A Novel Hybrid Framework for Co-Optimization of Power and Natural Gas Networks Integrated with Emerging Technologies

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Abstract—This paper presents a novel hybrid information gap decision theory (IGDT)-stochastic co-optimization problem for integrating electricity and natural gas networks to minimize total operation cost with the penetration of wind energy. The proposed model considers not only the uncertainties regarding electrical load demand and wind power output but also the uncertainties of gas load demands for the residential consumers. The impact of gas load uncertainty associated with the residential consumers is more significant on the power dispatch of gas-fired plants and power system operation cost since residential gas load demands are prior than gas load demands of gas-fired units. The proposed framework is a bi-level problem that can be reduced to a one-level problem. Also, it can be solved by the implementation of a simple concept without the need for Karush-Kuhn-Tucker (KKT) conditions. Moreover, emerging flexible energy sources such as the power to gas (P2G) technology and demand response (DR) program are considered in the proposed model to facilitate integration of renewable energy sources and to decrease the total operation cost of the integrated network. Numerical results indicate the applicability and effectiveness of the proposed model under different working conditions.

Index Terms—hybrid IGDT-stochastic, co-optimization of integrated gas and power system, power-to-gas (P2G) technology, demand response (DR) program, wind power.

NOMENCLATURE

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<td>( t )</td>
<td>time periods</td>
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<td>P2G technology</td>
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<tr>
<td>( b, b' )</td>
<td>buses</td>
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</table>

Decision variables

- \( j \) loads
- \( L \) transmission lines

Constants

- \( NT \) Number of time periods
- \( NGL \) Number of natural gas loads
- \( NU \) Number of non-gas fired units
- \( NS \) Number of scenarios
- \( NSP \) Number of gas suppliers
- \( NST \) Number of gas storages
- \( NR \) Number of wind power plants
- \( NB \) Number of buses
- \( GU \) Number of gas-fired units
- \( \max \) Max/Min capacity of thermal unit \( i \) (MW)
- \( \min \) Ramp up/down thermal unit \( i \) (MW)
- \( \Delta t \) Minimum up/down time of unit \( i \) (h)
- \( \delta_{L} \) Reactance of line \( L \) (Ohm)
- \( \beta_{L} \) Maximum capacity of line \( L \) (MW)
- \( \gamma_{L} \) Expected hourly load (MW)
- \( \delta_{pl} \) Constant of pipeline \( pl \) (kcf/Psig)
- \( \delta_{G} \) Max/Min pressure (Psig)
- \( \delta_{in} \) Max/Min natural gas injection (kcf)
- \( \delta_{out} \) Max/Min natural gas load (kcf)
- \( \delta_{s} \) Max release/store capacity of gas storage (kcf)
- \( \delta_{s} \) Storing/releasing efficiency of gas storage
- \( \delta_{L} \) Efficiency of P2G technology
- \( \delta_{sp} \) Max/min gas stored in gas storage system (kcf)
- \( \delta_{sup} \) Operation cost of natural gas supplier \( sp \) ($)
- \( \delta_{s} \) Operation cost of gas storage ($)

OMENCLATURE

Indices

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<th>Symbol</th>
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<td>( C_{pl} )</td>
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<td>Dispatch of wind power</td>
</tr>
<tr>
<td>( \delta_{L} )</td>
<td>Line flow at line ( L )</td>
</tr>
<tr>
<td>( \delta_{L} )</td>
<td>Voltage angle of network buses</td>
</tr>
</tbody>
</table>

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A bi-level framework for co-optimization of integrated gas and electricity networks has been introduced in [11] with alternating direction method of multipliers [9]. A security-constrained model for integrated gas and electricity networks is presented in [12], which intends to study the operation of the electricity network and supplying the gas network in upper-level and lower-level, respectively. The authors have analyzed the impact of cooperation of gas-fired power generation plants in integrated networks and energy market considering gas network constraints [13]. The role of the P2G system in optimal management of integrated networks is studied proposing a robust framework [14].

