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Stochastic Optimal Operation and Risk Assessment for Integrated Power and Gas Systems

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Abstract- *The increment integration of renewable distributed energies means the desired operation of the electric power system will significantly depend on the performance of primary energy. In this order, an integrated approach for mutual interaction between the electricity and natural gas systems has been considered for the purpose of ensuring optimal energy exchanging between the electric power system and the natural gas network. We propose a scenario based optimal operation approach to optimize the operation of integrated power and gas systems (IPGS). Regarding the unpredictable nature of wind speed and solar radiation as well as uncertain load demand, random scenarios are generated by a normal probability density function. Then, Latin hypercube sampling is applied to realize the stochastic framework of IPGS operation. The proposed model minimizes the operation cost of conventional power system generators and gas wells over a 24 h operation horizon. In addition, the conditional value-at-risk is utilized to manage financial risks and uncertainties due to the operation cost-minimizing in the proposed IPGS optimal operation problem. The proposed integrated operating approach is applied to a 24-Bus power system with renewable resources of a photovoltaic, wind turbine, energy storage, with a 7-node natural gas network and two gas wells.*

Keyword: Power system, gas network, uncertainty, stochastic scheduling, MINLP.

NOMENCLATURE

Constants & Parameters

α	Confident level
Δx	Length of pipe
η	Efficiency [%]
Γ	Coefficient of pressure-gas
γ	Coefficient of temperature-power
Ω_{TG}	Set of TGs
Ω_{W}	Set of Wells
ϕ	Occurrence Probability of each ε
a,b	Coefficient of WTs configuration
C_p	Power price [$/MWh]
C_w	Gas price [$/kcf]
C_{np}/C_{ng}	Not-supplied power/gas cost [$/MW]/[$/kcf]
D	Diameter of pipe [m]
E	Total number of stochastic scenarios
HHV	High heat value [MJ/m^3]
I	Total number of power system buses
K	Total number of gas network nodes
N^s/N^p	Number of series/parallel PV panels
NOCT	Normal operation cell temperature[^{o}C]
$P_{r,WT}$	Rated power of WTs [p.u.]
R	Specific constant of gas [bar m3/kg ^{o}C]
RD	Maximum ramp-down value [p.u.]
RU	Maximum ramp-up value [p.u.]
T_{Amb}	Ambient temperature
υ_{ci}	Cut-in wind speed [m/s]
υ_{co}	Cut-out wind speed [m/s]
υ_r	Rated wind speed [m/s]
x	Reactant of line [Ω]
Z	Factor of compressibility
K	Coefficient of power-gas
Φ	Coefficient of gas-power

Indices

$\in$	Superscript of scenario numbers
cell	Subscript of PV panels
i, j	Subscript of buses in power system
k, l	Subscript of nodes in gas network
max	Superscript of maximum value
min	Superscript of minimum value
STC	Superscript of standard test condition

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Variables

δ	Voltage angle of each bus [rad]
ξ_{α}	Auxiliary variables for calculating CVaR
ξCVaR	CVaR with confident level α
G_d	Gas demand [kcf/hr]
G_W	Derived gas from wells [kcf/hr]
G_{GT}	Consumed gas of GTs [p.u.]
G_{PtG}	Generated gas from PtG [p.u.]
ng	Not supplied gas [kcf/hr]
np	Not supplied power [p.u.]
p	Gas pressure [bar]
P_d	Power demand [p.u.]
P_{ch} / P_{dch}	Charging/discharging power [p.u.]
P_{DER}	Generated power from DERs [p.u.]
P_{GT}	Generated power from GTs [p.u.]
P_{ij}	Transmitted power between buses [p.u.]
P_{PtG}	Consumed power of PtG [p.u.]
P_{PV}	Generated power from PVs [p.u.]
P_{TG}	Generated power from TGs [p.u.]
P_{WT}	Generated power from WTs [p.u.]
q	Gas flow [kcf/h]
SOC	State of charge [%]
SR	Solar radiation [W/m2]
T	Temperature $[^{\circ}C]$
υ	Wind speed [m/s]

