be observed in Figure 12 and Table 2 that the consumption of NG of Case2 is larger than the consumption in Case1, and especially in MT4 the NG consumption variation reaches 28.15MBtu (Million Britain Thermal Unit) during scheduling period.

The power of point of common coupling (PCC) node is shown in Figure 14. The power transferred from the distribution network to main grid is decreasing in Case2 because of the increasing electricity load and decreasing output power of DG in the worst case, which result in the higher costs on the electricity side. In addition, the gas load is decreasing in worst case which result in the lower profits on the NG side. Eventually, the operation costs of IENG in Case2 is higher than that in Case1.

2) THE EFFECT OF DSR

As shown in Figure 15, the ice-storage AC load makes and storages ice in the evening leading to the increase of load from 22:00 to 7:00 of the next day, and in the daytime the ice is melted from 9:00 to 18:00 leading to load decreasing. The DSR of centralized AC load directly affects the change in the node voltage. The voltage variation of node 24 in Case3 is

---

### TABLE 1. The operation cost of system.

<table>
<thead>
<tr>
<th></th>
<th>Case1</th>
<th>Case2</th>
<th>Case3</th>
<th>Case4</th>
</tr>
</thead>
<tbody>
<tr>
<td>NG-side Cost/$</td>
<td>2280</td>
<td>2279</td>
<td>2283</td>
<td>2282</td>
</tr>
<tr>
<td>Electricity-side Cost/$</td>
<td>-21190</td>
<td>-16985</td>
<td>-21632</td>
<td>-17443</td>
</tr>
<tr>
<td>Total Cost/$</td>
<td>-18910</td>
<td>-14706</td>
<td>-19349</td>
<td>-15161</td>
</tr>
</tbody>
</table>

### TABLE 2. The specific natural gas consumption variation in case2 compared with case1 (MBtu).

<table>
<thead>
<tr>
<th>Time/h</th>
<th>MT1</th>
<th>MT2</th>
<th>MT3</th>
<th>MT4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>-0.003</td>
<td>-0.028</td>
<td>1.438</td>
</tr>
<tr>
<td>2</td>
<td>-0.114</td>
<td>0</td>
<td>0</td>
<td>0.566</td>
</tr>
<tr>
<td>3</td>
<td>0.110</td>
<td>0</td>
<td>0</td>
<td>0.022</td>
</tr>
<tr>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>-0.069</td>
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<tr>
<td>5</td>
<td>0.359</td>
<td>0.359</td>
<td>0.132</td>
<td>-0.009</td>
</tr>
<tr>
<td>6</td>
<td>0.337</td>
<td>0</td>
<td>-0.046</td>
<td>0.106</td>
</tr>
<tr>
<td>7</td>
<td>0.337</td>
<td>-0.250</td>
<td>-0.055</td>
<td>0.084</td>
</tr>
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<td>8</td>
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<td>0.637</td>
<td>1.483</td>
<td>2.222</td>
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<td>-0.142</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0.005</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>0</td>
<td>0</td>
<td>-0.134</td>
<td>1.872</td>
</tr>
<tr>
<td>12</td>
<td>0</td>
<td>0.190</td>
<td>-0.041</td>
<td>0.510</td>
</tr>
<tr>
<td>13</td>
<td>0</td>
<td>0</td>
<td>-0.175</td>
<td>1.203</td>
</tr>
<tr>
<td>14</td>
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<td>-0.070</td>
<td>0</td>
<td>1.043</td>
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<tr>
<td>15</td>
<td>-0.023</td>
<td>-0.125</td>
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</tr>
<tr>
<td>16</td>
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<td>-0.098</td>
<td>1.2668</td>
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<tr>
<td>17</td>
<td>0</td>
<td>0.382</td>
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<tr>
<td>18</td>
<td>0.449</td>
<td>0</td>
<td>0.449</td>
<td>1.673</td>
</tr>
<tr>
<td>19</td>
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<td>0.975</td>
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<tr>
<td>20</td>
<td>0</td>
<td>0.206</td>
<td>0</td>
<td>3.145</td>
</tr>
<tr>
<td>21</td>
<td>0.538</td>
<td>0</td>
<td>0.516</td>
<td>0.265</td>
</tr>
<tr>
<td>22</td>
<td>0.449</td>
<td>0.449</td>
<td>0</td>
<td>1.796</td>
</tr>
<tr>
<td>23</td>
<td>0</td>
<td>0.449</td>
<td>-0.209</td>
<td>0.898</td>
</tr>
<tr>
<td>24</td>
<td>-0.223</td>
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<td>0</td>
<td>1.052</td>
</tr>
<tr>
<td>Total</td>
<td>2.89</td>
<td>2.16</td>
<td>1.181</td>
<td>21.85</td>
</tr>
</tbody>
</table>
shown in Figure 16. The voltage drops during the day due to the decrease of the load consumption and the voltage rises at night due to the increase of the ice-storage AC load.

