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Multifactor-influenced Reliability-constrained Reserve Expansion of Integrated Electricity-Gas Systems Considering Failure Propagation

Minglei Bao, Xiaocong Sun, Yi Ding, *Member, IEEE*, Chengjin Ye, Changzheng Shao, Sheng Wang, Yonghua Song, *Fellow, IEEE*

***Abstract*—With the increasing interactions between natural gas system (NGS) and power system, the component failures in one system may propagate to the other one, threatening the reliable operation of the whole system. Due to the neglect of such cross-sectorial failure propagation in integrated electricity-gas systems (IEGSs), the traditional economy-oriented reserve expansion model may lead to unreasonable planning results. In order to address this, an innovative reserve expansion model is proposed to determine the allocation of energy production components through the harmonization between costs and reliability. Firstly, the novel multifactor-influenced reliability indices are defined considering the synthetic effects of multiple uncertainties, including failure propagation, load uncertainties and generation failures. In the reliability index formulation, the contribution of failure propagation on system reliability is analytically expressed. To avoid the high computational complexity, the fuzzy set theory is combined with conventional methods, e.g. Monte-Carlo simulation technique to reduce the numerous contingency states. The sampled contingency states are aggregated into several clusters represented by a fuzzy number. To effectively solve the planning model, the decomposition approach is introduced applied to decompose the original problem into a master problem and two correlated reliability subproblems. Numerical studies show that the proposed model can plan reasonable reserve to guarantee the reliability levels of IEGSs considering failure propagation.**

***Index Terms*—Reliability, integrated electricity-gas systems, cross-sectorial failure propagation, long-term reserve planning, fuzzy model.**

I. INTRODUCTION

OWING to their high efficiency and low carbon emissions, the gas-fired power plants (GPPs) have a significant share in electric power generation. The ever-increasing utilization of GPPs strengthens the coupling relationship between natural gas system (NGS) and electric power system (EPS), bringing new reliability problems of integrated electricity-gas systems (IEGSs) [1]. In specific, different from coal-fired power plants whose fuel supply is traditionally considered sufficient, the power output of GPPs relies on gas supply from NGS. Random failures occurring in NGS may cause the interruption of gas supplied to GPPs, leading to the shortage of generating capacity and finally jeopardizing power system security [2]. Such failure amplification process from NGS to EPS through coupled components can be defined as cross-sectorial failure propagation [3]. When considering the failure propagation from NGS to EPS, small disturbances may propagate to the whole system and further engender widespread damage. The catastrophic outages in Texas, America on 15th February 2021 can be served as a demonstration of cross-sectorial failure propagation [4].

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In recent years, the failure propagation issues have gained increasing attention in both industry and academic sectors. In [5] and [6], an integrated simulation framework is proposed to simulate the bi-directional cascading failure propagation in IEGSs. Reference [7] evaluates the vulnerability of IEGSs by combining the cascading failure simulation and a machine learning method. A graph theory-based method is proposed in [8] to assess the impacts of failure propagation on network robustness. In [9], a non-sequential Monte Carlo simulation framework is proposed to analyze the reliability of IEGSs considering failure propagation. The previous works mainly focus on failure propagation simulation [5, 6] and reliability/ robustness analysis [7-9]. However, the countermeasures to guarantee the reliability level of IEGSs under failure propagation are seldom investigated.

As an effective measure to improve the reliability of IEGSs, the long-term reserve expansion aims to determine the deployment of different energy production components, such as power plants, to fulfill more securely the energy consumption of consumers [10]. Reasonable reserve planning results can provide system operators with sufficient standby resources to deal with demand growth or component failures. Considering that, several studies have been carried out on the reserve expansion of IEGSs by allocating new components. A bi-level multi-stage programming model is proposed in [11] considering the bi-directional energy conversion between power system and NGS. In [12], a two-stage stochastic optimization model is developed to realize the trade-offs between constructing gas pipelines, GPPs and other units. Reference [13] proposes a dynamic stochastic joint expansion planning of IEGSs considering long-term uncertainties of gas prices. The authors in [14] propose a bi-level model to allocate the gas storage and uncertain wind farms considering the temporal correlation of wind power. A multi-period framework is proposed in [15] to determine the optimal generation, transmission and gas network expansions. However, the system reliability issues, especially the impacts of component failures on system operation, are seldom considered in the system expansion of the previous studies.

Motivated by the catastrophic outages in Texas attributed to insufficient reserve capacity, the security and reliability issues are essential in the reserve planning of IEGSs for reliable energy delivery. To model the random component failures, the N-1 criterion is widely used in combined energy system planning as a deterministic approach [16, 17]. Nevertheless, the N-1 standard can only ensure the reliable operation of IEGSs under the single component outage, whereas neglecting the simultaneous failures of multiple components. Alternatively, the probabilistic reliability indices, e.g. loss of load probability (LOLP) and expected energy not supplied are considered in [2] and [18]. The existing reliability indices of different energy subsystems are individually formulated considering their autogenic uncertainties, such as gas/electric load variation and electric component failure [18-20]. However, the gas component failures and the corresponding failure propagation, on reliability indices of power systems are seldom considered, which may make the long-term reserve expansion results unreasonable. To address this, the multifactor-influenced reliability indices are proposed in this paper considering the synthetic effects of autogenic and external uncertainties, including cross-sectorial failure propagation, component and load uncertainties. On this basis, a synthetic reserve expansion model is developed to coordinate the planning of energy production components in IEGSs, while guaranteeing the reliability of both subsystems.

Considering the superposed influence of multiple uncertainties, the system contingency states for the calculation of reliability indices can be enormous which requires high computation resources [21]. Under this circumstance, the traditional planning model that considers all system states may not be applicable due to high computation complexity. In order to address that, clustering methods are required to aggregate adjacent system states of IEGSs to decrease the computation burden. As a typical clustering method, the fuzzy set theory can effectively characterize the performance behavior of system states in one cluster (set) instead of using a single crisp number. The degree of different system states that belong to the same set is measured by a membership function, based on which the features of the clustered set can be described in detail [22]. The fuzzy set theory proved as an effective measure for the reliability analysis [23] and operation optimization [24] of energy systems.

Due to its effectiveness and advantage in dealing with data clustering, the fuzzy set theory is introduced and combined with traditional methods, e.g. Monte-Carlo simulation (MCS) technique, to achieve great computational improvement [16]. In specific, based on the component failure states sampled by the MCS technique, the fuzzy theory is applied to aggregate adjacent states into one cluster. In each cluster, the system failure degree is represented by a fuzzy parameter, which is a set of possible values and each value has its own membership. Similarly, the 8760-hour load curve can also be combined with fuzzy set theory to represent a set of aggregate load values using fuzzy representation. On this basis, the number of system contingency states can be significantly reduced. Accordingly, the reserve expansion model is formulated as a fuzzy optimization problem.

In this paper, a multifactor-influenced reliability-constrained reserve expansion is proposed to reduce the adverse effects of failure propagation on IEGSs. Compared with previous studies, the innovative contributions of our paper are summarized as:

(1) By analytically expressing the contribution of failure propagation on system reliability, the novel multifactor-influenced reliability indices are defined considering the autogenic and external uncertainties. The reliability-constrained expansion model is then developed to guarantee the long-term adequacy of IEGSs.

(2) This paper firstly combines the fuzzy set theory and MCS technique to decrease system states for computation efficiency improvement. Based on the defined measurement of system failure degree, the fuzzy method is utilized to aggregate the discrete generation failure states into one cluster.

(3) This paper proposes an efficient algorithm to solve the developed fuzzy reserve expansion model. Optimism parameters are introduced to deal with fuzzy numbers considering the risk propensity of system planners. The decomposition technique is applied to decompose the proposed decision problem into a master problem and two correlated reliability subproblems, where the multifactor-influenced reliability indices can be effectively calculated considering failure propagation.

II. THE RELATIONSHIP BETWEEN LONG-TERM RESERVE PLANNING AND FAILURE PROPAGATION

A. Impacts of cross-sectorial failure propagation on long-term reserve planning of IEGSs

Cross-sectorial failure propagation can be defined as the complicated sequences of dependent events triggered by disruptive events. Due to the coupling relationship between two systems, the random failures occurring in NGS may propagate to EPS through coupled components, i.e. GPPs. The detailed cross-sectorial failure propagation mainly includes the following steps [25].

Step 1) Initial disturbance in NGS: The initial component failures triggered by various disturbances may make the NGS change its operation state.

Step 2) Gas load curtailments: Due to the initial disturbance, several measures may be adopted for the reliable operation of NGS, such as gas production adjustment or gas load curtailments. Due to the interruptible contracts signed between generation units and gas companies, the gas supply of GPPs will be firstly curtailed if the gas production cannot satisfy gas loads [26].

Step 3) Power output reduction GPPs: The gas load curtailments may result in the interruption of gas supply of GPPs. Considering that, the GPPs have to reduce their output due to insufficient gas supply.

Step 4) Electric load curtailments: Due to the reduction of power output, all the available power plants and loads will be re-dispatched to eliminate the power imbalance. If the adjusting of generating output cannot realize power balance, the electric load shedding will be utilized.

Based on the failure propagation process, we can conclude that the random failures occurring in NGS can simultaneously affect the reliability of NGS and EPS, leading to the increasing requirement of power capacity. Accordingly, it is essential to develop an integrated framework for the synergetic planning of gas and power production capacity.