1. INTRODUCTION

With the significant utilization of renewable energy sources (RESs) into the electricity grid, a new challenge of load oversupply and undersupply becomes apparent due to uncertain renewable resource availability. To solve this issue integration between the electrical powers system and other energy infrastructures has created abundant interest. Among all types of primary energy infrastructures, the electric power system relies significantly on the natural gas network in which additional gas-fired power plants are installed in power systems driven by technical, economic,and environmental reasons [1]. In this regard, by utilizing power to gas (P2G) technologies the coordination between the power system and the gas network becomes a bidirectional interdependency. With reviewing previous researches in the context of integrated power and gas system (IPGS), two main topics are discussed: optimal planning and optimal operation.

Traditionally, the power generation expansion planning of the electric power system is defined as the problem of determining *which*, *where*, and *when* new generator/transmission construction should be installed within a long term planning horizon [2]. The main objective function of this sort of optimization problem is to minimize the total investment costs in order to supply both electrical and gas demand under technical constraints. Infrastructure constraints can be alternated with the expansion of pipeline capacity, liquefied natural gas imports, storage for peakshaving, dual-fueled generation, and more inter-regional electric power transmission [3]. In Ref. [4], a novel expansion co-planning model of IPGS is addressed considering market uncertainties. In Ref. [5], a decomposition method based on the alternating direction method of multipliers is proposed to solve the electricity and gas expansion planning problem. Overall, reconfiguration or expansion of the electrical networks is an operational goal [6]. The optimal operation is another challenge in the area of IPGS application. To achieve an optimal value of variables in IPGS it is essential to have proper objective function subject to miscellaneous constraints [7]. In Ref. [8], the dispatch problem of an IPGS is solved considering bidirectional coordination between the two energy infrastructures. In Ref. [9], the optimal operation of an IPGS is proposed incorporating deterministic, two-stage stochastic programming, and multi-stage stochastic programming approach with uncertain wind speed. In Ref. [10], a multi-period IPGS probabilistic optimal power flow model with bidirectional power exchange was addressed. In addition, the effectiveness of the P2G units for accommodating wind power volatility was analyzed. In Ref. [11], the stochastic optimal operation was investigated for an IPGS including carbon-capture-based P2G technologies. A scenariobased stochastic optimization is utilized in Ref. [12] to capture the wind generation outputs uncertainty for analyzing the operation of IPGS. In Ref. [13], uncertain wind generation outputs and demand are addressed, and the optimal operation of the IPGS is modeled and solved based on robust optimization. Accordingly, the economic operation of a multi-energy infrastructure is the main challenge that was optimized for a multi-carrier micro grid considering demand response in Ref. [14]. Overall, the optimal operation complexity of integrated energy systems because of utilizing numerous power sources have been analyzed by authors [15]. A series of multi-step approach incorporating surrogate Lagrange relaxation to achieve a co-optimal operation of IPGS was proposed in Ref. [16]

Overall, the main research gaps in earlier literature can be addressed as follows. 1) Most of the IPGS only consider the unidirectional energy transfer between the power system and gas network. 2) The risk of stochastic decision-making under load and RESs uncertainties are neglected. 3) The utilization of technologies such as gas turbine (GT) and power to gas (P2G) is not well optimized.

Given the aforementioned background, in order to address the challenge of analyzing the steady-state coordination between power system and gas network with considering that the generated power from RESs and load demand are uncertain, this paper proposes a stochastic optimal operation approach for IPGS. In addition, to reach the desired solution under the stochastic framework financial risk analysis is considered as a contribution in comparison with our former research [1].

The proposed approach is described in detail in the rest of the paper as follows: the formulation of integrated power and gas system is modeled in Section 2. The approach to solving the stochastic operation problem of IPGS is presented in Section 3. The case study is analyzed to show numerical results in Section 4. The conclusion is the last section of this paper.