Similarly, the decentralized AC load is curtailed. Affected by the centralized ice-storage AC load and decentralized AC load, the power of PCC in Case3 is changed compared with that in Case1, which is shown in Figure 14. The power of PCC, where the power is transferred from the distribution network to the main grid, is decreased during 0:00 to 8:00 because the increasing of the centralized ice-storage AC load is larger than the decreasing load of the decentralized AC load. After 8:00, the power of PCC starts increasing. Besides, the load variation also affects the voltage of the corresponding nodes. The voltage of node 8, 14, 30 is changed because of the DSR of decentralized AC load, and the voltage of node 8 is shown in Figure 17 as an example. Owing to the power transferring from the distribution network to the main grid, the high power of lines could result in high voltage loss, which further lead to high node voltage. Therefore, the voltage of three nodes are decreased due to the decrease of power and

**FIGURE 11.** Forecasted hourly total load.

**FIGURE 12.** The natural gas consumption variation in case2 compared with case1.

**TABLE 3.** The specific natural gas consumption variation in case3 compared with case1 (MBtu).

<table>
<thead>
<tr>
<th>Time/h</th>
<th>MT1</th>
<th>MT2</th>
<th>MT3</th>
<th>MT4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.021</td>
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<tr>
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<td>-0.771</td>
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<td>0.0452</td>
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<td>0.299</td>
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<td>0.449</td>
<td>-0.209</td>
<td>1.347</td>
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<td>Total</td>
<td>-2.133</td>
<td>-0.343</td>
<td>0.478</td>
<td>1.998</td>
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</table>
voltage loss during 0:00 to 8:00, and after 8:00 the voltage of these nodes is increased which is raised by the increased of power and voltage loss.

The NG consumption variations in Case3 compared with Case1 are shown in Figure 18 and Table 3. It can be observed that the total NG consumption of Case1 is the same as the entire dispatch cycle in the case of DSR only. Moreover, in Case3 the storage amount is declined from 9:00 to 17:00 comparing with Case1 which leads to increased gas consumption of MT. More NG is stored in low electricity price time from 24:00 to next 8:00, and released in high electricity price time from 18:00 to 23:00, which produce more profits. Despite the slightly increased storage cost, the introducing of DSR decrease the cost of entire system.

B. COMPARISONS ON STANDARD ADMM AND FAST-ADMM WITH RESTART

In this section, costs and the deviations between local variables are given to compare the iteration characteristic of standard ADMM and fast-ADMM with restart. As is shown in Figure 19, the costs in standard ADMM has converged with 25 iterations, and the costs in fast-ADMM with restart has converged with 47 iterations. In contrast, as shown in Figure 20, convergence accuracy in fast-ADMM with restart meet the convergence conditions with only 53 iterations. However, convergence accuracy in standard ADMM cannot reach the convergence conditions even after 80 iterations. Therefore, the fast-ADMM with restart algorithm has higher convergence accuracy than standard ADMM within limited iteration times.
VI. CONCLUSION

This paper proposes an IENG system model at a distributed level and provides a day-ahead scheduling framework. In this model, both the electric network and the linearized NG network model are established. Based on the worst case obtained by C&CG algorithm and fast-ADMM with restart algorithm, the scheduling scheme is optimized under the day-ahead scheduling framework. Case studies with our theory show that:

1) With the scheduling framework, the complement characteristic of the decentralized AC load and the centralized AC load are considered, and the total electric load is curtailed which reduces the operation costs;

2) The uncertainties, especially the uncertainties from the NG, are considered in this paper, which indicates the robustness of the proposed scheduling scheme obtained by solving TSRO problem. In other words, it guarantees the feasibility and economy in the worst case.

3) We implement the fast-ADMM with restart algorithm in this design. Compared to the standard ADMM algorithm, the fast-ADMM with restart algorithm has higher convergence accuracy within limited iteration.

REFERENCES


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