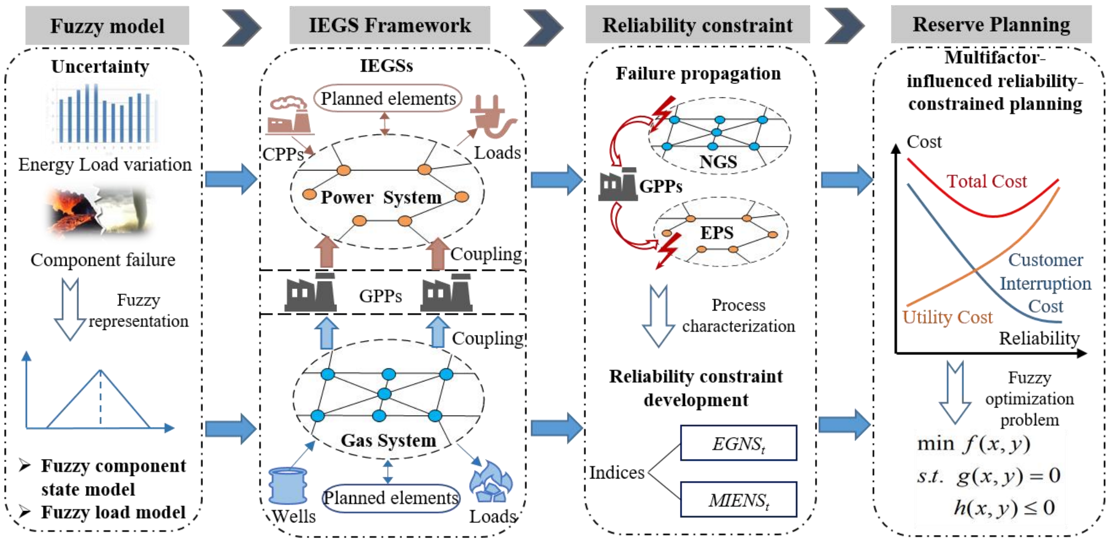

Fig. 1. The outline of this paper to determine long-term reserve expansion

Note that failure propagation is a result of the adjustment/dispatch decisions after the failure occurs, which can be naturally embedded in the optimization model. However, in the previous studies about system planning, the components in gas systems are assumed completely available and the gas-fired power plants can obtain sufficient fuel supply [2, 18]. Hence, the gas component failures and the corresponding failure propagation from gas system to power system are seldom modeled in the previous planning models.

B. The outline of this paper to determine long-term reserve

The outline to determine the long-term reserve of IEGSs is illustrated in Fig.1. Firstly, the MCS technique and fuzzy set theory are combined to aggregate adjacent system states into one cluster represented by a fuzzy number. Similarly, the fuzzy set theory is combined with the LDC model to achieve load representation with fewer load states. According to the fuzzy models of energy loads and component failures, multifactor-influenced reliability indices are formulated, where the cross-sectorial failure propagation is considered. Moreover, the reliability-constrained reserve expansion model is developed to determine the construction of power units, gas suppliers and power-to-gas (P2G) units. In specific, the proposed model is to minimize the total system costs, including investment costs, operation costs and load interruption costs. Finally, an efficient algorithm to solve the proposed fuzzy models by introducing optimism parameters and benders decomposition.

III. FUZZY MODELS TO CHARACTERIZE LOAD AND GENERATION UNCERTAINTIES

A. Fuzzy component operation state curve to characterize generation uncertainties

Considering the failures and maintenance of components in IEGSs, the component operation states in each year can be numerous. Taking EPS as an example, the sequential operation curves of units in one year can be obtained according to their failure and repair rates utilizing the MCS technique [27]. However, the discrete generation operation states, i.e. 1 and 0, cannot be directly clustered using fuzzy set theory since the quantification of failure degree is missing. Considering that, the measurement, i.e. available generating capacity is proposed to quantify the failure degree of power system at different states. By aggregating the sampled unit operation states in Fig. 2, the 8760-hour generating capacity curve of EPS can be determined.

$$\boldsymbol{GC}_t^0 = [GC_{t1}^0, \cdots, GC_{t\varsigma}^0, \cdots, GC_{t8760}^0] \quad (1)$$

where $GC_{t\varsigma}^0$ represents the system available generating capacity at hour ς and year t.

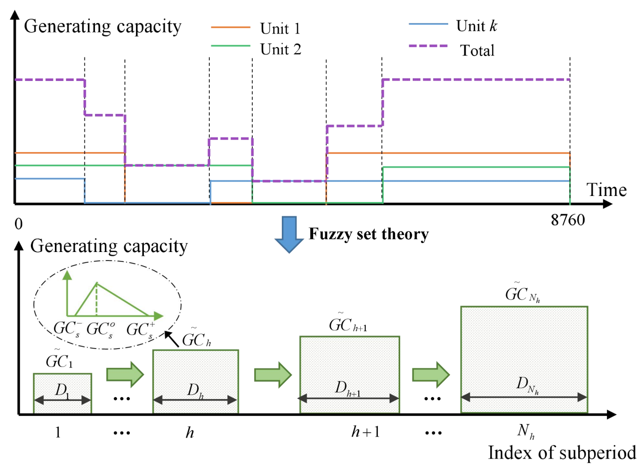

Fig. 2. Description of fuzzy component state curve model

The corresponding 8760-hour operation state curve of different units $\boldsymbol{O}_t^0$ can be expressed as:

$$\boldsymbol{O}_t^0 = [\boldsymbol{O}_{t1}^0, \cdots, \boldsymbol{O}_{t\varsigma}^0, \cdots, \boldsymbol{O}_{t8760}^0], \text{ where } \boldsymbol{O}_{t\varsigma}^0 = [O_{1t\varsigma}^0, \cdots, O_{kt\varsigma}^0] \quad (2)$$

Through the clustering technique, the 8760 hourly generating capacity curve $\boldsymbol{GC}_t^0$ can be divided into N_s clusters. The N_s clusters can be expressed as , where each cluster $\boldsymbol{GC}_{ts}$ represents multiple hourly generating capacities.

$$\boldsymbol{GC}_t = [\boldsymbol{GC}_{t1}, \cdots, \boldsymbol{GC}_{ts}, \cdots, \boldsymbol{GC}_{tN_s}] \quad (3)$$

In the clustering process, the within-cluster sum of squares (WCSS) is minimized [28]. The WCSS can be expressed as:

$$\Omega = \arg\min_{\boldsymbol{GC_t}} \sum_{s=1}^{N_s} \sum_{GC_{t\varsigma}^0 \in \boldsymbol{GC_{ts}}} \left\| GC_{t\varsigma}^0 - \kappa_s \right\| \tag{4}$$

where κ_s is the mean value of hourly generating capacity in cluster s. Then the clustered unit operation state curve can be expressed as:

$$\boldsymbol{O_t} = [\boldsymbol{O_{t1}}, \cdots, \boldsymbol{O_{ts}}, \cdots, \boldsymbol{O_{tN_s}}] \tag{5}$$

As shown in Fig.2, the annual generating capacity curve is divided into N_s subperiods, where each subperiod can represent a generating capacity cluster. The duration of subperiod s can be represented as:

$$\boldsymbol{D}^{FE} = [D_1^{FE}, \cdots, D_s^{FE}, \cdots, D_{N_s}^{FE}] \tag{6}$$

For conventional probability theory, the performance rate of cluster s is usually represented by a certain value, e.g. the mean value of load levels in this cluster. However, a single crisp value may not effectively describe the detailed features of the load cluster. Considering that, the fuzzy set theory is then introduced to represent each generating capacity cluster using a triangular membership function, as illustrated in Fig. 2. The fuzzy representation of the performance rate of cluster s is $GC_{ts} \in \dot{GC}_{ts} = \left(GC_{ts}^-, GC_{ts}^0, GC_{ts}^+\right)$, where the most possible membership GC_{ts}^0 corresponds to the mean value of generating capacity in cluster s, i.e. κ_s. GC_{ts}^- and GC_{ts}^+ denote the smallest and the largest values of possible generating capacity in cluster s, respectively. Accordingly, the fuzzy operating state of unit k in cluster s can be expressed as $O_{kts} \in \dot{O}_{kts} = \left(O_{kts}^-, O_{kts}^0, O_{kts}^+\right)$, where O_{kts}^-, O_{kts}^0 and O_{kts}^+ represent the unit operating states when generating capacities are GC_{ts}^-, GC_{ts}^0 and GC_{ts}^+, respectively. The triangular membership function can be represented as:

$$\Psi\left(GC_{ts}\right) = \begin{cases} 0, & GC_{ts} \le GC_{ts}^- \\ \left(GC_{ts} - GC_{ts}^-\right) / \left(GC_{ts}^0 - GC_{ts}^-\right), & GC_{ts}^- < GC_{ts} \le GC_{ts}^0 \\ \left(GC_{ts}^+ - GC_{th}\right) / \left(GC_{ts} - GC_{ts}^0\right), & GC_{ts}^0 < GC_{ts} \le GC_{ts}^+ \\ 0, & GC_{ts} \ge GC_{ts}^+ \end{cases} \tag{7}$$

The values of membership $\Psi\left(GC_{ts}\right)$ are between 0 and 1, which can represent the weight of GC_{ts} in cluster s. By representing the cluster s as a fuzzy value $\dot{GC}_{ts}$, the degree of different generation capacity states GC_{ts} that belong to cluster s can be determined by the membership function, based on which the features of generation capacity can be described in detail. Besides, the probability of cluster s can be determined by the duration of this cluster, which can be calculated as $\Pr\left(\dot{GC}_{ts}\right) = D_s^{FE} \Big/ \sum_{s=1}^{N_s} D_s^{FE}$. Note that in accordance with the conventional probability theory, the performance characteristics of load cluster s can also be described using the probabilities $\Pr\left(\dot{GC}_{ts}\right)$ and performance rates $\dot{GC}_{ts}$ of this cluster. Due to the advantage in state aggregation and cluster representation, the fuzzy set theory has proven an effective method in the reliability analysis of energy systems [22].

