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

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***Abstract*—In a power system with high penetration of renewable power sources, gas-fired units can be considered as a back-up option to improve the balance between generation and consumption in short-term scheduling. Therefore, closer coordination between power and natural gas systems is anticipated. This article presents a novel hybrid information gap decision theory (IGDT)-stochastic cooptimization 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 uncertainties of electric load and wind power are handled through a scenario-based approach, and residential gas load uncertainty is handled via IGDT approach with no need for the probability density function. The introduced hybrid model enables the system operator to consider the advantages of both approaches simultaneously. 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 bilevel 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 conditions. Moreover, emerging flexible energy sources such as the power to gas technology and demand response program are considered in the proposed model for increasing the wind power dispatch, decreasing the total operation cost of the integrated network as well as reducing the effect of system uncertainties on the total operating cost. Numerical results indicate the applicability and effectiveness of the proposed model under different working conditions.**

***Index Terms*—Co-optimization of integrated gas and power system, demand response (DR) program, hybrid information gap decision theory (IGDT)-stochastic, power-to-gas (P2G) technology, wind power.**

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NOMENCLATURE

Indices

t	Time periods.
i,r	Thermal/wind power plants.
j,g	Electrical/Natural gas loads.
s	Scenarios.
sp	Natural gas suppliers.
m, n	Nodes in natural gas network.
k	P2G technology.
b, b'	Electric buses.
L,pl	Electrical/gas transmission lines.

Parameters

NT	Number of time periods.
NG, NJ	Number of residential gas/electrical loads.
NS	Number of scenarios.
NSP	Number of gas suppliers.
NR	Number of wind power plants.
NGU, NEU	Number of gas-fired/nongas fired units.
$P_i^{\min}$, $P_i^{\max}$	Min/Max capacity of thermal unit i (MW).
RU_i, RD_i	Ramp up/down of thermal unit i (MW).
T_i^{On}, T_i^{Off}	Minimum up/down time of unit i (h).
$\mathrm{PF}_L^{\max}$	Maximum capacity of line L (MW).
$D_{j,t,s}$	Expected hourly load (MW).
C_{pl}	Constant of pipeline pl (kcf/Psig).
$\pi_m^{\max}$, $\pi_m^{\min}$	Max/Min pressure (Psig).
$U_{\mathrm{sp}}^{\max}$, $U_{\mathrm{sp}}^{\min}$	Max/Min natural gas injection.
$L_{\mathrm{l}}^{\max}$, $L_{\mathrm{l}}^{\min}$	Max/Min natural gas load (kcf).
$U_{\mathrm{s,max}}^{\mathrm{out}}$, $U_{\mathrm{s,max}}^{\mathrm{in}}$	Max release/store capacity of gas storage (kcf).
η_s^{in}, η_s^{out}	Storing/releasing efficiency of gas storage.
η_k^{p2g}	Efficiency of P2G technology.
$E_s^{\max}$, $E_s^{\min}$	Max/min gas stored in storage (kcf).
$C_{\mathrm{sp}}^{\mathrm{SUP}}$, C^{GST}	Cost of gas supplier/storage ($).
π_s	Probability of each scenario s.

Variables

F_i^C	Cost function of thermal unit i.
$F_{i,t,s}^{\text{gas unit}}$	Fuel function of gas-fired unit i.
$F_{\text{pl},t,s}$	Gas flow on pipe pl.
$P_{i,t,s}$	Dispatch of unit i.
$I_{i,t,s}$	Binary on/off status indicator of unit i.
$\pi_{m,t,s}$	Pressure of natural gas node m.
$U_{\text{sp},t,s}$	Gas delivery of supplier.
$\text{LG}_{\text{m,t,s}}$	Natural gas load connected to node m.
$P_{r,t,s}$	Dispatch of wind power.
$\text{PF}_{L,t,s}$	Line flow at line L.
$\delta_{b,t,s}$	Voltage angle of network bus b.
$P_{k,t,s}^{\text{p2g}}$	Dispatch of P2G technology.
$U_{k,t,s}^{\text{p2g}}$	Natural gas production of P2G technology.
$U_{t,s}^{\text{in}}$, $U_{t,s}^{\text{out}}$	Storing/rate of gas storage.
$E_{t,s}$	Natural gas stored in gas storage system.
$\text{DR}_{j,t,s}$	Adjustable load.
$d_{j,t,s}^{\text{DR}}$	Load after implementation of DR program.
$\text{DR}_{j,t}^{\max}$	Load factor in percent.

I. Introduction

THE penetration of renewable energy sources such as wind turbines and photovoltaics have been dramatically increased due to concerns on the reduction of fossil fuels and global issues of bluehouse gases emissions [1], [2]. The speculation of 2182 TWh wind power generation by 2030, reported by International Energy Agency, highlights such contribution of renewable sources in supplying demand in power systems [3]. However, the variation of wind power generation with respect to the forecasted amount and uncertain nature of such energy source makes it important to find an appropriate strategy to control such situations. A practical solution for handling the above-mentioned issue is to develop natural gas-fired generation plants, which can not only decrease emissions of pollutant gases up to 60% compared to the coal-fired plants, but also can deal with the variation of renewable energy generation by high ramp-rates and fast start-up characteristics [4]. In addition, introduction of shale gas production technology in USA had a significant effect on reducing the natural gas price leading to extending gas combined-cycle plants. The statistics proves considerable alteration in employing gas-fired plants in power systems such as growth rate of gas consumption in USA for power generation to 39% in 2012. The effective role of natural gas is observed not only in expansion of natural gas-fired plants but also in employment of power to gas (P2G) technology. P2G as a novel approach for storing energy as natural gas plays an important role for accommodation of renewable energy variability [5]. Accordingly, a heated topic on integrated energy systems has enlivened the previous studies regarding interdependency of electrical and gas networks according to the influence of natural gas-fired units and P2G systems.

Integrated electricity and gas networks are hotly studied in recent publications focusing on co-optimization models of such networks, as well as technologies developed such as P2G system and demand response (DR) programs. Several works have concentrated on proposing approaches for relaxation of coupling constraints including a convex relaxation model [6], Lagrangian relaxation [7], Benders decomposition [8], and alternating direction method of multipliers [9]. A security-constrained model for integrated gas and electricity networks has been proposed investigating the effect of gas pipelines disruptions and power transmission losses [10]. A bilevel framework for co-optimization of integrated gas and electricity networks has been introduced in [11] with two agents, where the former agent aims at minimizing the operation cost of the integrated network, and the latter one seeks to maximize the profit of private owners. A bilevel model for the optimal operation of 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]. Zlotnik *et al.* in [15] proposed a novel approach for controlling the gas flows within gas pipelines in management of power plants and operation of gas compressor by investigating various levels of combination, spanning from separate prediction, and integrated optimal control. However, the uncertainties associated with parameters of both power system and gas network have not been studied in this reference.