Information gap-decision theory (IGDT) is introduced as a high-performance modeling concept for studying uncertainties of systems’ parameters and data, which does not need the probability distribution function of the uncertain parameters in contrast with conventional methods such as Monte Carlo simulation method and scenario-based programming procedure. Moreover, one other advantage of the IGDT is to provide flexible different strategies for the operator since the radius upper bound of the uncertain parameter is not needed to be known when employing this method. In other words, IGDT determines the maximum uncertainty radius of the uncertain parameters by satisfying the objective function in the predefined interval. Notable efforts have been made in the area of studying uncertainty in electrical energy networks such as bidding strategies in the power systems [15], unit commitment [16] and restoration of electrical distribution systems [17], self-scheduling of generation companies [18].

Table I indicates the comparison of the main contributions of the literature and the proposed model in studying the integrated gas and electricity networks by providing summarized cases on the remarkable contribution of models. In comparison with the literature, this study presents a new IGDT-stochastic-based model for the optimal operation of integrated power and gas systems in the presence of wind power and emerging technologies. The proposed model makes it possible to deal with uncertainties associated with both power and gas systems in contrast with the recent studies, where robust and stochastic modeling methods are applied to investigate the uncertain parameters in optimal operation of integrated gas and power systems, and the uncertainties of the gas network are not taken into account. The main contributions of this paper can be summarized as follows:

1) The proposed hybrid IGDT-stochastic framework takes advantages of both IGDT and stochastic programming methods, which makes the use of two risk-seeker and risk-averse strategies for modeling the uncertainty of residential gas load. This is effective in increasing the flexibility of the decision-making process of the network operator in overcoming such uncertainties, however, the robust model only considers the undesirable impact of the uncertain parameter. Also, the proposed hybrid method aims to determine the forecast error of uncertain parameter (i.e., residential gas load) with respect to its predicted value, where the error is obtained by the desirable operation cost of the network operator. Accordingly, the uncertainty radius is not known in contrast to the robust optimization method.

2) The presented hybrid IGDT-stochastic model is a bi-level problem, which can be changed to a single-level problem and can be solved with a simple approach without

\[
P^{2G}_{k,t,s} \quad \text{Dispach of P2G technology}
\]

\[
U^{2G}_{k,t,s} \quad \text{Natural gas production of P2G technology}
\]

\[
U^{st}_{st,t,s}, U^{out}_{st,t,s} \quad \text{Storing/Releasing rate of gas storage}
\]

\[
E_{st,t,s} \quad \text{Natural gas stored in gas storage system}
\]

\[
D_{j,t,s} \quad \text{Adjustable load}
\]

\[
d_{DR}_{j,t,s} \quad \text{Load after implementation of DR program}
\]

\[
D_{j,t,s}^{max} \quad \text{Load shiftable factor as present}
\]

\[
\pi_{s} \quad \text{Probability of each scenario}
\]
II. PROBLEM FORMULATION BASED ON HYBRID IGDT-STOCHASTIC APPROACH

The mutual connection of gas and electricity networks has been increased considering the increment of integrated gas-fired plants in the power systems. Accordingly, the solution of optimal management regarding the integrated network needs to consider not only the uncertain parameters of the electricity network but also the uncertainties associated with the gas network since the consideration of uncertainties associated with the gas network parameters plays a significant role in the commitment of gas-fired plants in power systems. In this paper, the uncertainties of electrical load demand, wind power output, and the residential gas load consumer have been estimated by IGDT approach.

A. Problem formulation based on Stochastic programming

In this section, the co-optimization problem of integrated gas and electricity networks is explained based on a stochastic model that is performed by Monte Carlo simulation method. The objective function and constraints are defined as follows:

1) Objective function: The main objective of the presented model is to minimize the operation cost in the integrated networks in presence of wind energy and emerging technologies. Equation (1) indicates the objective function of the proposed model, which is defined as the costs associated with coal-fueled generation units, natural gas-fired plants and operation cost of the gas storage system. It is notable that the cost of gas-fired units is considered in the cost of gas suppliers.

\[
\min \sum_{t=1}^{NT} \sum_{s=1}^{NS} \pi_s \left[ \sum_{i=1}^{NU} [P_i^C (P_{i,t,s} + SU_{i,t} + SD_{i,t})] + \sum_{sp=1}^{NSP} C_{sp} SU_{sp,t,s} + \sum_{st=1}^{NST} C_{st} GST_{st,t,s} + \sum_{s} \right]
\]

(1)

The objective function should be optimized considering several constraints including coal-fueled and natural gas-fired plants, natural gas storage, P2G system, DR program, electrical network and gas systems, which are described in the following.