Likewise, the fuzzy operation state curves of gas wells in NGS can be determined by the combination of MCS and fuzzy set theory. In specific, the fuzzy representation of production capacity in subperiod s is $\dot{PC}_{ts} = \left(PC_{ts}^-, PC_{ts}^0, PC_{ts}^+\right)$. The corresponding fuzzy operating states of gas well w in subperiod s is $\dot{O}_{wts} = \left(O_{wts}^-, O_{wts}^0, O_{wts}^+\right)$ with duration time D_s^{FG}.

B. Fuzzy load duration curve model to characterize load uncertainties

Considering the stochastic fluctuation of energy demands, the 8760-hour load curve is transformed into the fuzzy load duration curve (FLDC) model in this paper. The procedures to determine the fuzzy models of energy loads are in accordance with those of component state aggregation. Taking electric load as an example, the annual load curve before clustering is represented as:

$$\boldsymbol{PD_t^0} = [PD_{t1}^0, \cdots, PD_{t\varsigma}^0, \cdots, PD_{t8760}^0] \tag{8}$$

where $PD_{t\varsigma}^0$ represents the electric load at hour ς and year t.

Similarly, the clustering technique is introduced to divide 8760 hourly loads $\boldsymbol{PD_t^0}$ into N_h clusters, as expressed in .

$$\boldsymbol{PD_t} = [\boldsymbol{PD_{t1}}, \cdots, \boldsymbol{PD_{th}}, \cdots, \boldsymbol{PD_{tN_h}}] \tag{9}$$

The corresponding duration of cluster h determined by the size of the corresponding cluster, as shown in .

$$\boldsymbol{D^E} = [D_1^E, \cdots, D_h^E, \cdots, D_{N_h}^E] \tag{10}$$

By means of fuzzy set theory, the fuzzy representation of cluster h is $PD_{th} \in \dot{PD}_{th} = \left(PD_{th}^-, PD_{th}^0, PD_{th}^+\right)$, where PD_{th}^0, PD_{th}^- and PD_{th}^+ denote the mean, the smallest and the largest values of hourly loads in cluster h, respectively.

Likewise, the annual gas loads in NGS can be transformed into the FLDC model. The fuzzy representation of gas load cluster h is $\dot{GD}_{th} = \left(GD_{th}^-, GD_{th}^0, GD_{th}^+\right)$ with duration time D_h^G. Compared to the annual load duration curve model that is usually approximated as a limited number of states, the FLDC model can make load presentation more accurate [29].

IV. Reserve expansion model considering Multifactor-influenced reliability constraints

A. Objective Function

The proposed long-term reserve expansion model is to minimize the total costs of IEGSs in the planning horizon. The objective function includes energy asset investments IC, the operation costs OC of IEGSs and the costs of unserved energy. Equation calculates the investment costs of new power plants and Gas suppliers. Equation represents the operation costs of non-gas thermal units and new power plants in EPS, gas wells and new Gas suppliers in NGS. The costs of unserved energy are determined by multiplying the energy load curtailments and load shedding costs. The $1/(1+d)^{t-1}$ denotes the present-worth value, where d is the discount rate and t is the planning year. The system state b can be obtained by combining the load uncertainties and component failures.

$$\min\ TC = IC + OC + \sum_{t} \frac{MIENS_t \cdot C_t^E + EGNS_t \cdot C_t^G}{(1+d)^{t-1}} \tag{11}$$

$$\begin{aligned} IC = &\sum_{t}\sum_{e \in \boldsymbol{CS}} \frac{C_{et}}{(1+d)^{t-1}} P_{et}^{\max}\left(z_{et} - z_{e(t-1)}\right) \\ &+\sum_{t}\sum_{g \in \boldsymbol{CG}} \frac{C_{gt}}{(1+d)^{t-1}} W_{gt}^{\max}\left(z_{gt} - z_{g(t-1)}\right) \\ &+\sum_{t}\sum_{\chi \in \boldsymbol{PG}} \frac{C_{\chi t}}{(1+d)^{t-1}} W_{\chi t}^{\max}\left(z_{\chi t} - z_{\chi(t-1)}\right) \end{aligned} \tag{12}$$

$$\begin{aligned} OC = &\sum_{t}\sum_{b} \frac{1}{(1+d)^{t-1}} \cdot \left(\sum_{k \in \boldsymbol{EG}} C_k \cdot P_{ktb} + \sum_{e \in \boldsymbol{CS}} C_e \cdot P_{etb}\right) \cdot D_{tb}^E \\ &+\sum_{t}\sum_{b} \frac{1}{(1+d)^{t-1}} \cdot \left(\sum_{w \in \boldsymbol{EW}} C_w \cdot W_{wtb} + \sum_{g \in \boldsymbol{CG}} C_g \cdot W_{gtb}\right) \cdot D_{tb}^G \end{aligned} \tag{13}$$

where $MIENS_t$ and $EGNS_t$ represent the expected electric and gas load curtailments at year t, respectively. C_t^E and C_t^G are the shedding costs for power loads and gas loads. $P_{et}^{\max}$ and C_{et} are the generating capacity of candidate unit e and the investment costs, respectively. $W_{gt}^{\max}$ and C_{gt} are the production capacity of candidate gas suppliers g and the investment costs, respectively. $W_{\chi t}^{\max}$ and $C_{\chi t}$ are the capacity of P2G facility χ and the investment costs, respectively. $z_{\chi t}$, z_{et} and z_{gt} denote the construction state of candidate P2G facility χ, power unit e and gas supplier g, respectively. P_{gtb} and P_{etb} denote the output of power unit g and candidate unit e for system state b at year t. W_{wtb} and W_{ktb} denote the gas production of gas well w and candidate gas supplier k for system state b at year t. C_g and C_e represent generation costs of power unit g and candidate unit e, respectively. C_w and C_k are gas production costs of gas well w and candidate gas supplier k, respectively.

Note that the basic planning thing of the proposed model is power unit e, gas supplier g and P2G facility χ, whose construction states represented as z_{et}, z_{gt} and $z_{\chi t}$ and size represented as $P_{et}^{\max}$, $W_{gt}^{\max}$ and $W_{\chi t}^{\max}$.

B. Multifactor-influenced reliability constraints considering failure propagation

1) Comparison between multifactor-influenced reliability indices and traditional indices

In the previous studies, the reliability indices of different energy subsystems are individually formulated considering their autogenic uncertainties, such as load variation and component failure [30]. For example, the electric not supplied (*EENS*) is a traditional reliability index that can be calculated by the probability-weighted sum of electric load curtailments for different contingency states b.

$$EENS = \sum_{b} \mathrm{Pr}_b\left(x^e, y^e\right) \cdot LC_b\left(x^e, y^e\right) \cdot 8760 \tag{14}$$

where $\mathrm{Pr}_b\left(x^e, y^e\right)$ and $LC_b\left(x^e, y^e\right)$ represent the probability and electric load curtailments of state b. x^e and y^e denote the electric load variation factor and electric component failure factor in power systems.

In this paper, besides autogenic uncertainties, the effects of failure propagation on system reliability indices are quantified. Following the formulation process of traditional reliability indices, the multifactor-influenced expected electric not supplied (*MENS*) is proposed considering the synthetic effects of failure propagation, load uncertainties and component failures.

$$\begin{aligned} MIENS = &\sum_{b} \mathrm{Pr}_b\left(x^e, y^e \mid z^g\right) \cdot \mathrm{Pr}_b\left(z^g\right) \cdot \\ &\left[LC_b\left(x^e, y^e\right) + LC_b\left(z^g\right)\right] \cdot 8760 \end{aligned} \tag{15}$$

where $\mathrm{Pr}_b\left(x^e, y^e \mid z^g\right)$ represents the conditional probability of electric load variation x^e and electric component failures y^e for certain conditions that failures propagate from the gas system z^g. $\mathrm{Pr}_b\left(z^g\right)$ is the probability of failure propagation from gas system to power system. $LC_b\left(z^g\right)$ denotes the electric load curtailments caused by the failure propagation factor z^g.

Compared to the traditional reliability index *EENS*, the proposed reliability index *MIENS* can more accurately quantify the reliability levels of IEGSs and further guide reasonable planning results.