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 [16], [17] 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 [18], unit commitment [19] and restoration of electrical distribution systems [20], and self-scheduling of generation companies [21].

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 article 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 article can be summarized as follows.

1) The proposed hybrid IGDT-stochastic framework takes advantages of both IGDT and stochastic programming

TABLE I
COMPARISON OF THE LITERATURE WITH THE CURRENT WORK

Reference	Co-optimization	Uncertainties				Uncertainty modeling	Flexible Technologies	
		Gas load	Electric load	Wind	Line outage		P2G	DR
[22]			✓		✓	Stochastic		
[25]			✓	✓		Stochastic		
[26]			✓	✓		Stochastic		✓
[14]	✓		✓	✓		Robust	✓	
[27]	✓		✓	✓		Robust	✓	
[28]	✓				✓	Robust		
[24]	✓		✓	✓	✓	Robust		
[29]	✓		✓	✓		Stochastic		
Proposed	✓	✓	✓	✓		IGDT-Stochastic	✓	✓

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 (RO) method.

2) The presented hybrid IGDT-stochastic model is a bilevel problem, which can be changed to a single-level problem and it can be solved with a simple approach without requiring the Karush–Kuhn–Tucker (KKT) conditions.
3) The uncertainties of both gas and power networks are considered in the proposed hybrid model. On the contrary, recent studies considered only the uncertainties of the power system. The proposed hybrid IGDT-stochastic model addresses the uncertainties regarding wind power output and power and residential gas load demands, where the Monte Carlo simulation method is applied for modeling the power system uncertainties, and IGDT is employed to deal with the uncertainty of natural gas system.
4) The emerging technologies in power and gas networks such as DR programs and P2G technology are taken into account to boost the flexibility of the integrated network. Moreover, the influence of such technologies is investigated in increasing and decreasing the penetration of wind power and the operation cost of the system, respectively.

This article is organized as follows: Section II deals with coordinated operation strategies of power and gas systems. Section III provides the problem formulation for the proposed co-optimization of gas and power systems based on hybrid IGDT-stochastic approach. The studied system and simulation results are given in Section IV. The main findings and performance of the proposed model is concluded in Section V.

II. Coordinated Operation Strategies of Power and Gas Systems

Considering the increasing level of interdependency between the power network and the natural gas system, it may not be reasonable or physically possible to model the two networks separately and optimize them independently. Three types of main approaches have been presented in the literature to examine the interdependency of the power grid and the natural gas system. In the first approach, a network-constrained unit commitment problem is solved by a power system operator while considering natural gas network constraints [22]. In the second approach, the optimization of power and gas systems are implemented as a sequential optimization problem [23]. In the third approach, unlike the sequential approach, co-optimization problem considers the power network and the natural gas system as a whole for minimizing the total operation cost concerning both systems [24]. This article has focused on the third approach to model interdependency between power and gas systems as a co-optimization problem.

III. 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 article, 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, gas suppliers, operation cost of the gas storage system, and the cost of lost electric load. It is notable that the cost of gas-fired units is considered in the cost of gas suppliers

$$\mathrm{OF} = \mathbf{min} \sum_{t=1}^{\mathrm{NT}} \sum_{s=1}^{\mathrm{NS}} \pi_s \begin{bmatrix} \sum_{i=1}^{\mathrm{NEU}} \left[F_i^C \left(P_{i,t,s}\right) + \mathrm{SU}_{i,t} + \mathrm{SD}_{i,t}\right] \\ + \sum_{sp=1}^{\mathrm{NSP}} C_{sp}^{\mathrm{SUP}} U_{sp,t,s} + C^{\mathrm{GST}}\, U_{t,s}^{\mathrm{out}} \\ + \sum_{j=1}^{\mathrm{NJ}} C^{\mathrm{LO}} \mathrm{Voll}_{j,t,s} \end{bmatrix}. \tag{1}$$

The objective function should be optimized considering several constraints including coal-fueled and natural gas-fired plants, gas suppliers, 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 nongas 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 nongas-fired units and gas consumption associated with start-up and shutdown of gas-fired plants [28]

$$P_i^{\min} I_{i,t} \le P_{i,t,s} \le P_i^{\max} I_{i,t} \tag{2}$$

$$P_{i,t,s} - P_{i,t-1,s} \le (1 - Y_{i,t}) R_i^{up} + Y_{i,t} P_i^{\min} \tag{3}$$

$$P_{i,t-1,s} - P_{i,t,s} \le (1 - Z_{i,t}) R_i^{dn} + Z_{i,t} P_i^{\min} \tag{4}$$

$$Y_{i,t} - Z_{i,t} = I_{i,t} - I_{i,t-1} \tag{5}$$

$$Y_{i,t} + Z_{i,t} \ge 1 \tag{6}$$

$$\left(X_{i,t-1}^{\mathrm{on}} - T_i^{\mathrm{on}}\right)\left(I_{i,t-1} - I_{i,t}\right) \ge 0 \tag{7}$$

$$\left(X_{i,t-1}^{\mathrm{off}} - T_i^{\mathrm{off}}\right)\left(I_{i,t} - I_{i,t-1}\right) \ge 0 \tag{8}$$

$$\mathrm{SU}_{i,t} \ge su_i \left(I_{i,t} - I_{i,t-1}\right) \quad i \notin \mathrm{NGU} \tag{9}$$

$$\mathrm{SD}_{i,t} \ge sd_i \left(I_{i,t-1} - I_{i,t}\right) \quad i \notin \mathrm{NGU} \tag{10}$$

$$\mathrm{SUG}_{i,t} \ge sug_i \left(I_{i,t} - I_{i,t-1}\right) \quad i \in \mathrm{NGU} \tag{11}$$

$$\mathrm{SDG}_{i,t} \ge sdg_i \left(I_{i,t-1} - I_{i,t}\right) \quad i \in \mathrm{NGU}. \tag{12}$$