2. MODELING AND FORMULATION OF INTEGRATED POWER AND GAS SYSTEM

The main propose of this paper is the optimal operation of the integrated power and gas system (IPGS) under a stochastic framework. In this regard, the IPGS formulation is divided into three sections: power system, gas network, and joint units. These equations are considered for each scenario.

2.1. Power system

The model of power system are shown in Eqns. (1)-(16). According to Eq. (1), DC power flow is utilized for power dispatching. It is assumed, in the power system the reactive power is supplied properly.

$$P_{ij}(t) = \left(\delta_i(t) - \delta_j(t)\right) / x_{ij} \tag{1}$$

The transmitted powers between buses are limited as (2).

$$0 \le P_{ij}(t) \le P_{ij}^{\max} \tag{2}$$

In addition, Eq. (3) demonstrates the limitation of generated power from conventional power generators [17].

$$0 \le P_{TG,i}(t) \le P_{TG}^{\max} \tag{3}$$

The ramp-up and ramp-down constraints of each conventional power generators are shown as Eq. (4) and Eq. (5).

$$P_{TG,i}(t) - P_{TG,i}(t-1) \le RU_g \tag{4}$$

$$P_{TG,i}(t) - P_{TG,i}(t-1) \le RD_g \tag{5}$$

Meanwhile, the wind turbines (WTs) and photovoltaic panels (PVs) are utilized as distributed energy resources

$$P_{DER,i}(t) = P_{WT,i}(t) + P_{PV,i}(t) \tag{6}$$

In this regard, Eq. (7) shows the relation between wind speed and generated power from WTs that is constrained by Eq. (8).

$$P_{WT,i}(t) = \begin{cases} 0 & V_i(t) < \upsilon_{ci} \ \& \ \upsilon_{\infty} \le \upsilon(t) \\ a\upsilon_i(t)^3 - bP_{r.WT} & V_{ci} \le \upsilon(t) < \upsilon_r \\ P_{r,WT} & \upsilon_r \le \upsilon(t) < \upsilon_{\infty} \end{cases} \tag{7}$$

$$0 \le P_{WT}(t) \le P_{WT}^{Max} \tag{8}$$

Similarly, Eq. (9) show the relation between solar radiation and generated power from PVs.

$$P_{PV,i}(t) = \left[P_{PV}^{STG} + \frac{SR(t)}{SR^{STG}} \times \left(1 - \gamma \times \left(T_{cell}(t) - T_{cell}^{STG}\right)\right)\right] \times N_{p\upsilon}^{s} \times N_{p\upsilon}^{P}$$

$$T_{cell}(t) = T_{Amb}(t) + \frac{SR(t)}{SR^{STG}} \times (NOCT - 20) \tag{9}$$

This power has a limitation according to Eq. (10).

$$0 \le P_{PV,i}(t) \le P_{PV}^{\max} \tag{10}$$

In the IPGS to store excess generated power from DERs and low-price power from power system ES units are utilized. Furthermore, the stored power in energy storages (ESs) supplies demands in high-price and high-load time. Accordingly, the state of charge is related to exchange power in ES according to Eq. (11).

$$\mathrm{SOC_i(t) = SOC_i(t-1) + \left(P_{ch,i}(t)\eta_{ch} - P_{dch,i}(t)\eta_{dch}\right)\Delta t} \tag{11}$$

As well, Eqns. (12)-(15) are charging power, discharging power and state of charge constraints, respectively.

$$0 \le P_{ch,i}(t) \le P_{ch}^{\max} \tag{12}$$

$$0 \le P_{dch,i}(t) \le P_{dch}^{\max} \tag{13}$$

$$0 \le P_{dch,i}(t) \le P_{dch}^{\max} \tag{14}$$

$$0 \le SOC_i(t) \le SOC^{\max} \tag{15}$$

In addition, Eq. (16) demonstrates the state of charge in the begging and end of operation time are equal.