2) Reliability index formulation in IEGSs

Considering the failure propagation process, the reliability indices of NGS and power system are developed in sequence. Since the reliability level of NGS is mainly affected by gas load variation and gas well failures, the reliability index is formulated according to the formulation process in . Hence, the expected gas not supplied (*EGNS*) can be calculated based on gas load curtailments in state b.

$$EGNS_t = \sum_{m}\sum_{b} \mathrm{Pr}\left(\overset{:}{GD}_{th}, \overset{:}{O}_{wts}\right) \cdot GLC_{mtb}\left(\overset{:}{GD}_{th}, \overset{:}{O}_{wts}\right) \cdot 8760 \tag{16}$$

where $\mathrm{Pr}\left(\overset{:}{GD}_{th}, \overset{:}{O}_{wts}\right)$ represents the probability of gas load curtailment $GLC_{mtb}\left(\overset{:}{GD}_{th}, \overset{:}{O}_{wts}\right)$ at node m in state b and year t, which can be calculated by aggregating the fuzzy load states $\overset{:}{GD}_{th}$ and gas well states $\overset{:}{O}_{wts}$. Hence, $EGNS_t$ can be represented as:

$$EGNS_t = \sum_{m}\sum_{b} \frac{D_s^{FG}}{\sum_{s=1}^{N_s} D_s^{FG}} \cdot \frac{D_h^G}{\sum_{h=1}^{N_h} D_h^G} \cdot GLC_{mtb}\left(\overset{:}{GD}_{th}, \overset{:}{O}_{wts}\right) \cdot 8760 \tag{17}$$

The reliability of EPS is simultaneously influenced by electric load variation, unit outages and failure propagation from gas systems. According to , the reliability index of power system at year t can be represented as:

$$MIENS_t = \sum_m \sum_b \Pr_b\left(\overset{:}{PD}_{th}, \overset{:}{O}_{kts} \mid GLC_{mtb}\right) \cdot \Pr_b\left(GLC_{mtb}\right) \cdot \left[ELC_b\left(\overset{:}{PD}_{th}, \overset{:}{O}_{kts}\right) + ELC_b\left(GLC_{mtb}\right)\right] \cdot 8760 \tag{18}$$

It should be noted that the failure probabilities of uncertainties in power system and gas load curtailments are independent. Therefore, the failure probability of electric load curtailments in can be represented as the product of $\Pr_b\left(\overset{:}{PD}_{th}, \overset{:}{O}_{kts}\right)$ and $\Pr_b\left(GLC_{mtb}\right)$.

By aggregating the fuzzy representations of load variation, unit failures and gas load curtailment states, the $MIENS_t$ can be represented as:

$$MIENS_t = \sum_i \sum_b \frac{D_s^{FG} \cdot D_h^G}{\sum_{s=1}^{N_s} D_s^{FG} \cdot \sum_{h=1}^{N_h} D_h^G} \cdot \frac{D_s^{FE} \cdot D_h^E}{\sum_{s=1}^{N_s} D_s^{FE} \cdot \sum_{h=1}^{N_h} D_h^E} \cdot \left[ELC_b\left(\overset{:}{PD}_{th}, \overset{:}{O}_{kts}\right) + ELC_b\left(GLC_{mtb}\right)\right] \cdot 8760 \tag{19}$$

Compared to the general reliability indices in , it can found that the load and generation uncertainties in are represented as fuzzy numbers.

On the basis, the annual reliability indices are limited as:

$$EGNS_t \le EGNS^{\text{limit}} \tag{20}$$

$$MIENS_t \le MIENS^{\text{dlimit}} \tag{21}$$

where $EGNS^{\text{limit}}$ and $MIENS^{\text{limit}}$ represent the limits of reliability indices in NGS and EPS, respectively.

C. State and construction constraints

If the candidate device is installed in IEGSs, its construction state will be set as 1 in the following years. Hence, the construction states of candidate power unit k, gas supplier g and P2G facility χ are restricted by:

$$z_{e(t-1)} \le z_{et} \tag{22}$$

$$z_{g(t-1)} \le z_{gt} \tag{23}$$

$$z_{\chi(t-1)} \le z_{\chi t} \tag{24}$$

The total gas and electricity production capacity in the IEGSs must supply the forecasted energy loads and reserve requirements, which can be expressed as:

$$\sum_i \sum_{e \in \boldsymbol{CS}} P_{iet}^{\max} \cdot z_{et} + \sum_i \sum_{k \in \boldsymbol{EG}} P_{ik}^{\max} \ge \overset{:}{PD}_{tb} + PR_{tb} + W_{\chi t}^{\max} / \eta_{p2g} \tag{25}$$

$$\sum_m \left(\sum_{g \in \boldsymbol{CG}} W_{mgt}^{\max} \cdot z_{gt} + \sum_{\chi \in \boldsymbol{PG}} W_{m\chi t}^{\max} \cdot z_{\chi t} \right) + \sum_{w \in \boldsymbol{EW}} W_{mw}^{\max} \ge \overset{:}{GD}_{tb} + GR_{tb} \tag{26}$$

where $P_{ik}^{\max}$ represents the maximum output of power unit k at node i. $W_{mw}^{\max}$ represents the maximum gas production of gas well w at node m. ER_{tb} and GR_{tb} denote the gas reserve and power reserve requirements of power system and NGS for system state b at year t. η_{p2g} denotes the conversion efficiency of P2G facilities.

D. System operation constraints

1) Natural gas system

Gas system operation constraints in - describe the operating conditions of gas wells, pipelines and gas suppliers. The gas nodal balance equation is given in . The Nonlinear Weymouth equation shows that the pipeline flow is a function of the squared gas pressures [31]. Constraints - restrict the gas flow direction through pipelines. Nodal squared pressures and pipeline flows are limited in and , respectively. Constraints and describes the operating characteristics of gas compressors. Production limits of candidate gas suppliers and gas wells are given in and , respectively. Constraint limits gas load curtailments at each node.

$$\sum_{w \in \boldsymbol{EW}} W_{mwtb} + \sum_{g \in \boldsymbol{CG}} W_{mgtb} + \sum_{\chi \in \boldsymbol{PG}} W_{m\chi tb} = \overset{:}{GD}_{mtb} - GLC_{mtb} + \sum_{p \in \boldsymbol{GL}} \tau_{ptb} + \sum_{c \in \boldsymbol{GC}} \tau_{ctb} \tag{27}$$

$$\left(\sigma_{ptb}^{+} - \sigma_{ptb}^{-}\right) \cdot \left(\pi_{mtb} - \pi_{ntb}\right) = \tau_{ptb}^{2} / M_p \tag{28}$$

$$-\left(1 - \sigma_{ptb}^{+}\right) \cdot \tau_p^{\max} \le \tau_{ptb} \le \left(1 - \sigma_{ptb}^{-}\right) \cdot \tau_p^{\max} \tag{29}$$

$$-\left(1 - \sigma_{ptb}^{+}\right) \cdot \tau_p^{\max} \le \pi_{mtb} - \pi_{ntb} \le \left(1 - \sigma_{ptb}^{-}\right) \cdot \tau_p^{\max} \tag{30}$$

$$\sigma_{ptb}^{+} + \sigma_{ptb}^{-} = 1 \tag{31}$$

$$\pi_m^{\min} \le \pi_{mtb} \le \pi_m^{\max} \tag{32}$$

$$-\tau_c^{\max} \le \tau_{ctb} \le \tau_c^{\max} \tag{33}$$

$$\Gamma_{ctb} = \pi_{cmtb} / \pi_{cntb} \tag{34}$$

$$\Gamma_c^{\min} \le \Gamma_{ctb} \le \Gamma_c^{\max} \tag{35}$$

$$0 \le W_{mgtb} \le W_{mg}^{\max} \cdot z_{gt} \tag{36}$$

$$0 \le W_{m\chi tb} \le W_{m\chi}^{\max} \cdot z_{\chi t} \tag{37}$$

$$0 \le W_{mwtb} \le W_{mw}^{\max} \cdot \%_{wtb} \tag{38}$$

$$GLC_{mtb} \le GD_{mtb} \tag{39}$$

where W_{mwtb}, W_{mktb} and $W_{m\chi tb}$ represent the production of gas well w, candidate gas supplier k and P2G facility χ at node m, respectively. $\overset{:}{GD}_{mtb}$ denotes the fuzzy gas load for system state b at node m and year t. τ_{ptb} denotes gas flow through pipeline p for system state b at year t. π_{mtb} represents the squared pressure at node m for system state b and year t. M_p is the transmission coefficient of pipeline p. σ_{ptb}^{+} and σ_{ptb}^{-} are binary variables indicating gas flow direction of pipeline p. $\tau_p^{\max}$ is the maximum gas flows through pipeline p. τ_{ctb} and $\tau_c^{\max}$ represent the gas flow and the transmission capacity of compressor c, respectively. $\pi_m^{\min}$ and $\pi_m^{\max}$ are the minimum and maximum squared gas pressures at node m, respectively.

Γ_{ctb} denotes the squared compressor ratio of compressor c for system state b at year t. $\Gamma_c^{\min}$ and $\Gamma_c^{\max}$ are the minimum and maximum squared compressor ratios of compressor c, respectively.

2) Electric power system

The model in - describes the operating features of EPS. Equation represents nodal power balance. Equation calculates network power flow using DC model. Line flow limits and nodal phase angles are limited by and , respectively. Constraints and limit the power output of candidate units and coal-fired power plants, respectively. The power output of GPPs is calculated by the corresponding gas supplied to them, as shown in . Constraint limits power load curtailments at each node.

$$\sum_{e\in \boldsymbol{CS}} P_{ietb} + \sum_{k\in \boldsymbol{EG}}\left(P_{iktb}^{GG}+P_{iktb}^{CG}\right)-\sum_{l\in \boldsymbol{EL}} f_{ltb} = \tilde{PD}_{itb} - PLC_{itb} - W_{m\chi tb}\big/\eta_{p2g} \tag{40}$$

$$f_{ltb} = \left(\theta_{itb}-\theta_{jtb}\right)\big/x_l \tag{41}$$

$$-f_l^{\max} \le f_{ltb} \le f_l^{\max} \tag{42}$$

$$-\theta_i^{\max} \le \theta_{itb} \le \theta_i^{\max} \tag{43}$$

$$-P_{ie}^{\max}\cdot z_{et} \le P_{ietb} \le P_{ie}^{\max}\cdot z_{et} \tag{44}$$

$$0 \le P_{iktb}^{CG} \le P_{ik}^{\max}\cdot \tilde{u}_{ktb} \tag{45}$$

$$P_{iktb}^{GG} = \left(GD_{mtb}-GLC_{mtb}\right)\cdot \vartheta \cdot \tilde{u}_{ktb} \tag{46}$$

$$PLC_{itb} \le PD_{itb} \tag{47}$$

where P_{iktb}^{CG} and P_{iktb}^{GG} represent the power outputs of GPPs and coal-fired power plants for system state b at node i. P_{ietb} represents the output of candidate unit e for system state b at node i. $\tilde{PD}_{itb}$ denotes the fuzzy electric load for system state b at node i. f_{ltb} denotes the electricity flow through power line l for system state b at year t. θ_{itb} and x_l represent the angle of node i for system state b and the reactance of line l, respectively. $f_l^{\max}$ denotes the transmission capacity of line l.