3) DR Program Constraints: In this article, the proposed DR program is modeled as a 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 that the curtailed load at a time interval should be shifted to another time [26]

$$d_{j,t,s}^{\mathrm{DR}} = D_{j,t,s} + \mathrm{DR}_{j,t,s} \tag{13}$$

$$|\mathrm{DR}_{j,t,s}| \le \mathrm{DR}_{j,t}^{\max} D_{j,t,s} \tag{14}$$

$$d_{j,t,s}^{\mathrm{DR}} - d_{j,t-1,s}^{\mathrm{DR}} \le \Delta d_j^{\mathrm{up}} \tag{15}$$

$$d_{j,t-1,s}^{\mathrm{DR}} - d_{j,t,s}^{\mathrm{DR}} \le \Delta d_j^{\mathrm{dn}} \tag{16}$$

$$\sum_{t=1}^{\mathrm{NT}} \mathrm{DR}_{j,\,t,\,s} = 0. \tag{17}$$

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

$$\sum_{i=1}^{\mathrm{NU}_b} P_{i,t,s} + \sum_{r=1}^{\mathrm{NR}_b} P_{r,t,s} - \sum_{k=1}^{\mathrm{NK}_b} P_{k,t,s}^{\mathrm{p2g}} - \sum_{j=1}^{\mathrm{NJ}_b} \left(d_{j,t,s}^{\mathrm{DR}} - \mathrm{Voll}_{j,t,s}\right) = \sum_{l=1}^{\mathrm{NL}_b} \mathrm{PF}_{L,t,s} \tag{18}$$

$$\mathrm{PF}_{L,t,s} = \frac{\delta_{b,\,t,s} - \delta_{b',\,t,s}}{x_L} \tag{19}$$

$$-\,\mathrm{PF}_L^{\max} \le \mathrm{PF}_{L,t,s} \le \mathrm{PF}_L^{\max}. \tag{20}$$

5) Natural Gas Storage: The natural gas storage system has been considered in this article to inject the stored 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

$$0 \le U_{t,s}^{\mathrm{out}} \le U_{\max^{\mathrm{out}}} \tag{21}$$

$$0 \le U_{t,s}^{\mathrm{in}} \le U_{\max^{\mathrm{in}}} \tag{22}$$

$$E_{\,t,\,s} = E_{\,t-1,\,s} + \eta^{\mathrm{in}} U_{t,\,s}^{\mathrm{in}} - \frac{U_{t,\,s}^{\mathrm{out}}}{\eta^{\mathrm{out}}} \tag{23}$$

$$E^{\min} \le E_{\,t,\,s} \le E^{\max} \tag{24}$$

$$E_{\,0,\,s} = E_{\,\mathrm{intial},\,s} \tag{25}$$

$$E_{\,0,\,s} = E_{\,\mathrm{end},\,s}. \tag{26}$$

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 [26]

$$F_{pl,t,s} = \mathrm{sgn}(\pi_{m,t,s}, \pi_{n,t,s})\ C_{m,n} \sqrt{\left|\pi_{m,t,s}^2 - \pi_{n,t,s}^2\right|} \tag{27}$$

$$\mathrm{sgn}(\pi_{m,t,s}, \pi_{n,t,s}) = \begin{cases} 1 & \pi_{m,t,s} \geq \pi_{n,t,s} \\ -1 & \pi_{m,t,s} < \pi_{n,t,s} \end{cases} \tag{28}$$

$$\mathrm{LG}_{m,t,s} = \sum_{g=1}^{\mathrm{NG}_m} \mathrm{RG}_{g,t} + \sum_{i=1}^{\mathrm{NGU}_m} F_{i,t,s}^{\mathrm{gas}} \qquad i \in \mathrm{GU} \tag{29}$$

$$F_{i,t,s}^{\mathrm{gas}} = \alpha_i + \beta_i P_{i,t,s} + \gamma_i P_{i,t,s}^2 + \mathrm{SUG}_{i,t} + \mathrm{SDG}_{i,t} + \sum_{s=1}^{\mathrm{NS}_i} (U_{t,s}^{\mathrm{in}} - U_{t,s}^{\mathrm{out}}) \qquad i \in \mathrm{GU} \tag{30}$$

$$U_{k,t,s}^{\mathrm{p2g}} = \varphi\, P_{k,t,s}^{\mathrm{p2g}}\, \eta_k^{\mathrm{p2g}} \tag{31}$$

$$\sum_{sp=1}^{\mathrm{NSP}_m} U_{sp,t,s} - \mathrm{LG}_{m,t,s} + \sum_{k=1}^{Nk_m} U_{k,t,s}^{\mathrm{p2g}} = \sum_{pl=1}^{\mathrm{NPL}_m} F_{pl,t,s} \tag{32}$$

$$\pi_m^{\min} \leq \pi_{m,t,s} \leq \pi_m^{\max} \tag{33}$$

$$U_{sp}^{\min} \leq U_{sp,t,s} \leq U_{sp}^{\max}. \tag{34}$$

B. Problem Formulation Based on Hybrid IGDT-Stochastic Approach

In this article, 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 with details in Fig. 1. In the field of day-ahead scheduling of coupled power and gas systems, let us assume a set of gas demand forecasts for the next day is accessible. An IGDT-based problem solution guarantees a specified cost, provided the after-the-fact demand falls into a maximized demand band centered at the forecast gas demands. This band is often referred to as a robustness range. IGDT technique has practical benefits over scenario-based models. In the context of day-ahead scheduling, an IGDT-based model determines optimal schedules in order to achieve a target cost, whereas scenario-based approaches attain optimal schedules based on a limited number of possible demands scenarios. In addition, unlike scenario-based techniques, the IGDT-based problem guarantees a predefined level of cost. In well-known RO problems, the robustness range of the uncertain parameter is defined before solving the problem. RO optimization and risk-constrained stochastic programming often stated as a performance maximization model, where cost is minimized regarding an uncertainty budget and risk factor [32]. However, IGDT categorized as a performance satisfying environment, where a robust solution is determined such that specified expectations are fulfilled [34]. Therefore, the IGDT method cannot be directly compared to these techniques since they follow different objectives and are in different categories. Moreover, it differs from the stochastic programming method and RO in two aspects.

1) In stochastic optimization problem [30], [31], the probability distribution of uncertain parameter is needed to be known. However, such function is not required in the IGDT model. In addition, this technique does not need to generate scenarios. Therefore, the problem execution time is less than the stochastic model.
2) Compared with the RO [32], [33] that includes just one risk-averse approach for an uncertain parameter (worst case), in an IGDT approach, 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.