$$SOC^{\min}(\circ) = SOC(T) \tag{16}$$

2.2. Gas network

Another infrastructure of IPGS is the gas network. Same as the power system, in the gas network there is a need for a gas flow approach. In this regard, the Weymouth's formula is used in steady-state condition as Eq. (17) and Eq. (18).

$$\tilde{q}_{kl}(t) \,|\, \tilde{q}_{kl}(t)| = \Gamma\left(p_k^2(t) - p_l^2(t)\right) \tag{17}$$

$$\Gamma = \left(\frac{\pi}{4}\right)^2 \frac{D_{kl}^2}{\Delta x_{kl} F_{kl} RTZ} \tag{18}$$

In fact, the mean value of flowing gas between gas network nodes ($\tilde{q}_{ij}$) depends on nodal pressure differences. In Eq. (17), the flowing gas in a pipeline can be positive if there is a compressor to increase pressure. Otherwise, it is negative. Meanwhile, gas in each pipeline flows in a predefined single direction. According to Eq. (19), $\tilde{q}_{ij}$ is averaged value of input/output gas to/from each pipeline.

$$\tilde{q}_{kl}(t) = \frac{q_{kl}^{out}(t) + q_{kl}^{in}(t)}{2} \tag{19}$$

As well, pressure of each node and derived gas amount from gas wells are limited as Eqns. (20) and (21), respectively.

$$p_k^{\min} \le p_k(t) \le p_k^{\max} \tag{20}$$

$$G_\omega^{\min} \le G_\omega(t) \le G_\omega^{\max} \tag{21}$$

2.3. Joint units

In this paper, for the gas to power conversation, GT and P2G unit is utilized as a common point between the power system and the gas network [18]. GT consumes the natural gas as a fuel to produce power according to Eqns. (22) and (23).

$$P_{GT,i}(t) = \Phi G_{GT}(t) \tag{22}$$

$$P_{GT}^{\min} \le P_{GT,i}(t) \le P_{GT}^{\max} \tag{23}$$

While the PtG unit consumes power to generate gas in two-stage: electrolysis and methanization. In the electrolysis stage, PtG uses electrical power to decompose water into hydrogen and oxygen. In the methanization stage, the generated hydrogen is combined with carbon to produce gas. These process are modeled by Eqns. (24) and (25).

$$G_{Pt,G,K} = kP_{Pt,G,i}(t) \tag{24}$$

$$k = \frac{\eta_{ptG}}{HHV} \tag{25}$$

Finally, Eqns. (26) and (27) are power and gas balance model in IPGS, respectively.

$$\begin{bmatrix} P_{i,j}(t) + P_{TG,i}(t) + P_{PV,i}(t) + P_{WT,i}(t) + \\ np_i(t) + P_{dch,i}(t) + P_{GT,i}(t) \end{bmatrix} = \left[P_{d,i}(t) + P_{PtG,i}(t) + P_{ch,i}(t) \right] \tag{26}$$

$$\left(q_{kl}^{out}(t) - q_{kl}^{in}(t)\right) + G_{w,k}(t) + ngk(t) + G_{PtG,k}(t) = G_{GT,k}(t) + G_{d,k}(t) \tag{27}$$

According to Eq. (26), the transmitted power between buses, generated power from power generators, generated power from DERs, not-supplied power, ES discharge power, and generated power from GT is equal to demanded power includes load power, consumed power of PtG, and ES charging power. Meanwhile, In Eq. (27), transmitted gas between nodes, derived gas from wells, not-supplied gas, and generated gas from PtG is equal to demanded gas by gas load and GT.

2.4. Risk analysis

In our stochastic programming, where uncertainty variables are modeled under the stochastic framework, the final optimal operation cost is an uncertain variable specified by a probability value. Hence, the IPGS optimal operation problem involving an uncertain objective function. It is essential to regard a function specifying the distribution of this uncertain variable. This function includes risk analysis criterion general utilizing in stochastic programming problems [19].