V. Solution Methodology

A. The treatment of fuzzy parameters

As discussed in section II, both the energy loads and component states are expressed as fuzzy numbers. The reserve planning model is formulated as a mixed-integer non-linear optimization problem with fuzzy parameters (MNOFP). Considering that, one effective method is to convert the fuzzy parameters into a crisp parameter using an optimism value [32]. In specific, the fuzzy electric loads $\tilde{PD}_{tb}=\left(PD_{tb}^-, PD_{tb}^0, PD_{tb}^+\right)$ can be replaced by which allows the MNOFP to be solved with a compromise approach.

$$\tilde{PD}_{tb} = \left(\frac{\omega_d PD_{tb}^-}{2}+\frac{PD_{tb}^0}{2}+\frac{\left(1-\omega_d\right)PD_{tb}^+}{2}\right) \tag{48}$$

where the optimism value $0\le\omega_d\le1$ can be adjusted based on the risk propensity of system planners.

To deal with the fuzzy unit states, the corresponding fuzzy system generating capacity $\tilde{GC}_{tb}$ is firstly converted into a crisp parameter using optimism value ω_c in . Based on the calculated $\tilde{GC}_{tb}$, the operating states $\tilde{u}_{ktb}$ for different units in subperiod b can be determined.

$$\tilde{GC}_{tb} = \left(\frac{\left(1-\omega_c\right)GC_{tb}^-}{2}+\frac{GC_{tb}^0}{2}+\frac{\omega_c GC_{tb}^+}{2}\right) \tag{49}$$

Similarly, the fuzzy gas loads and gas well state can be replaced by crisp parameters using optimism values. On this basis, the proposed MNOFP can be converted into a mixed-integer non-linear programming (MINLP) problem.

It can be should that the robustness of planning results can be guaranteed by setting a smaller optimism value. Taking electric load $\tilde{PD}_{tb}$ as an example, the system electric load level can increase with the decrease of optimism values ω_d. Under this circumstance, more energy production components need to be constructed to satisfy the requirements of energy loads.

B. The solution of the reliability-constrained reserve expansion model

This proposed reserve planning model cannot be efficiently solved due to the reliability constraints in (14) and (17). Benders decomposition is therefore applied to decompose the original optimization problem into a master problem to optimize the base-case investment decisions, and two subproblems to check the reliability constraints of EPS and NGS [33].

In the steady-state analysis of gas systems, the gas flow models can be divided into two categories [34]. The first one is the controllable-flow model where the pipeline flows are fully controllable and are modeled as control variables limited by pipeline limits [2]. The second one is the noncontrollable-flow model, i.e. Weymouth function where the pipeline flows are modeled as state variables restricted by nodal pressures [35]. In the gas reliability subproblem, the controllable-flow model is utilized to guarantee the convergence and optimality of benders cuts. The simplification of gas flow model has proved to be acceptable for investment problems over a long time horizon and has been widely used in system planning [2, 36]. The measures in [35] to deal with the nonlinear and nonconvex gas flow model in the subproblems will be introduced for future studies about the optimal operation of IEGSs.

1) Master investment problem

The master investment problem is presented in , where the dual cuts generated from gas system and power system reliability subproblems are iteratively added. The master problem mainly determines the optimal investment and operation decisions in the base case considering load variations. The stochastic failures of components are considered in the two subproblems to check the reliability requirements of IEGSs. Hence, the operating states of gas wells $\tilde{u}_{wtb}$ and generating units $\tilde{u}_{ktb}$ are set as 1 in the master problem. Optimal solutions $\hat{z}_{et}$, $\hat{z}_{gt}$ and $\hat{z}_{\chi t}$ are sent to the two subproblems.

$$
\begin{aligned}
&\min\ TC \\
&\text{S.t. } TC \geq IC{+}OC \\
&\quad \text{Constraints (22)-(38), (40)-(46)} \\
&\quad \text{Dual reliability cuts generated} \\
&\quad \text{Optimality cuts generated}
\end{aligned} \tag{50}
$$

It should be noted that the master problem is a MINLP problem due to gas flow equations . The auxiliary variables λ_{ptb} are firstly defined to replace $\left(\sigma_{ptb}^{+}-\sigma_{ptb}^{-}\right)\cdot\left(\pi_{mtb}-\pi_{ntb}\right)$. Based on the second-order cone relaxation technique, the gas flow equation can then be relaxed as [18]:

$$\lambda_{ptb}\cdot M_p \geq \tau_{ptb}^2 \tag{51}$$

$$\lambda_{ptb}=\left(\sigma_{ptb}^{+}-\sigma_{ptb}^{-}\right)\cdot\left(\pi_{mtb}-\pi_{ntb}\right) \tag{52}$$

The non-linear function can then be linearized by a standard McCormick relaxation [37], which can be represented as:

$$\lambda_{ptb} \geq \pi_{ntb}-\pi_{mtb}+\left(\sigma_{ptb}^{+}-\sigma_{ptb}^{-}+1\right)\left(\pi_m^{\min}-\pi_n^{\max}\right) \tag{53}$$

$$\lambda_{ptb} \geq \pi_{mtb}-\pi_{ntb}+\left(\sigma_{ptb}^{+}-\sigma_{ptb}^{-}-1\right)\left(\pi_m^{\max}-\pi_n^{\min}\right) \tag{54}$$

$$\lambda_{ptb} \leq \pi_{ntb}-\pi_{mtb}+\left(\sigma_{ptb}^{+}-\sigma_{ptb}^{-}+1\right)\left(\pi_m^{\max}-\pi_n^{\min}\right) \tag{55}$$

$$\lambda_{ptb} \leq \pi_{mtb}-\pi_{ntb}+\left(\sigma_{ptb}^{+}-\sigma_{ptb}^{-}-1\right)\left(\pi_m^{\min}-\pi_n^{\max}\right) \tag{56}$$

Hence, the original MINLP model can be transformed into a mixed-integer second-order cone program (MISOCP) problem.

2) Gas system reliability subproblem

Once the construction states of gas suppliers and P2G facilities are identified by the master problem, the NGS reliability subproblem is to determine whether the planning decisions satisfy the reliability requirements. The problem objective is to minimize the total gas load curtailments for each system state. The proposed reliability subproblem needs to follow the constraints .

$$\min \sum_m\sum_t\sum_b \sigma_m\cdot GLC_{mtb}\cdot D_{tb} \tag{57}$$

$$
\begin{aligned}
\text{s.t. } & z_{gt}=\hat{z}_{gt} \quad (\mu_{gt}) \\
& z_{\chi t}=\hat{z}_{\chi t} \quad (\mu_{\chi t}) \\
& \text{Constraints } (27),(32)-(39)
\end{aligned} \tag{58}
$$

where σ_m represents the weights of gas loads at node m that distinguish the shedding sequence of loads supplied to GPPs and remainders, e.g. heaters. Considering the prior curtailment of gas supplied to GPPs, the corresponding values of σ_m can be slightly smaller than those for remaining loads.

Based on the gas load curtailments solved by the subproblem, the annual $EGNS_t$ can be calculated using . When the annual $EGNS_t$ reliability constraint is not satisfied, the dual cut will be added to the master investment problem for the solution in the next iteration.

$$
\begin{aligned}
\sum_m\sum_b GLC_{mtb}\cdot D_{tb}+\sum_{g\in\mathbf{CG}}\mu_{gt}\left(z_{gt}-\hat{z}_{gt}\right) \\
+\sum_{\chi\in\mathbf{PG}}\mu_{\chi t}\left(z_{\chi t}-\hat{z}_{\chi t}\right)\leq EGNS^{\text{limit}}
\end{aligned} \tag{59}
$$

where μ_{gt} and $\mu_{\chi t}$ is the dual values of the constraints associated with the construction states of gas suppliers and P2G facilities.