2) Unit commitment constraints: The power generated by the non-gas-fired and gas-fired plants should be restricted to the upper and lower bounds as stated in (2). Ramp-up and ramp-down rates for generation plants are formulated as (3) and (4), respectively. The relation between auxiliary variables applied in ramp-up and ramp-down rates are pointed out in (5) and (6). Equations (7) and (8) indicate that each generation plant should be limited by minimum up-time and down-time constraints. Also, (9)-(12) show the start-up and shut-down cost of non-gas-fired units and gas consumption associated with start-up and shut-down of gas-fired plants.

\[
P_{i,t,s}^\text{max} \leq P_{i,t,s} \leq P_{i,t,s}^\text{min}
\]

(2)

\[
P_{i,t,s} - P_{i,t-1,s} \leq (1 - Y_{i,t}) R_{i,t}^{up} + Y_{i,t} P_{i,t,s}^\text{min}
\]

(3)

\[
P_{i,t-1,s} - P_{i,t,s} \leq (1 - Z_{i,t}) R_{i,t}^{dn} + Z_{i,t} P_{i,t,s}^\text{min}
\]

(4)

\[
Y_{i,t} - Z_{i,t} \geq I_{i,t} - I_{i,t-1}
\]

(5)

\[
Y_{i,t} + Z_{i,t} \geq 1
\]

(6)

\[
\left(X_{i,t-1}^{on} - T_{i}^{on}\right) (I_{i,t-1} - I_{i,t}) \geq 0
\]

(7)

\[
\left(X_{i,t-1}^{off} - T_{i}^{off}\right) (I_{i,t} - I_{i,t-1}) \geq 0
\]

(8)

\[
SU_{i,t} \geq su_i (I_{i,t} - I_{i,t-1}) \quad i \notin GU
\]

(9)

\[
SD_{i,t} \geq sd_i (I_{i,t-1} - I_{i,t}) \quad i \notin GU
\]

(10)

\[
SUG_{i,t} \geq sug_i (I_{i,t} - I_{i,t-1}) \quad i \in GU
\]

(11)

\[
SDG_{i,t} \geq sdg_i (I_{i,t-1} - I_{i,t}) \quad i \in GU
\]

(12)

3) Demand response program constraints: In this paper, the proposed DR program is modeled as shiftable approach. In this concept, the responsive loads can be programmed to run within a particular time due to lower electricity prices. Equation (13) demonstrates the network load after the execution of the DR program. Equation (14) presents the limitation of the shiftable load at each hour. Equations (15) and (16) indicate the boundary of the variation rate of sensitive loads to price in continuous time intervals. Finally, (17) shows the curtailed load as the determined time should be shifted to another time.

\[
d_{DR,j,t,s} = D_{j,t,s} + DR_{j,t,s}
\]

(13)

\[
|DR_{j,t,s}| \leq DR_{j,t,s} \quad j \notin DR_{max}
\]

(14)

\[
d_{DR,j,t,s} - d_{DR,j,t-1,s} \leq \Delta d_{j}^{up}
\]

(15)

\[
d_{DR,j,t-1,s} - d_{DR,j,t,s} \leq \Delta d_{j}^{dn}
\]

(16)

\[
\sum_{t=1}^{NT} DR_{j,t,s} = 0
\]

(17)

4) Power system security constraints: Equation (18) shows that the power balance of the network should be taken into consideration to ensure the supply of power load demand by the generation plants and power flow through system lines. Moreover, (19) and (20) demonstrate DC power flow and the line capacity limitation of DC power flow, respectively.

\[
PF_{L,t,s} = \frac{\delta_{b,t,s} - \delta_{b',t,s}}{x_L}
\]

(18)

\[
-PPF_{L}^{max} \leq PF_{L,t,s} \leq PPF_{L}^{max}
\]