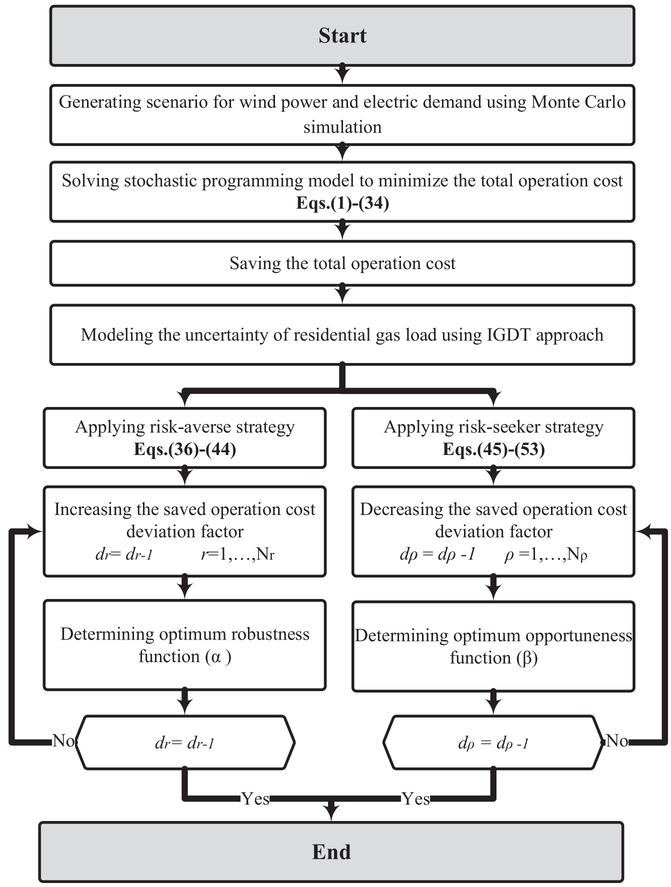

Fig. 1. Flowchart of proposed hybrid IGDT-stochastic framework.

The uncertainty in an optimization problem using IGDT is modeled as (35) [34], where U is the set of input uncertain parameter. $\overline{\Psi}$ is the predicted amount of the uncertain parameter Ψ. Also, the deviation of lower bound of the uncertain parameter from the predicted amount is defined by ϵ. This parameter is introduced as an uncertain unknown radius of the decision maker

$$U = U(\bar{\Psi}, \varepsilon) = \left\{ \Psi : \left| \frac{\Psi - \bar{\Psi}}{\bar{\Psi}} \right| \leq \varepsilon \right\}. \tag{35}$$

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.

1) 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 article 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 strategy can be formulated as follows [34]:

$$\alpha(X, \Delta_C) = \mathbf{min}\left\{\varepsilon : \left(\underset{\Psi\in U(\bar{\Psi},\varepsilon)}{\text{Max}} \quad \text{OF} \leq \Delta_C = (1+d_r)\text{OF}_b\right)\right\}. \tag{36}$$

Δ_C defines the acceptable value of operation cost. d_r is the critical level of operation cost. Also, 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 bilevel problem in

$$\alpha = \text{ Max } \varepsilon \tag{37}$$

Subject to:

$$\mathbf{max}\sum_{t=1}^{\text{NT}}\sum_{s=1}^{\text{NS}}\pi_s\begin{bmatrix}\sum_{i=1}^{\text{NEU}}\left[F_i^C(P_{i,t,s})+\text{SU}_{i,t}+\text{SD}_{i,t}\right]\\+\sum_{sp=1}^{\text{NSP}}C_{sp}^{\text{SUP}}U_{sp,t,s}+C^{\text{GST}}\,U_{t,s}^{\text{out}}\\+\sum_{j=1}^{NJ}C^{\text{LO}}\text{Voll}_{j,t,s}\end{bmatrix}\leq\Delta_C \tag{38}$$

$$(1-\varepsilon)R\hat{G}_{g,t} \leq RG_{g,t} \leq (1+\varepsilon)R\hat{G}_{g,t} \tag{39}$$

$$(2)-(34). \tag{40}$$

Bilevel optimization is described as a mathematical problem, where an optimization problem includes another optimization problem as a constraint. Solving a bilevel optimization problem is complex by using common optimization software. To this end, it can be converted to a single-level problem applying KKT conditions [34] or an innovative approach since the decrement of residential gas load has positive influence on operation cost. On the other hand, increment of the gas load has undesirable effect on the operation cost. Accordingly, in the proposed risk-averse model, the maximum operation cost is related to the condition that gas load is increased with respect to the predicted value. Thus, the proposed bilevel model in (37)–(40) is converted to a single-level problem as pointed out by

$$\alpha(X, \Delta_C) = \text{ Max } \varepsilon \tag{41}$$

Subject to:

$$\sum_{t=1}^{\text{NT}}\sum_{s=1}^{\text{NS}}\pi_s\begin{bmatrix}\sum_{i=1}^{\text{NEU}}\left[F_i^C(P_{i,t,s})+\text{SU}_{i,t}+\text{SD}_{i,t}\right]\\+\sum+\sum_{sp=1}^{\text{NSP}}C_{sp}^{\text{SUP}}U_{sp,t,s}+C^{\text{GST}}\,U_{t,s}^{\text{out}}\\+\sum_{j=1}^{\text{NJ}}C^{\text{LO}}\text{Voll}_{j,t,s}\end{bmatrix}\leq\Delta_C \tag{42}$$

$$\text{LG}_{m,t,s} = \sum_{g=1}^{\text{NG}_m}\text{RG}_{g,t}(1+\varepsilon) + \sum_{i=1}^{\text{NGU}_m}F_{i,t,s}^{\text{gas}} \tag{43}$$

$$(2)-(28) \text{ and } (30)-(34). \tag{44}$$

2) Risk-Seeker Strategy: It should be mentioned that the uncertainty of parameters does not always have the detrimental effect on the objective function. Consequently, risk-seeker 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 [34]:

$$\beta(X, \Delta_C) = \mathbf{min}\left\{\varepsilon : \left(\underset{\Psi\in U(\bar{\Psi},\varepsilon)}{\text{Min}} \quad \text{OF} \leq \Delta_C = (1-d_p)\text{OF}_b\right)\right\} \tag{45}$$

$$\beta(X, \Delta_C) = \text{ Min } \varepsilon \tag{46}$$

Subject to:

$$\mathbf{min}\sum_{t=1}^{\text{NT}}\sum_{s=1}^{\text{NS}}\pi_s\begin{bmatrix}\sum_{i=1}^{\text{NU}}\left[F_i^C(P_{i,t,s})+\text{SU}_{i,t}+\text{SD}_{i,t}\right]\\+\sum_{sp=1}^{\text{NSP}}C_{sp}^{\text{SUP}}U_{sp,t,s}+C^{\text{GST}}\,U_{t,s}^{\text{out}}\\+\sum_{j=1}^{NJ}C^{\text{LO}}\text{Voll}_{j,t,s}\end{bmatrix}\leq\Delta_C \tag{47}$$