3) Power system reliability subproblem

Based on the planning decisions of power units from the master problem, the reliability requirements of EPS are evaluated in this subproblem. The problem objective is to minimize the total electric load curtailments subject to the constraints . To simplify the calculation, the power outputs of GPPs can be determined according to the expected gas load curtailments $EGNS_{mt}$ at the corresponding nodes.

$$\min \sum_i\sum_t\sum_b PLC_{itb}\cdot D_{tb} \tag{60}$$

$$
\begin{aligned}
\text{s.t. } & z_{et}=\hat{z}_{et} \quad (\mu_{et}) \\
& P_{iktb}^{GG}=\left(GD_{mtb}-EGNS_{mt}\right)\cdot\vartheta\cdot\tilde{\omega}_{ktb} \\
& \text{Constraints } (40)-(45),(47)
\end{aligned} \tag{61}
$$

Likewise, the annual $MIENS_t$ can be calculated using to identify whether the reliability constraint can be satisfied. If violated, the corresponding dual cut will be generated:

$$\sum_i\sum_b PLC_{itb}\cdot D_{tb}+\sum_{e\in\mathbf{CS}}\mu_{et}\left(z_{et}-\hat{z}_{et}\right)\leq MIENS^{\text{limit}} \tag{62}$$

When the reliability constraints and are satisfied, The optimal reliability subproblem for IEGSs is modeled subjected to . Then the reliability cost obtained in this subproblem will be added into the investment and operation costs to calculate the total planning cost. If it is not equal to the total planning costs TC, the optimality cut will be added to the master problem.

$$\min\ lc=\sum_m\sum_t\sum_b\frac{\sigma_m GLC_{mtb}D_{tb}C_t^G}{(1+d)^{t-1}}+\sum_i\sum_t\sum_b\frac{PLC_{itb}D_{tb}C_t^E}{(1+d)^{t-1}} \tag{63}$$

$$
\begin{aligned}
\text{s.t. } & z_{gt}=\hat{z}_{gt} \quad (\mu'_{gt}) \\
& z_{et}=\hat{z}_{et} \quad (\mu'_{et}) \\
& z_{\chi t}=\hat{z}_{\chi t} \quad (\mu'_{\chi t}) \\
& \text{Constraints } (27),(32)-(47)
\end{aligned} \tag{64}
$$

$$TC\geq ic{+}oc+lc+\sum_{e\in\mathbf{CS}}\sum_t\mu'_{et}\left(z_{et}-\hat{z}_{et}\right)+\sum_{g\in\mathbf{CG}}\sum_t\mu'_{gt}\left(z_{gt}-\hat{z}_{gt}\right) \tag{65}$$

where ic, oc and lc denotes the variables of investment costs, operation costs and load curtailments for the certain component construction states determined in the master problem. Hence, the values of ic, oc and lc can change for each iteration.

C. Solution procedures of the proposed model

Fig. 3 shows the solution procedures of the long-term reserve expansion problem.

Step 1. Determine the fuzzy models of energy loads and component failures using the fuzzy set theory.

Step 2. Introduce optimism values to convert fuzzy parameters into a crisp value using and . Set iteration number $\upsilon = 1$.

Step 3. Solve the master investment problem - and send the optimal results $\hat{z}_{gt}$, $\hat{z}_{et}$ and $\hat{z}_{\chi t}$ to steps 4 and 5. The calculated total results of the master problem at iteration υ is $TC^{\min,(\upsilon)}$, which is the lower bound for the optimal value of the original problem.

Step 4. Solve the gas system reliability subproblem - with respect to $\hat{\Sigma}_{gt}$ and $\hat{\Sigma}_{\chi t}$. Calculate the annual reliability index and send $EGNS_{mt}$ to step 5. If the reliability constraint is violated, add the dual cut to the master problem and go to Step 3.

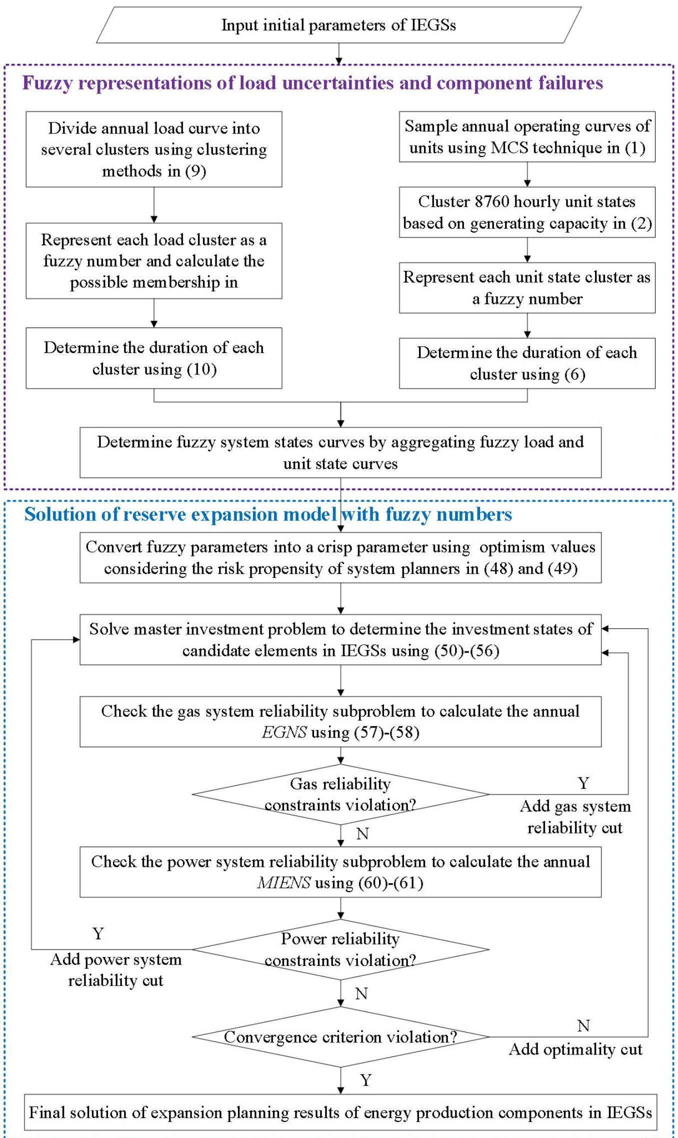

Fig. 3 The flow chart of the solution procedures

Step 5. Solve the power system reliability subproblem - for certain values of $\hat{\Sigma}_{et}$ and $MIENS_t$, and calculate reliability index. If the reliability constraint is violated, add the dual cut to the master problem and go to Step 3.

Step 6. If all the reliability constraints in both NGS and EPS are satisfied, solve the optimal *reliability* subproblem in -. Calculate the lower bound for the optimal value of the original problem by adding up the investment, operation and reliability costs, which can be represented as $TC^{\max,(\upsilon)} = IC^{(\upsilon)} + OC^{(\upsilon)} + LC^{(\upsilon)}$.

Step 7. Determine if the convergence criterion of the Benders decomposition is satisfied. If the convergence criterion is violated, add the dual cut to the master problem. Let $\upsilon = \upsilon + 1$ and go to Step 3. If the convergence criterion is satisfied, Terminate.

$$\frac{2\left|TC^{\max,(\upsilon)} - TC^{\min,(\upsilon)}\right|}{TC^{\max,(\upsilon)} + TC^{\min,(\upsilon)}} \le \varepsilon \tag{66}$$

where ε is the tolerance of convergence.

Here, the convergence of the solution method is demonstrated. Fig. 4 shows the relation between the master problem and two reliability subproblems, whose solution can be divided into two phases. In the first phase (①+②), the master investment problem calculates the construction states of gas suppliers based on the feasibility cuts from the gas reliability subproblem. The two problems are calculated iteratively until the reliability constraint of the gas subsystem is satisfied. After the solution process is ended, the construction states of gas suppliers and P2G facilities, as well as gas load shedding results can be determined.

For certain gas load shedding results in the first phase, the generation losses of gas-fired power plants (GPPs) can then be determined, which remain unchanged in the second phase (①+③). Considering that, the interaction process between the master problem and power reliability subproblem is similar to that in the first phase. The construction states of power units can be determined until the reliability constraints of power subsystem can be satisfied. After both the feasibility of the two subproblems is satisfied, the optimality cuts will be fed back to the master problem for the next iteration. Note that the developed optimality cut combines the gas and power load curtailment costs of two subproblems, which are equivalent to two optimality cuts respectively formulated in two phases. Therefore, the optimization models in the two phases follow the specific structure that is particularly amenable to the Benders decomposition. The detailed proof of the convergence of the solution method in each phase can be seen in [38].

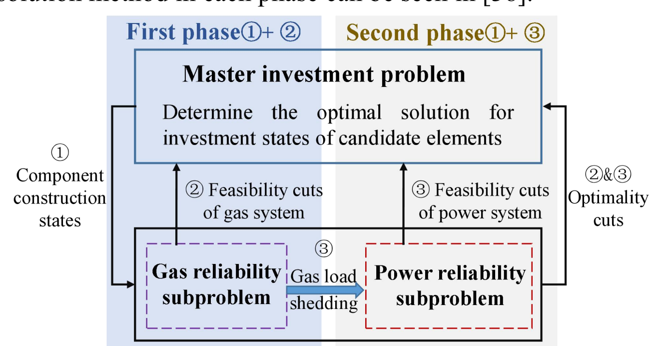

Fig. 4 The relation between master problem and two reliability subproblems

VI. CASE STUDY

The IEGSs composed of the modified IEEE 30-bus power system [39] and Belgian 20-node gas system [31] are introduced to show the effectiveness of the proposed model. The modified EPS is composed of six power units, where three GPPs at electric nodes 5, 8 and 13 obtain fuels from gas nodes 3, 7 and 20. The electric load data are derived from [40]. The modified gas system consists of 19 pipelines, three compressors and six gas wells. The physical parameters of pipelines, compressors and wells can be found in [31]. The hourly gas load levels in NGS are estimated according to the data in [41]. Both the electric loads and non-power gas loads have an average load growth rate of 3%. The discount rate d is set as 5% and the planning horizon is set as 10 years.

Table I and Table II respectively show the data of six candidate power units and five candidate gas suppliers. The listed data of power plants and gas suppliers include location, capacity, investment cost and operating cost. Note that the investment of P2G facilities is only considered in Case study D. The failure rates of power units and gas wells are both set as 0.001, while their repair rates are 0.02 and 0.01, respectively [25]. The reserve requirement is 5% of energy loads at each state. The shedding costs for electric loads and gas loads are set as 1000\$/MWh [42] and 0.64\$/m^3, respectively. The optimism values of system planners are assumed as 0.5. The pre-determined tolerance ε is set as 0.01.