(19)

\[
-PPF_{L}^{max} \leq PF_{L,t,s} \leq PPF_{L}^{max}
\]

(20)
TABLE I: Comparison of the literature with the current work

<table>
<thead>
<tr>
<th>Reference</th>
<th>Co-optimization</th>
<th>Uncertainties</th>
<th>Uncertainty modeling</th>
<th>Flexible Technologies</th>
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<td>Gas load</td>
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<td>P2G</td>
</tr>
<tr>
<td>[20]</td>
<td>✓</td>
<td>Electric load</td>
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<td>DR</td>
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<tr>
<td>[21]</td>
<td>✓</td>
<td>Wind</td>
<td>Stochastic</td>
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<tr>
<td>[14]</td>
<td>✓</td>
<td>Line outage</td>
<td>Robust</td>
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<tr>
<td>[22]</td>
<td>✓</td>
<td></td>
<td>Stochastic</td>
<td></td>
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<tr>
<td>[24]</td>
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<td></td>
<td>Robust</td>
<td></td>
</tr>
<tr>
<td>[25]</td>
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<td></td>
<td>Stochastic</td>
<td>IGDT-Stochastic</td>
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<tr>
<td>Proposed</td>
<td>✓</td>
<td></td>
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</table>

5) Natural gas storage: The natural gas storage system has been considered in this study to inject the storage gas to the integrated network for flattening the gas load profile. The gas storage unit can be utilized as an appropriate option when the gas load cannot be supplied due to the limitation of the gas capacity supplier or gas transmission pipeline capacity. Equations. (21) and (22) restrict the storage and release capacity of the gas storage. The storage balance and capacity limitations are provided by (23) and (24), respectively. Also, (25) and (26) meet the initial and final requirements of the natural gas storage unit.

\[ 0 \leq U_{st,\text{out}}^{\text{out}} \leq U_{st,\text{max}} \]  
\[ 0 \leq U_{st,\text{in}}^{\text{in}} \leq U_{st,\text{max}} \]  
\[ E_{st, t, s} = E_{st, t-1, s} + \eta_{st}^{\text{in}} U_{st, t, s}^{\text{in}} - \frac{U_{st, t, s}^{\text{out}}}{\eta_{st}} \]  
\[ E_{st, 0, s} = E_{st, \text{initial}, s} \]  
\[ E_{st, 0, s} = E_{st, \text{end}, s} \]

6) Natural gas network constraints: The natural gas flow through the gas pipeline is provided in (27) and (28), which is a function of gas pressure at two ends of the pipeline. Equation (29) specifies the connection of residential gas demands and gas-fired units to each node of the gas system. The consumption of gas by gas-fired generation plants is formulated in (30), which is connected to a gas storage unit. Also, (31) considers the P2G system as a gas supplier. The limitation of gas supplier and node pressure are mentioned in (32) and (33). Finally, (34) indicates the natural gas balance considering gas suppliers, gas load, gas injected by P2G system, and gas flow through the gas pipeline.

\[ F_{pl, t, s} = \text{sgn}(\pi_{m, t, s}, r \pi_{n, t, s}) C_{m, n} \sqrt{\pi_{m, t, s}^2 - \pi_{n, t, s}^2} \]  
\[ \text{sgn}(\pi_{m, t, s}, r \pi_{n, t, s}) = \begin{cases} 
1 & \pi_{m, t, s} \geq r \pi_{n, t, s} \\
-1 & \pi_{m, t, s} \leq r \pi_{n, t, s} 
\end{cases} \]  
\[ L_{G_{m, t, s}} = \sum_{g=1}^{NG_{m}} RG_{g, t} + \sum_{i=1}^{NGC_{m}} F_{gas}^{g, i} \]  
\[ F_{gas}^{g, i} = \alpha_{i} + \beta_{i} P_{i, t, s}^{g} + \gamma_{i}^{2} t_{i, t, s}^{g} + SUG_{i, t}^{g} + SDG_{i, t}^{g} \]  
\[ + \sum_{s=1}^{NS} \left( U_{s, t, s}^{\text{in}} - U_{s, t, s}^{\text{out}} \right) \]  
\[ U_{k, t, s}^{\text{out}} = \varphi_{k} P_{k, t, s}^{\text{out}} \eta_{k}^{\text{out}} \]  
\[ NSP_{m} \sum_{sp=1}^{U_{sp, t, s}} - LG_{m, t, s} + \sum_{k=1}^{NK_{m}} U_{k, t, s}^{\text{out}} = \sum_{pl=1}^{NP_{pl, m}} F_{pl, t, s} \]  
\[ \pi_{m}^{\min} \leq \pi_{m, t, s} \leq \pi_{m}^{\max} \]  
\[ U_{sp}^{\min} \leq U_{sp, t, s} \leq U_{sp}^{\max} \]  