$$(1-\varepsilon)\text{R}\overset{\wedge}{\text{G}}_{g,t} \leq \text{RG}_{g,t} \leq (1+\varepsilon)\text{R}\overset{\wedge}{\text{G}}_{g,t} \tag{48}$$

$$(2)-(34). \tag{49}$$

d_p is the optimistic level of operation cost. As mentioned before, the decrease of residential gas load shows a positive influence on the operation cost. Therefore, in the introduced risk-seeker framework, the minimum operation cost is achieved when the gas load is decreased with respect to the forecasted amount. Consequently, the single-level problem in (50)–(53) can be presented instead of the proposed bilevel model in (45)–(48)

$$\beta(X, \Delta_C) = \text{ Min } \alpha \tag{50}$$

Subject to:

$$\sum_{t=1}^{\text{NT}}\sum_{s=1}^{\text{NS}}\pi_s\begin{bmatrix}\sum_{i=1}^{\text{NEU}}\left[F_i^C(P_{i,t,s})+\text{SU}_{i,t}+\text{SD}_{i,t}\right]\\+\sum_{sp=1}^{\text{NSP}}C_{sp}^{\text{SUP}}U_{sp,t,s}+C^{\text{GST}}\,U_{t,s}^{\text{out}}\\+\sum_{j=1}^{\text{NJ}}C^{\text{LO}}\text{Voll}_{j,t,s}\end{bmatrix}\leq\Delta_C \tag{51}$$

$$\text{LG}_{m,t,s} = \sum_{g=1}^{\text{NG}_m}\text{RG}_{g,t}(1-\varepsilon) + \sum_{i=1}^{\text{NGU}_m}F_{i,t,s}^{\text{gas}} \tag{52}$$

$$(2)-(28) \text{ and } (30)-(34). \tag{53}$$

IV. 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. 2, is an integrated 6-bus

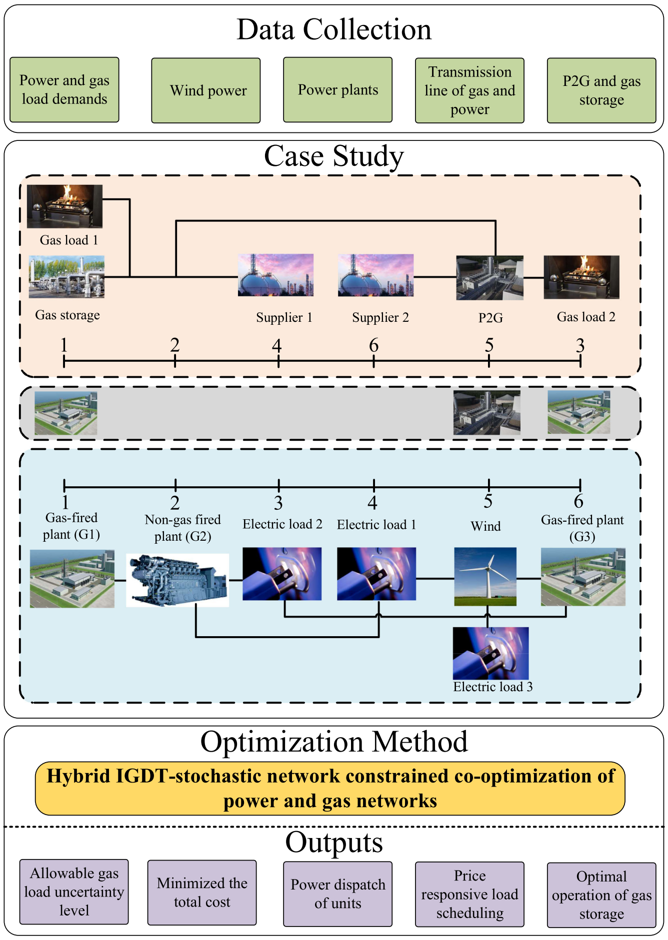

Fig. 2. Proposed case study.

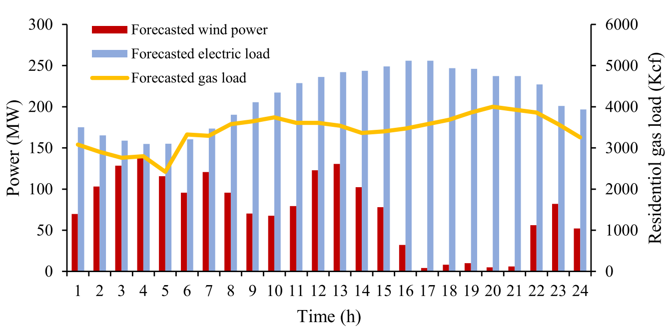

Fig. 3. Forecasted wind power, electric load, and residential gas load.

electrical network to a 6-node gas system. The coefficients of operation cost and operational characteristics of the thermal plants are adapted from [22]. The information of forecasted wind power generation, the electricity load, and residential gas load demands are demonstrated in Fig. 3.

The proposed mixed integer nonlinear programming model is solved in general algebraic modeling system environment using discrete and continuous optimizer solver. The forecasted error of electric load is based on a normal distribution function with a 5% standard deviation. Additionally, a normal probability distribution function was applied for the prediction error of

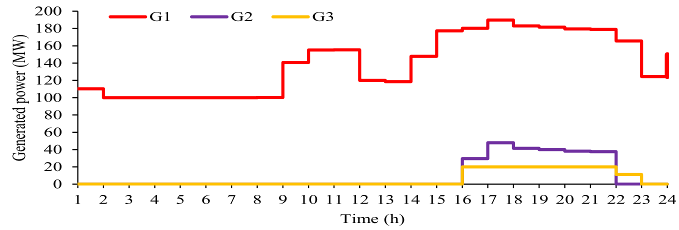

Fig. 4. Hourly power dispatch of generation units.

wind power output. The statistical schemes for wind speeds at determined locations clarify that such models do not follow normal distribution function, but rather Rayleigh distribution function [35]. Accordingly, considering wind speed-to-power output relations of wind power generation plants, the probability distributions of individual wind turbines power supply are not considered as normal probability distributions. On the other hand, the geographical dispersion and large number of wind turbines allow the application of central limitation theorem [36], [37] for justifying the assumption of normal distribution of the whole wind power prediction error [36], [38], [39]. A thousand scenarios are generated using Monte Carlo simulation approach, which is reduced to five scenarios utilizing fast-backward approach. Five case studies are taken into account to ensure the practicality and effectiveness of the proposed framework as follows.