TABLE I
CANDIDATE POWER UNITS DATA

Power units	Bus	Capacity (MW)	Investment cost (10^3\$/MW)	Operating cost (\$/MWh)
ES1	30	80	250	50
ES2	26	60	210	45
ES3	17	50	190	55
ES4	15	60	230	45
ES5	10	50	220	40
ES6	4	30	180	40

TABLE II
CANDIDATE GAS SUPPLIER AND P2G DATA

Gas suppliers	Node	Capacity (10^4m^3)	Investment cost (\$/m^3)	Operating cost (\$/m^{3}h)
GS1	7	4	6000	0.020
GS2	17	3.5	6300	0.015
GS3	16	2.8	6200	0.025
GS4	20	2.8	6200	0.025
GS5	4	3.2	6300	0.015

A. Effectiveness analysis of the proposed model compared to conventional existing models

In this case, the effectiveness of the proposed model with multifactor-influenced reliability indices is demonstrated compared to other conventional existing models. In the previous studies, the gas components are assumed completely available and the failure propagation from gas system to power system is not considered [18]. The traditional reliability indices, e.g. *EENS* are usually utilized to characterize the reliability levels of power systems [17]. In the proposed model, component failures in gas system and the corresponding failure propagation are considered. The *MIENS* index and *ENGS* index are utilized to quantify the reliabilities of power system and gas system, respectively. In this case, the limits of *EENS* and *MIENS* indices are identical, which are set as 10000 MWh. The limit of *EGNS* index is set as 1.5×10^7 m^3.

Table. III shows the comparison of planning results between the proposed model and the existing planning models. Firstly, it can be found that more gas suppliers and power plants are deployed in the proposed model. Secondly, both the installation of power plants and gas suppliers are brought forward in the proposed model. This is mainly because gas system uncertainties and failure propagation are not considered in the conventional models and deployment of candidate elements only needs to meet the forecasted loads.

TABLE III
INSTALLATION YEAR OF CANDIDATE ELEMENTS FOR DIFFERENT MODELS

Candidate units	Proposed model	Existing model	Candidate gas suppliers	Proposed model	Existing model
ES1	-	-	GS1	1	-
ES2	-	-	GS2	-	-
ES3	3	2	GS3	7	-
ES4	-	-	GS4	-	-
ES5	5	7	GS5	3	7
ES6	1	6	-	-	-

Based on the determined candidate element installation in Table III, the reliabilities of IEGSs at different years are evaluated considering gas component failures and failure propagation. Fig. 5 shows the reliability evaluation results of the proposed model and the existing planning model. Firstly, it can be found that the neglect of gas component failures in the existing model may lead to over-optimistic planning results, which cannot guarantee the reliable operation of NGS. It can be found that the maximum value of *ENGS* of the existing model is 4.25×10^7 m^3, which is over 4 times than *ENGS* requirements. In contrast, the *ENGS* values in the proposed model are all smaller than *ENGS* requirements. The analysis results indicate that the reliability requirements of NGS cannot be achieved in the existing model when considering component failures.

Considering the cross-sectorial failure propagation, unreasonable gas supplier plans in the existing model also make the deployment of power plants cannot satisfy reliability requirements. As illustrated in Fig. 5, the *EENS* values calculated in the existing model increase rapidly from year 2 to year 10, which are all larger than reliability requirements. On the contrary, the maximum value of *MIENS* in the proposed model is only 9290.23 MWh, which is smaller than reliability requirements. The reliability analysis results further demonstrate that the proposed model can plan reasonable reserve to guarantee the reliability levels of IEGSs.

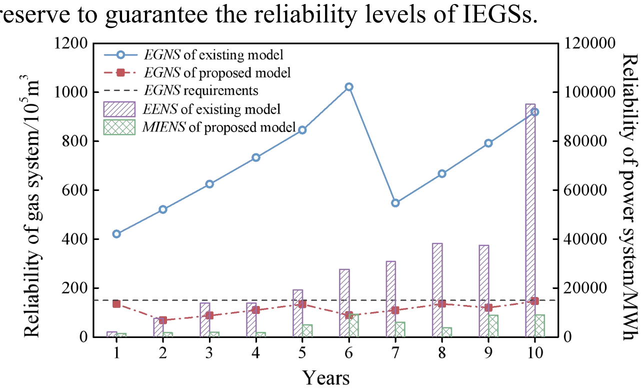

Fig. 5 Comparisons of reliability indices in different models considering cross-sectorial failure propagation

The total planning costs of different models are also compared in Table IV. At the end of the planning horizon, the investment costs of the proposed model can be 5.76×10^8 \$ (much higher than that in the existing model) since more gas suppliers are deployed. Nevertheless, the operation costs in the proposed model are relatively smaller due to the lower operation costs of new power plants and gas suppliers. In specific, the operation costs of the proposed model are

1.617×10^8 \$, which is 0.90 times those of the existing model. Despite the investment cost saving in the previous model with fewer gas supplier construction, the neglect of gas contingencies can lead to more energy curtailment costs. The unserved energy costs of the previous model are nearly 5 times those of the proposed model. Synthesizing the investment costs, operation costs and unserved energy costs, the total planning costs of the proposed model can save 2.23×10^8 \$ costs. The analysis results demonstrate that the proposed model can realize the coordination between economy and reliability.

TABLE IV
OPERATION SCHEDULING RESULTS OF DIFFERENT MODELS

Cost ($\times10^8$ \$)		Existing model	Proposed model
Investment costs	Gas suppliers	1.504	5.524
	Power plants	0.236	0.231
Operation costs		1.783	1.617
Unserved energy costs		6.805	0.734
Total co-optimization costs of IEGSs		10.33	8.105

In order to demonstrate the effectiveness of the second-order cone relaxation technique for convexifying the gas flow model, another widely-used linearization technique, i.e. piecewise linearization method is introduced in this paper as a comparative method to solve the proposed model. The total optimal objective calculated by the piecewise linearization method is 8.112×10^8 \$, with only 0.08% difference from the objective value obtained by the second-order cone relaxation method. The difference of pipeline flows between these two methods at different states of year 10 is calculated, as illustrated in Fig. 6, whose largest value is smaller than 2%. With regard to computation efficiency, the computation time of the MCE method is 1101.89 s, which is 0.48 times that of the piecewise linearization technique.

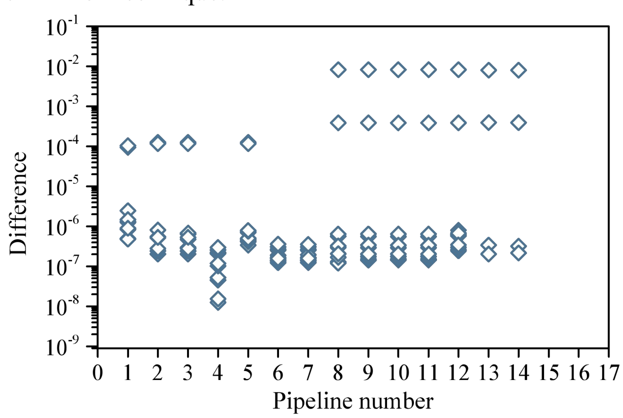

Fig. 6 Difference of pipeline flows at different states of year 10 between second-order cone relaxation and piecewise linearization methods

Moreover, the second-order cone relaxation technique has been widely used in the expansion and optimization of gas systems [18, 37, 43], whose optimality gap and efficiency have also been explained in [37]. By potentially modifying the gas components in Belgium gas network topology, different test systems are developed in [37] to compare the optimal objective value, optimality gap and the efficiency between different methods. The analysis results in reference [37] show that the second-order cone relaxation technique can derive high-quality solutions compared to other methods. Besides, the optimality gaps of the second-order cone relaxation technique are provably tight, which can also lead to global optimal solutions in some cases. Furthermore, the computation efficiency of the second-order cone relaxation technique is much higher than other methods.

B. Sensitivity analysis of reliability requirements on planning results

In this case, the impacts of reliability requirements $EGNS^{\mathrm{limit}}$ and $MIENS^{\mathrm{limit}}$ on the reserve planning results of IEGSs are analyzed. When $EGNS^{\mathrm{limit}}$ changes from 0.6×10^7 m^3 to 2.7×10^7 m^3 and $MIENS^{\mathrm{limit}}$ changes from 4000 MWh to 12000 MWh, the variation of deployed energy reserve and the corresponding planning costs are analyzed.

With the change of reliability requirements in both NGS and EPS, the total gas reserve and electric reserve at the end of the planning horizon are given in Fig. 7 and Fig. 8, respectively. With regard to NGS, we can find that the deployed gas reserve increases with the decrease of $EGNS^{\mathrm{limit}}$ values. As shown in Fig. 7, the deployed gas reserve decreases from 1.35×10^7 m^3 to 0.95×10^7 m^3 when $EGNS^{\mathrm{limit}}$ changes from 0.9×10^7 m^3 to 2.1×10^7 m^3. In contrast, the variation of reliability requirements in the power system has no impact on the gas reserve planning results. Hence, the expansion planning of gas reserve mainly depends on *EGNS* requirements due to the unidirectional energy interaction between NGS and EPS through GPPs.