7) Hybrid IGDT-stochastic framework: In this paper, an IGDT-stochastic model is proposed to minimize the total operation cost, which is a co-optimization problem for integrating electricity and natural gas networks. The proposed hybrid model is described in algorithm. (1) in details. Moreover, it differs from the stochastic programming method in three aspects: 1) In stochastic programming only based on scenarios, the load demand is a function of scenarios, where the increment of the calculations has a direct relationship with the number of scenarios. On the other hand, IGDT requires no scenario generation. 2) In stochastic programming only based on scenarios, the probability distribution of uncertain parameter is needed to model; however, such function is not required in IGDT model. 3) In the proposed model, the decision makers can decide on two various strategies when encountering with the uncertain parameter, which increases the flexibility of decision making in response to the uncertainties of the system parameters.

Algorithm 1 THE PROPOSED HYBRID IGDT-STOCHASTIC FRAMEWORK

Require: Data collection

1) Scenario Generation (uncertainty methods)
2) Scenario Reduction
3) Stochastic programming (Eqs. (1)-(34))
4) Calculation (Eq. (1))
5) Uncertainty modeling (Eqs. (53)-(55))
6) Risk-averse (Eqs. (36)-(44))
7) while d_r = d_{r-1} do Increment of cost deviation factor: d_r = d_{r-1}, r=1,..., NR obtaining optimal robustness factor
8) end while
9) Risk-seeker (Eqs. (45)-(53))
10) while d_p = d_{p-1} do Decrement of cost deviation factor: d_p = d_{p-1}, p=1,..., NP obtaining optimal opportunistic factor Save the variables
11) end while

The uncertainty in an optimization problem using IGDT is modeled as (35), where U is the set of input uncertain...
parameter. \(\bar{\Psi}\) is the predicted amount of the uncertain parameter \(\Psi\). Also, the deviation lower bound of the uncertain parameter from the predicted amount is defined by \(\epsilon\). This parameter is introduced as an uncertain unknown radius of the decision maker.

\[
U = U(\bar{\Psi}, \epsilon) = \left\{ \Psi : \left| \frac{\Psi - \bar{\Psi}}{\bar{\Psi}} \right| \leq \epsilon \right\} \tag{35}
\]

In the proposed hybrid IGDT-stochastic model, the system operator can present two strategies to control the uncertainty of the system, which is discussed as follows:

8) Risk-averse strategy: In this strategy, the operator separates the uncertain parameter having an undesirable effect on the objective function. Given that the main goal of this paper is to reduce the total operation cost, the risk-averse utilizes a schedule to overcome the decrement of operation cost resulting from the undesirable variation of the residential gas load from the predicted value. Hence, the mathematical model of the risk-averse can be formulated as follows:

\[
\alpha(X, \Delta C) = \max \left\{ \epsilon : \max \{ \text{OF} \leq \Delta C = (1 + d_p)\text{OF}_b \} \right\} \tag{36}
\]

\(\Delta C\) defines the critical value of operation cost. \(d_p\) is critical level of operation cost. Also, \(\text{OF}_b\) is the operation cost in the base condition, where the uncertain parameter has no variation concerning the predicted value. Moreover, renewable sources are not considered in the base condition. \(X\) is also an array containing the decision variables. The main aim of implementing the IGDT model for the operator is to decrease the radius of the uncertain parameter between the uncertain and forecasted values, which is proposed as a bi-level problem in (37)-(40).

\[
\alpha = \max \epsilon \tag{37}
\]