A. *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. Fig. 4 demonstrates the obtained optimal management of generation units. As it is obvious from this figure, the power generation of the plant G1 as the cheapest unit is committed during the whole scheduling period. However, the power output of unit G1 has decreased in peak hours due to priority of residential gas load and accordingly shortage of gas supply by the natural gas network, which necessitates dispatch of units G2 and G3 to meet the system load. It should be noted that G3 has received gas supply to generate power at peak hours due to the location of such unit in gas network, which relates to the pressure condition of the gas network nodes and consequently gas flow through pipelines. The interaction between the wind power dispatch and natural gas storage without considering P2G is shown in Fig. 5. 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 co-operation 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 \$144604.998. We also investigate the

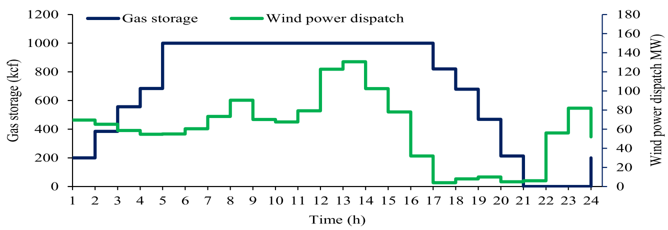

Fig. 5. Relation between energy level stored in gas storage and wind power dispatch in case 1.

TABLE II
IMPACT OF THE SCENARIO REDUCTION ON THE OPERATION COST

Selected the number of scenarios	5	10	15	20
Total system operation cost ($)	144604.998	145212.310	146025.252	146892.161
Computation time (Second)	29.563	73.689	209.735	338.452

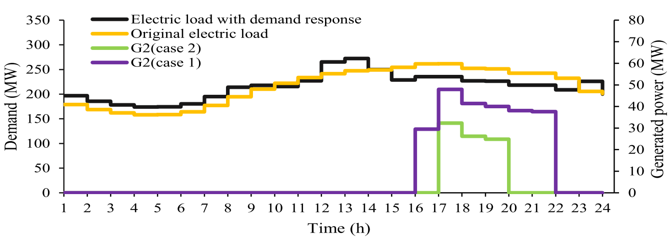

Fig. 6. Impact of DR program on electricity load profile and power dispatch of unit G2 in case 2.

TABLE III
IMPACT OF LPF OF DR ON THE OPERATION COST AND DISPATCHED WIND POWER

LPF in DR program (%)	2	4	6	8
Gas system operation cost ($)	134545.4	134554.14	134689.51	134810.37
Power system operation cost ($)	10207.96	8067.604	6974.621	5962.375
Total operation cost ($)	143744.91	142621.74	141664.13	140772.75
Dispatched wind power (MWh)	1451.133	1471.767	1492.364	1511.973

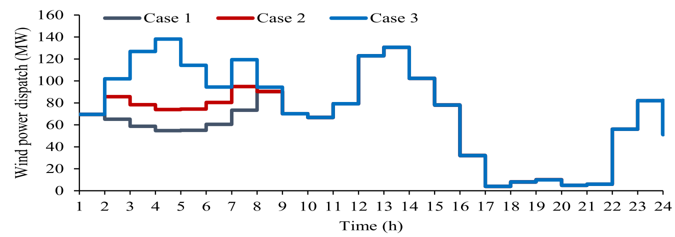

Fig. 7. Expected wind power dispatch for cases 1, 2, and 3.

TABLE IV
OPERATION COST AND WIND POWER DISPATCH IN DIFFERENT CASES

Cases	Case 1	Case 2	Case 3
Gas system operation cost ($)	134397.039	134898.33	134335.406
Power system operation cost ($)	10207.959	4459.1	4459.1
Total operation cost ($)	144604.998	139357.43	138794.506
Dispatched wind power (MWh)	1429.668	1531.450	1756.619

total operation cost without natural gas storage, which results in a higher operation cost of $146511.861. In addition, Table II shows the effect of the selected number of scenarios on the total operation cost. As can be seen, the daily operation cost depends on the number of scenarios chosen and increases with the number of scenarios. This increase is due to the larger range of uncertainty achieved by a greater number of scenarios. Also, by expanding the number of scenarios, computation time rises due to increasing of problem variables.

B. 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. 6. 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. At time intervals $t = 10$ and $t = 11$, the electric demand has been shifted to other time intervals by the increase of electric demand and reduction of produced wind power. Also, load consumption is increased by the increase of produced wind power at time intervals between $t = 12$ and $t = 14$. 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 III 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.

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. 7 and Table IV provide the effect of P2G technology on the wind power dispatch and total operation cost of the system in comparison with recent case studies, respectively. As can be seen, wind power dispatch is increased in this case study with respect to recent cases since P2G converts the extra wind P2G in off-peak hours, and the generated gas is used by natural gas consumers. The operation cost of this case is decreased because the 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 $138 794.506.

D. Case 4: Hybrid IGDT-Stochastic 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 $144 604.998. 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. 8, the robustness function α 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

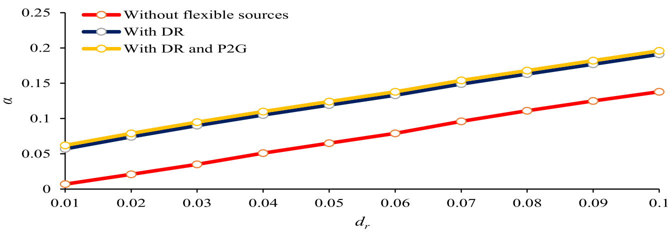

Fig. 8. Variation of robustness optimum function against robustness parameter d_r in case 4.

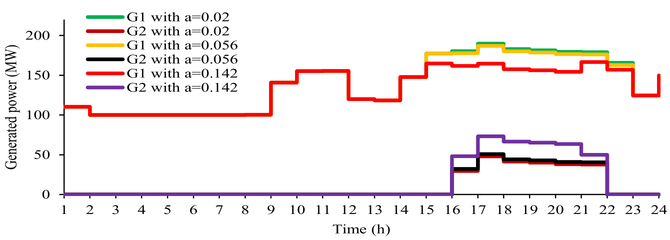

Fig. 9. Power dispatch of units in risk-averse strategy.

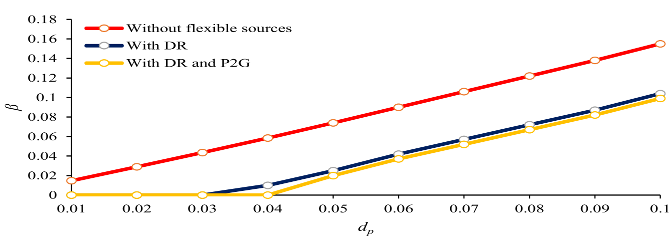

Fig. 10. Variation of opportuneness optimum function against opportunistic parameter d_ρ in case 4.