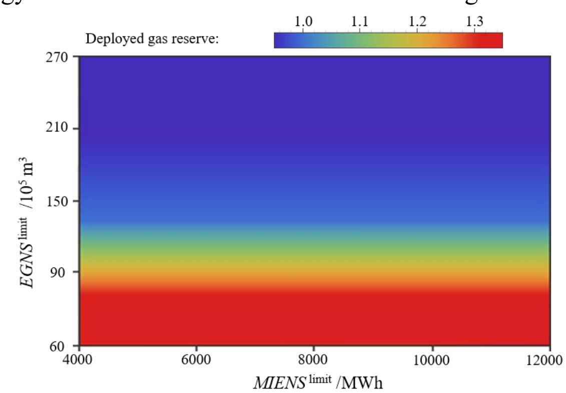

Fig. 7 Total deployed gas reserve with varying *MIENS* and *EGNS* limits

Regarding EPS, the planning results of electric reserve are simultaneously affected by the change of reliability requirements in NGS and EPS. Firstly, it can be noted that the reduction of $MIENS^{\mathrm{limit}}$ can increase the deployment of electric reserve in EPS. Moreover, we can find that the increase of reliability requirements in NGS can reduce the deployment of power units in EPS. This is mainly because that the decrease of $EGNS^{\mathrm{limit}}$ can reduce the probability of gas interruption to GPPs in contingency states. Due to the adequacy of gas fuels, the GPPs need not reduce their power output during contingencies. Considering that, the less electric reserve is required to guarantee the reliability level of EPS. The simulation results also indicate that we can improve the reliability of EPS by simultaneously optimizing the energy resources in both systems.

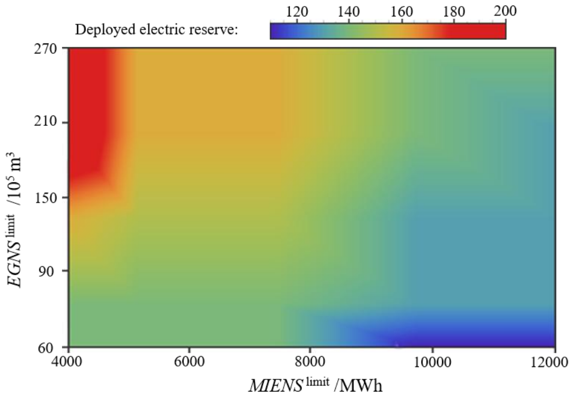

Fig. 8 Total deployed electric reserve with varying *MIENS* and *EGNS* limits

C. *The impacts of optimism values on planning results*

The impacts of optimism values on investment decisions of IEGSs are shown in Table V and Table VI. Three scenarios are considered: S1 is the based case where the optimism values are set as 0.5 in accordance with the previous studies. The optimism values of S2 and S3 are set as 0.2 and 0.8, respectively.

TABLE V
INSTALLATION YEAR OF CANDIDATE UNITS FOR DIFFERENT OPTIMISM VALUES

Candidate power units	S1: 0.5	S2: 0.2	S3: 0.8
ES1	-	-	-
ES2	-	-	-
ES3	3	1	4
ES4	-	6	-
ES5	5	9	9
ES6	1	1	1

TABLE VI
INSTALLATION YEAR OF CANDIDATE GAS SUPPLIERS FOR DIFFERENT OPTIMISM VALUES

Candidate gas suppliers	S1: 0.5	S2: 0.2	S3: 0.8
GS1	1	1	-
GS2	-	1	3
GS3	7	6	6
GS4	-	9	-
GS5	3	0	-

In conclusion, the increase of optimism values can decrease the allocation of energy production components by system planners. For example, the system planners tend to allocate the candidate components more conservatively if they are not very optimistic (with small optimism values in S2). The installation of power units and gas suppliers will be brought forward and more energy reserve will be allocated. Under this circumstance, more costs will be required to ensure the higher reliability of IEGSs. In contrast, the system planners will be more likely to postpone and reduce the allocation of production components if they are more optimistic (with small optimism values in S3). Accordingly, the costs of reserve expansion will be smaller and the system reliability level is relatively lower. The simulation results further demonstrate that the intermediate optimism values can realize the coordination between costs and reliability.

D. *Coordination analysis between P2G facilities and gas suppliers*

In this case, the allocation of P2G facilities and gas suppliers are coordinated for the reserve expansion of IEGSs. Four candidate P2G facilities are planned together with gas suppliers, whose data are shown in Table VII [44]. The conversion coefficient of P2G facilities is set as 50 m^3/MW [45]. Considering different costs of power generation in EPS, two scenarios are introduced. Scenario I is the base scenario where the operating and investment costs of power units are identical to those in Case A. In scenario II, the corresponding costs are set as 80% of those in scenario I.

TABLE VII
DATA OF CANDIDATE P2G FACILITIES

Gas suppliers	Gas Node	Electric node	Capacity (10^4m^3)	Investment cost (\$/m^3)
P2G-1	4	4	0.1	10000
P2G-2	4	9	0.08	9500
P2G-3	4	14	0.08	10500
P2G-4	4	20	0.1	10000

Table VII shows the planning results of candidate components for different scenarios. Firstly, it can be found that the installation of gas suppliers is appreciated in scenario I. With the decrease of power generation costs in scenario II, P2G facilities will be installed to satisfy the gas demand in IEGSs. Besides, more power units are planned in scenario II due to the installation of P2G facilities. The study results show that the P2G facilities tend to be installed for scenarios where the average power generation costs are relatively lower, e.g. power systems with a high proportion of renewable energy. On the contrary, the investment of P2G facilities will increase the installation of high-cost power units, which can be more expansive than the investment of gas suppliers.

TABLE VIII
INSTALLATION YEAR OF CANDIDATE ELEMENTS FOR DIFFERENT SCENARIOS

Candidate units	Scenario I	Scenario II	Candidate gas elements	Scenario I	Scenario II
ES1	-	10	GS1	1	7
ES2	-	-	GS2	-	1
ES3	3	2	GS3	7	3
ES4	-	1	GS4	-	-
ES5	5	6	GS5	3	-
ES6	1	3	P2G-1	-	2
-	-	-	P2G-2	-	2
-	-	-	P2G-3	-	-
-	-	-	P2G-4	-	-

VII. CONCLUSION

Considering the impacts of cross-sectorial failure propagation, a multifactor-influenced reliability-constrained reserve expansion is proposed to determine the allocation of energy production components. In the proposed model, the novel multifactor-influenced reliability indices are defined considering the synthetic effects of multiple uncertainties, including failure propagation, load uncertainties and component failures. The fuzzy set theory is combined with conventional methods to reduce the number of system contingency states for computation efficiency improvement. Case studies demonstrate that the proposed model can realize the coordination between economy and reliability compared to the previous studies. Moreover, the simulation results indicate that we can improve the reliability of EPS by simultaneously optimizing the energy resources in both systems. Furthermore, the robustness of the proposed model can be guaranteed by setting a smaller optimism value. Hence, the proposed model in this paper can provide useful references for system planners to constitute reasonable reserve expansion plans to guarantee the reliability levels of IEGSs.

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BIOGRAPHIES

Minglei Bao received the B.S. degree in electrical engineering from Shandong University and the Ph. D degree in electrical engineering from Zhejiang University in 2016 and 2021, respectively. He is currently a postdoctor at Zhejiang University, Zhejiang, China. His research interests include reliability analysis of the integrated energy system, complex network, and the power market.

Xiaocong Sun received the B.S. degree in electric engineering from Shandong University, China in 2020. He is currently pursuing the Ph.D. degree in electric engineering from Zhejiang University, Hangzhou, China. His research interests include low-carbon electricity and the integrated energy system.

Yi Ding (M'12) received the bachelor's and Ph.D. degrees in electrical engineering from Shanghai Jiaotong University, Shanghai, China, and Nanyang Technological University, Singapore in 2000 and 2007, respectively. He is a Professor with the College of Electrical Engineering, Zhejiang University, Hangzhou, China. His current research interests include power systems reliability/performance analysis incorporating renewable energy resources, smart grid performance analysis, and engineering systems reliability modeling and optimization.

Chengjin Ye received the B.E. and Ph.D. degrees in electrical engineering from Zhejiang University, Hangzhou, China, in 2010 and 2015, respectively. From 2015 to 2017, he served as a distribution system planning engineer with the Economics Institute of State Grid Zhejiang Electric Power Company, Ltd. From 2017 to 2019, he was a Postdoc Researcher with Zhejiang University. Since 2020, he has been a Research Professor with the College of Electrical Engineering, Zhejiang University. His research interests include resilience enhancement of power and energy systems, and integration of new infrastructure flexible loads into power system operation.

Changzheng Shao(S'17-M'20) received the B.S. degree in electrical engineering from Shandong University and the Ph. D degree in electrical engineering from Zhejiang University in 2015 and 2020, respectively. He is currently an assistant professor at Chongqing University, Chongqing, China. His research interests include the operation optimization and reliability evaluation of the integrated energy system.

Sheng Wang received the B.S. degree and Ph.D. degree in electrical engineering from Zhejiang University, China in 2016 and 2021. He is currently working in State Grid (Suzhou) City & Energy Research Institute Co., Ltd, Suzhou, China.

His research interests include the modeling, optimization, and reliability evaluation of the integrated energy systems.

Yonghua Song (M'90–SM'94–F'08) received the B.Eng. and Ph.D. degrees from the Chengdu University of Science nd Technology (now Sichuan University) and China Electric Power Research Institute in 1984 and 1989, respectively.

He is currently the Rector of University of Macau and the Director of State Key Laboratory of Internet of Things for Smart City, and also an Adjunct Professor with the Department of Electrical Engineering, Tsinghua University, and the College of Electrical Engineering, Zhejiang University. He was Awarded D.Sc., Honorary D.Eng. and Honorary D.Sc. by Brunel University, University of Bath, and University of Edinburgh, respectively. He is a Fellow of the Royal Academy of Engineering and a foreign member of Academia European.