Subject to:
\[
\sum_{t=1}^{NT} \sum_{s=1}^{NS} \pi_s \left[ \sum_{i=1}^{NU} \left[ \sum_{p=1}^{NSP} \sum_{t'=1}^{GST} \left( C_{SP}^p (U_{i,p,t,t'}) + \sum_{x=1}^{NG} \sum_{t'=1}^{GST} C_{ST}^x (u_{x,t',s}) \right) \right] \right] \leq \Delta C \tag{38}
\]

\[
(1 - \epsilon) \hat{R}G_{g,t} \leq \hat{R}G_{g,t} \leq (1 + \epsilon) \hat{R}G_{g,t} \tag{39}
\]

Eqs. (2) – (34) \tag{40}

The reduction of the residential gas load has a positive influence on operation cost. In other words, the increment of the gas load has an undesirable effect. Accordingly, in the proposed risk-averse model, the maximum operation cost is related to the condition that the gas load is increased with respect to the predicted value. Thus, the proposed bi-level model in (37)-(40) is converted to a single-level problem as pointed out by (41)-(44).

\[
\alpha(X, \Delta C) = \max \epsilon \tag{41}
\]

Subject to:
\[
\sum_{t=1}^{NT} \sum_{s=1}^{NS} \pi_s \left[ \sum_{i=1}^{NU} \left[ \sum_{p=1}^{NSP} \left( C_{SP}^p (U_{i,p,t,t'}) + \sum_{x=1}^{NG} \sum_{t'=1}^{GST} C_{ST}^x (u_{x,t',s}) \right) \right] \right] \leq \Delta C \tag{42}
\]

\[
\hat{L}G_{m,t,s} = \sum_{g=1}^{NGm} \hat{R}G_{g,t} (1 + \epsilon) + \sum_{i=1}^{NGU_m} F_{g,t,s} \tag{43}
\]

Eqs. (2) – (28) and Eqs. (30) – (34) \tag{44}

9) Risk-seeker (RS) strategy: It should be mentioned that the uncertainty of parameters does not always have the detrimental effect on the objective function. Consequently, RS strategy is introduced for taking into account the situation that the objective function takes advantage of positive effect of the uncertain parameter. Actually, the aim of the decision maker is to provide lower objective function than the basic condition value. The formulation of the objective function regarding the RS strategy (called opportunity function) is stated as follows:

\[
\beta(X, \Delta C) = \min \left\{ \epsilon : \left\{ \text{Min} \{ \text{OF} \leq \Delta C = (1 - d_p)\text{OF}_b \} \right\} \right\} \tag{45}
\]

\[
\beta(X, \Delta C) = \min \epsilon \tag{46}
\]

Subject to:
\[
\sum_{t=1}^{NT} \sum_{s=1}^{NS} \pi_s \left[ \sum_{i=1}^{NU} \left[ \sum_{p=1}^{NSP} \sum_{t'=1}^{GST} \left( C_{SP}^p (U_{i,p,t,t'}) + \sum_{x=1}^{NG} \sum_{t'=1}^{GST} C_{ST}^x (u_{x,t',s}) \right) \right] \right] \leq \Delta C \tag{47}
\]

\[
(1 - \epsilon) \hat{R}G_{g,t} \leq \hat{R}G_{g,t} \leq (1 + \epsilon) \hat{R}G_{g,t} \tag{48}
\]

Eqs. (2) – (34) \tag{49}

\(d_p\) is optimistic level of operation cost. As previously mentioned, the reduction of the residential gas load has a positive impact on the operation cost. Therefore, in the introduced risk-seeker framework, the minimum operation cost belongs to the situation that the gas load is decreased regarding the forecasted amount. Consequently, the single-level problem in (50)-(53) can be presented instead of the proposed bi-level model in (45)-(48):

\[
\beta(X, \Delta C) = \min \alpha \tag{50}
\]

Subject to:
\[
\sum_{g=1}^{NGm} \hat{R}G_{g,t} (1 - \epsilon) + \sum_{i=1}^{NGU_m} F_{g,t,s} \tag{52}
\]