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 d_r 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 the network by 5%. Moreover, as can be seen in Fig. 8, the robustness function has greater values in the presence of flexible units that means the system operator can tolerate wider ranges of uncertainty and consequently the uncertainty of gas demand has a lower influence on the operation cost of the system. The effect of robustness function on power generation of units is demonstrated in Fig. 9, which indicates that the power dispatch of gas-fired unit G1 is decreased by the increment of the density of gas pipelines and lack of gas served to this unit. The opportunity parameter d_ρ 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., \$144 604.998). It can be observed from Fig. 10 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)× \$144 604.998 without considering flexible units. The opportuneness function β has a direct relation with increasing the amount of opportunity parameter d_ρ. 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.

TABLE V
COMPARISON BETWEEN IGDT, DETERMINISTIC, AND STOCHASTIC APPROACHES

Approaches	Deterministic	Stochastic with 5 scenarios	Stochastic with 10 scenarios	IGDT
Day-ahead operation cost (\$)	143633.31	145919.47	148161.96	150814.97
Single variables	1890	9718	19503	1891
Computation time (Second)	1.5	26.5	69.7	1.8

TABLE VI
REAL-TIME DISPATCH COST OF THE INTEGRATED SYSTEM UNDER DIFFERENT APPROACHES

Approaches	Deterministic	Stochastic	IGDT
Real-time dispatch cost (\$)	152886.97	151284.97	150814.97

E. Case 5: Comparison of IGDT With Deterministic and Stochastic Programming Technique

This part investigates the advantages of the proposed IGDT approach over existing stochastic programming models for managing the uncertainty of residential gas load as presented in Table V. The maximum forecast error in all these scenarios is 7.5%, which is equal α at $d_r = 0.05$ in the risk-averse strategy. It is noticeable that the uncertainties of wind power and electric load are not considered in this part. In addition, emerging technologies consisting of DR program, P2G technology, and gas storage have not been included in this case. The total execution time, single variables, and operation cost for the different approaches are indicated in Table V. According to the investigations carried out by Table V, some shortcomings of the stochastic method are classified as follows.

1) The outputs depend on the scenarios representing the uncertain parameters.
2) To accurately represent the uncertain parameter, the decision-maker requires a large number of scenarios. The computation time increases with the number of scenarios. For instance, in the analyzed case, the number of operating variables of power generation units will increase from (3×4) in IGDT to (3×4 × NS) in the stochastic technique.
3) The stochastic programming cannot present a confidence level for decision makers about the operating cost.

After determining the ON/OFFstates of power generation units by solving the mentioned approaches in Table V, an after-the-fact analysis is applied to represent the benefits of IGDT-based robust approach compared to deterministic and stochastic approach. The cost of lost load is assumed 3000 \$/MWh. It is assumed that the gas demand in real time is equal to the determined residential gas demand value in the risk averse strategy ($d_r = 0.05$). Table VI shows the real-time dispatch cost of the integrated system after realistic gas demand occurs. It can be seen in this figure, when residential gas demand happens in reality, the ON/OFFstate scheduling of units in risk-averse based IGDT approach causes a lower dispatch cost to supply demands in comparison with other approaches. In fact, no load shedding occurs in this technique, while in the deterministic model, the most load shedding happens. In addition, in the scenario-based stochastic approach due to no cover all possible happens in reality, some load has been lost, which is less than the deterministic approach.

V. Conclusion

This article 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 DR program and 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

[1] S. Chu and A. J. N. Majumdar, “Opportunities and challenges for a sustainable energy future,” *Nature Int. J. Sci.*, vol. 488, pp. 294–303, 2012.

[2] E. Heydarian-Forushani, M. E. H. Golshan, and P. Siano, “Evaluating the operational flexibility of generation mixture with an innovative techno-economic measure,” *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 2205–2218, Mar. 2018.

[3] IEA, “World energy outlook.” Accessed: Jul. 31, 2011. [Online]. Available: http://www.worldenergyoutlook.org/weo2011/.

[4] M. Henderson, “Energy system flexibility: The importance of being nimble [from the editor],” *IEEE Power Energy Mag.*, vol. 15, no. 1, pp. 4–6, Jan./Feb. 2017.

[5] H. Khani, N. El-Taweel, and H. E. Farag, “Power congestion management in integrated electricity and gas distribution grids,” *IEEE Syst. J.*, vol. 13, no. 2, pp. 1883–1894, Jun. 2019.

[6] S. D. Manshadi and M. E. Khodayar, “Coordinated operation of electricity and natural gas systems: A convex relaxation approach,” *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3342–3354, May 2019.

[7] C. Liu, M. Shahidehpour, and J. Wang, “Application of augmented lagrangian relaxation to coordinated scheduling of interdependent hydrothermal power and natural gas systems,” *IET Gener., Transmiss. Distrib.*, vol. 4, no. 12, pp. 1314–25, 2010.

[8] C. Liu, M. Shahidehpour, Y. Fu, and Z. Li, “Security-constrained unit commitment with natural gas transmission constraints,” *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1523–1536, Aug. 2009.

[9] Y. Wen, X. Qu, W. Li, X. Liu, and X. Ye, “Synergistic operation of electricity and natural gas networks via ADMM,” *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4555–4565, Sep. 2018.

[10] B. C. Erdener, K. A. Pambour, R. B. Lavin, and B. Dengiz, “An integrated simulation model for analysing electricity and gas systems,” *Int. J. Electr. Power Energy Syst.*, vol. 61, pp. 410–20, 2014.

[11] L. Bai, F. Li, H. Cui, T. Jiang, H. Sun, and J. Zhu, “Interval optimization based operating strategy for gas-electricity integrated energy systems considering demand response and wind uncertainty,” *Appl. Energy*, vol. 167, pp. 270–79, 2016.

[12] G. Li, R. Zhang, T. Jiang, H. Chen, L. Bai, and X. Li, “Security-constrained bi-level economic dispatch model for integrated natural gas and electricity systems considering wind power and power-to-gas process,” *Appl. Energy*, vol. 194, pp. 696–704, 2017.

[13] X. Zhang, L. Che, and M. Shahidehpour, “Impact of natural gas system on short-term scheduling with volatile renewable energy,” in *Proc. IEEE Power Energy Soc. General Meeting*, 2015, pp. 1–5.

[14] C. He, T. Liu, L. Wu, and M. Shahidehpour, “Robust coordination of interdependent electricity and natural gas systems in day-ahead scheduling for facilitating volatile renewable generations via power-to-gas technology,” *J. Modern Power Syst. Clean Energy*, vol. 5, no. 3, pp. 375–388, 2015.