Eqs. (2) – (28) and Eqs. (30) – (34) \tag{53}

III. CASE STUDY AND SIMULATION RESULTS

The introduced framework has been implemented on a test system for determining the efficiency of the model. The proposed case study, which is depicted in Fig. 1, is an integrated 6-bus electrical network to a 6-node gas system. The coefficients of operation cost and operational characteristics of the thermal plants are adapted from [19]. The information of forecasted wind power generation, the electricity load, and residential gas load demands are demonstrated in Fig. 1. The proposed mixed integer non-linear programming (MINLP) model is solved in GAMS environment using DICOPT solver. The forecasted error of uncertain parameters is based on a normal distribution function with a 5% and 10% standard deviation for the electric load and wind turbines, respectively. A thousand scenarios are generated using Monte Carlo simulation approach, which is reduced to five scenarios utilizing Fast-Backward approach. Four case studies are taken into account to ensure the practicality and effectiveness of the proposed framework as follows:
Data Collection

Power and gas load demands
Wind power
Power plants
Transmission line of gas and power
P2G and gas storage

Case Study

Hybrid IGDT-stochastic network constrained co-optimization of power and gas networks

Case 1: stochastic co-optimization of integrated gas and electricity networks without considering P2G technology and DR program

In this case, the uncertainties of the integrated network include the power generation of the wind turbines and the electric load of the network. The interaction between the wind power dispatch and natural gas storage without considering P2G is shown in Fig. 3. The analysis of this figure proves the extreme dependency of the gas and power networks to each other. In other words, the gas storage stored the natural gas when wind power dispatch is increased, and injected the stored gas to node 1 of the gas network when the wind power dispatch is decreased. Accordingly, the natural gas storage makes it possible to supply gas to the gas-fired plant G1 in peak hours when encountering gas supply shortage in the gas network. This is effective in cooperation of high-cost generation plants and decrement of the system operation cost. The operation cost of the system in this case study is equal to $114604.998.

Case 2: stochastic co-optimization of integrated gas and electricity networks considering DR program

In this case study, the effect of DR programs is investigated on the operation of integrated gas and power networks. The load participation factor (LPF) of the DR program is assumed to be 10%. The impact of the DR program on the load profile concerning the system and power dispatch of the expensive generation plant G2 is depicted in Fig. 4. As seen in this figure, the electric load demand is shifted from on-peak hours to off-peak hours, which leads to the participation reduction of plant G2 in supplying electric load demand. It should be mentioned that the generation of plant G2 is decreased to 82.933 MWh with regards to the production of 320.85 MWh in Case 1. Table II indicates the influence of the application of DR program with various LPF on the operation cost of the power and gas systems. As it is obvious from the results, the operation cost of power and gas systems and consequently total operation cost is reduced. Moreover, by enhancing the LPF, the wind power dispatch is increased due to the increment of load demand in off-peak hours.
TABLE II: The impact of LPF of DR on the operation cost and dispatched wind power

<table>
<thead>
<tr>
<th>LPF in DR program (%)</th>
<th>Case system operation cost ($)</th>
<th>Power system operation cost ($)</th>
<th>Total operation cost ($)</th>
<th>Dispatched wind power (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>134545.4</td>
<td>10207.96</td>
<td>134654.38</td>
<td>1451.133</td>
</tr>
<tr>
<td>4</td>
<td>134554.14</td>
<td>8067.604</td>
<td>134689.51</td>
<td>14261.74</td>
</tr>
<tr>
<td>6</td>
<td>134689.51</td>
<td>6974.621</td>
<td>134810.37</td>
<td>1492.364</td>
</tr>
<tr>
<td>8</td>
<td>134810.37</td>
<td>5962.375</td>
<td>134972.75</td>
<td>1511.973</td>
</tr>
</tbody>
</table>

Fig. 5: Expected wind power dispatch for different cases

C. Case 3: stochastic co-optimization of integrated gas and electricity networks considering P2G technology and DR program

In this situation, P2G technology and DR program are considered simultaneously. Fig. 5 and Table III provide the effect of P2G technology on the total operation cost of the system and wind power dispatch in comparison with recent studies. As can be seen, wind power dispatch is increased in this case study with respect to recent cases since P2G converts the extra wind power to gas in off-peak hours, and the generated gas is used by natural gas consumers. The operation cost of this case is decreased because this natural gas is produced by extra wind power, which would be lost if it is not used. The operation cost of the system, in this case, is equal to $138794.506.