[15] A. Zlotnik, L. Roald, S. Backhaus, M. Chertkov, and G. Andersson, “Coordinated scheduling for interdependent electric power and natural gas infrastructures,” *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 600–610, Jan. 2017.

[16] M. Imani, S. F. Ghoreishi, D. L. Allaire, and U. M. Braga-Neto, “MFBO-SSM: Multi-fidelity Bayesian optimization for fast inference in state-space models,” in *Proc. AAAI Conf. Artif. Intell.*, 2019, vol. 33, pp. 7858–7865.

[17] S. Xie, M. Imani, E. R. Dougherty, and U. M. Braga-Neto, “Nonstationary linear discriminant analysis,” in *Proc. 51st Asilomar Conf. Signals, Syst. Comput.*, 2017, pp. 161–165.

[18] F. S. Gazijahani and J. Salehi, “Game theory based profit maximization model for microgrid aggregators with presence of EDRP using information gap decision theory,” *IEEE Syst. J.*, vol. 13, no. 2, pp. 1767–1775, Jun. 2019.

[19] M. Ahmadigorji, N. Amjady, and S. Dehghan, “A robust model for multiyear distribution network reinforcement planning based on information-gap decision theory,” *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 1339–51, Mar. 2018.

[20] K. Chen, W. Wu, B. Zhang, and H. Sun, “Robust restoration decision-making model for distribution networks based on information gap decision theory,” *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 587–597, Mar. 2015.

[21] J. Aghaei *et al.*, “Optimal robust unit commitment of CHP plants in electricity markets using information gap decision theory,” *IEEE Trans. Smart Grid*, vol. 8, no. 5, pp. 2296–2304, Sep. 2017.

[22] A. Alabdulwahab, A. Abusorrah, X. Zhang, and M. Shahidehpour, “Stochastic security-constrained scheduling of coordinated electricity and natural gas infrastructures,” *IEEE Syst. J.*, vol. 11, no. 3, pp. 1674–1683, Sep. 2017.

[23] B. Zhao, A. Zlotnik, A. J. Conejo, R. Sioshansi, and A. M. Rudkevich, “Shadow price-based co-ordination of natural gas and electric power systems,” *IEEE Trans. Power Syst.*, vol. 34, no. 3, pp. 1942–1954, May 2019.

[24] F. Liu, Z. Bie, and X. Wang, “Day-ahead dispatch of integrated electricity and natural gas system considering reserve scheduling and renewable uncertainties,” *IEEE Trans. Sustain. Energy*, vol. 10, no. 2, pp. 646–658, Apr. 2019.

[25] M. A. Mirzaei, A. S. Yazdankhah, B. Mohammadi-Ivatloo, M. Marzband, M. Shafie-khah, and J. P. Catalão, “Stochastic network-constrained co-optimization of energy and reserve products in renewable energy integrated power and gas networks with energy storage system,” *J. Cleaner Prod.*, vol. 223, pp. 747–758, 2019.

[26] X. Zhang, L. Che, M. Shahidehpour, A. Alabdulwahab, and A. Abusorrah, “Electricity-natural gas operation planning with hourly demand response for deployment of flexible ramp,” *IEEE Trans. Sustain. Energy*, vol. 7, no. 3, pp. 996–1004, Jul. 2016.

[27] C. He, L. Wu, T. Liu, and M. Shahidehpour, “Robust co-optimization scheduling of electricity and natural gas systems via ADMM,” *IEEE Trans. Sustain. Energy*, vol. 8, no. 2, pp. 658–670, Apr. 2017.

[28] Y. He, M. Shahidehpour, Z. Li, C. Guo, and B. Zhu, "Robust constrained operation of integrated electricity-natural gas system considering distributed natural gas storage," *IEEE Trans. Sustain. Energy*, vol. 9, no. 3, pp. 1061–1071, Jul. 2018.

[29] C. Ordoudis, P. Pinson, and J. M. Morales, "An integrated market for electricity and natural gas systems with stochastic power producers," *Eur. J. Oper. Res.*, vol. 272, no. 2, pp. 642–54, 2019.

[30] Y. Zhang, J. Wang, B. Zeng, and Z. Hu, "Chance-constrained two-stage unit commitment under uncertain load and wind power output using bilinear benders decomposition," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3637–3647, Sep. 2017.

[31] M. A. Mirzaei, A. S. Yazdankhah, and B. Mohammadi-Ivatloo, "Stochastic security-constrained operation of wind and hydrogen energy storage systems integrated with price-based demand response," *Int. J. Hydrogen Energy*, vol. 44, no. 27, pp. 14 217–14 227, 2019.

[32] M. Nazari-Heris, B. Mohammadi-Ivatloo, G. B. Gharehpetian, and M. Shahidehpour, "Robust short-term scheduling of integrated heat and power microgrids," *IEEE Syst. J.*, vol. 13, no. 3, pp. 3295–3303, Sep. 2019.

[33] M. Nazari-Heris, B. Mohammadi-Ivatloo, and S. Asadi, "Robust stochastic optimal short-term generation scheduling of hydrothermal systems in deregulated environment," *J. Energy Syst.*, vol. 2, no. 4, pp. 168–179, 2018.

[34] M. Kazemi, B. Mohammadi-Ivatloo, and M. Ehsan, "Risk-constrained strategic bidding of gencos considering demand response," *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 376–384, Jan. 2015.

[35] R. Hemmati, H. Saboori, and S. Saboori, "Stochastic risk-averse coordinated scheduling of grid integrated energy storage units in transmission constrained wind-thermal systems within a conditional value-at-risk framework," *Energy*, vol. 113, pp. 762–775, 2016.

[36] M. A. Ortega-Vazquez and D. S. Kirschen, "Estimating the spinning reserve requirements in systems with significant wind power generation penetration," *IEEE Trans. Power Syst.*, vol. 24, no. 1, pp. 114–124, Feb. 2009.

[37] Z. Soltani, M. Ghaljehei, G. Gharehpetian, and H. Aalami, "Integration of smart grid technologies in stochastic multi-objective unit commitment: An economic emission analysis," *Int. J. Electr. Power Energy Syst.*, vol. 100, pp. 565–590, 2018.

[38] A. Y. Saber and G. K. Venayagamoorthy, "Resource scheduling under uncertainty in a smart grid with renewables and plug-in vehicles," *IEEE Syst. J.*, vol. 6, no. 1, pp. 103–109, Mar. 2012.

[39] M. Doostizadeh, F. Aminifar, H. Ghasemi, and H. Lesani, "Energy and reserve scheduling under wind power uncertainty: An adjustable interval approach," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2943–2952, Nov. 2016.