TABLE III: Operation cost and wind power dispatch in different cases

<table>
<thead>
<tr>
<th>Cases</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gas system operation cost ($)</td>
<td>134397.039</td>
<td>134898.33</td>
<td>134335.406</td>
</tr>
<tr>
<td>Power system operation cost ($)</td>
<td>10207.959</td>
<td>4459.1</td>
<td>4459.1</td>
</tr>
<tr>
<td>Total operation cost ($)</td>
<td>144604.998</td>
<td>139357.43</td>
<td>138794.506</td>
</tr>
<tr>
<td>Dispatched wind power (MWh)</td>
<td>1429.668</td>
<td>1531.450</td>
<td>1756.619</td>
</tr>
</tbody>
</table>

D. Case 4: hybrid stochastic IGDT co-optimization for cases 1-3

Under these circumstances, the uncertainty of residential gas load is considered using IGDT. The operation cost in base condition (i.e., Case 1) equals to $138794.506. The parameter $d_r$ is increased from 0.01 to 0.1 by 0.01 steps to implement the risk-averse strategy of IGDT. As it is obvious from Fig. 6, the robustness function $\alpha$ is boosted, which means that the system operator can tolerate a wider range of gas load uncertainty by the increment of $d_r$. Also, the operator attains a more robust decision making considering the uncertainty of gas load demand by the increment of robustness parameter $d_r$. For instance, the robustness function for a value of 0.05 for without the presence of flexible units, is 0.065, which means that a forecast error of 0.065 for gas load unacceptable for the system operator by increasing the operation cost of

Fig. 6: Variation of robustness optimum function against robustness parameter

Fig. 7: Power dispatch of units in risk-averse strategy

The opportunity parameter $d_\rho$ is raised from 0.01 to 0.1 to address the risk-seeker strategy, which resulted in a decrease of operation cost from its base condition (i.e., $138794.506$). It can be observed from Fig. 8 that the network operator should consider the gas load demand reduction by 4.35% concerning its predicted value to attain an optimistic desirable operation cost of (1-0.03) $134630.671$ without considering flexible units. The opportuneness function $\beta$ has a direct relation with increasing the amount of opportunity parameter $d_\rho$. Moreover, as can be seen in this figure, when the emerging flexible units are taken into account, the network operator attains to the desired operation cost with a lesser optimistic error concerning the condition that such units do not exist. Indeed, the network operator considers optimistic error in the residential gas load to attain a desirable operation cost of (1-0.04) $138794.506$. Consequently, it results in the decrement of the operation cost belong to the uncertainty associated with the residential gas load demand.

IV. CONCLUSION

This study proposed a novel hybrid IGDT-stochastic framework for co-optimization of integrated gas and power
networks with penetration of wind turbines. The proposed model considered uncertainties associated with both gas and power networks, where the uncertainty of power system including wind power output and load demand was modeled using the scenario-based method, and the uncertainty of gas network containing residential gas consumers was estimated by applying IGDT. The proposed hybrid model took advantages of both scenario-based modeling method and IGDT and applied two risk-seeker and risk-averse strategies enabling the network operator to make decisions on system operation with higher inflexibility rate. Moreover, the effect of emerging technologies such as demand response program and power to gas (P2G) unit was studied in the proposed model. The investigation of the presented model provides some remarkable achievements in co-optimization of integrated gas and power networks as follows:

1) The simultaneous consideration of emerging flexible technologies was influential in decreasing total operation cost of the system in comparison with the consideration of such technologies individually.

2) The simultaneous presence of emerging flexible technologies was beneficial in increasing the penetration of wind power in the power system.

3) The network operator reaches the profit regarding the emerging flexible technologies in both risk-averse and risk-seeker strategies in a way that the operator was able to take into consideration the risk against the uncertainty of gas network in risk-averse strategy with the lower cost. Also, the operator benefited from the risk in better condition against the uncertainty in risk-seeker strategy.

REFERENCES