One of the most widely used risk measures is value-at-risk (VaR) demonstrated as the (1-α) [20]. In fact, to reach a confidence level of α. (28) should be satisfied with operation cost (OC) in each stochastic scenario.

$$\xi_\alpha(OC) = \max\left\{\alpha \,\middle|\, f(OC \le \alpha) \le 1-\alpha\right\} \tag{28}$$

In this paper, the conditional value-at-risk (CVaR) is utilized to manage financial risks and uncertainties due to the OC minimizing in the proposed IPGS optimal operation problem. The main disadvantages of VaR are nonconvexity and discontinuity. These cause non-linearity, discontinuity, and decreasing in solution convexity of entire the problem. In addition, the ability of VaR to simultaneously control the uncertainty variables and risk management is less than CVaR. Therefore, the risk analysis of the proposed optimal operation problem under VAR yields a significant difference between the costs of the best and the worst scenarios more than utilizing CVaR. So, compared with VAR, CVaR is coherent defined as presented in Eq. (29) for expected operation cost of $(1-\alpha)\times 100\%$ [21].

$$\xi_{CVaR}(OC) = E\left[OC \,\middle|\, OC \le \xi_\alpha\right] \tag{29}$$

2.5. Objective function

The propose of solving IPGS operation problem is minimizing the operation and risk costs for a 24h time period.Thus, the objective function is stated as Eq. (30).

$$Minimize\left(OC + \beta\xi_{CVaR}\right) \tag{30}$$

Accordingly, the objective function composes of the two financial criteria. The first one is OC obtained from Eqns. (31)-(35) consisting power cost (PC), gas cost

(GC), not-supplied power cost (NPC) and not-supplied gas cost (NGC).

$$OC = \sum_{\varepsilon=1}^{E}\varphi_\varepsilon \sum_{t=1}^{T} [PC(t)+GC(t)+NPC(t)+NGC(t)] \quad (31)$$

$$PC(t) = \sum_{\forall\Omega_{TG}} P_{TG}(t)C_P(t) \quad (32)$$

$$GC(t) = \sum_{\forall\Omega w} G_w(t)C_\omega(t) \quad (33)$$

$$NPC(t) = \sum_{i=1}^{I} np_i(t)C_{np}(t) \quad (34)$$

$$NGC(t) = \sum_{k=1}^{k} ng_k(t)C_{ng}(t) \quad (35)$$

The second one is the risk associated with uncertain OC which is explicitly captured by the model through incorporating the CVaR metric modeled in Eq. (36).

$$\xi_{CVaR} = \xi_\alpha + \frac{1}{1-\alpha}\sum_{\varepsilon=1}^{E} OC_\varepsilon \varphi_\varepsilon \quad (36)$$

3. METHODOLOGY

We propose a stochastic programming approach with incorporating risk analysis to minimize OC of IPGS. The proposed method is affected by uncertainty variables i.e. wind speed, solar radiation, and electrical load. In this regard, the scenario-based strategy is utilized to develop a related formulation.

The source of variation in generated power from WT and PV are uncertain wind speed and solar radiation, respectively. As well, the variety in power demand of consumers causes uncertain load. In this paper, to model these uncertainty variables random scenarios are generated by normal probability density function (PDF) [22]. Then, Latin hypercube sampling (LHS) is applied to realize the stochastic framework of IPGS operation.

The LHS method is a satisfied-random procedure for sampling variables from a specific distribution. Accordingly, there is a vector for each uncertainty variable χ_n from the prescribed PDF. To select M sample, the LHS approach divides this vector into an M subset. Each subset is characterized by equal probability P_{nm} in which $n = 1,2,...,N$ and $m = 1,2,...,M$. The sampling process from each vector extremely depends on the subset. LHS method is done by transform the cumulative distribution function (CDF) of n^{th} uncertainty variable into the value with the inverse of the identical and independent normal PDF. The normal PDF of each χ is defined on the range of $[D_m, U_m]$ with $D_m = (m-1)/M$ and $U_m = m/M$. This procedure repeats M time for each χ.

With assuming N uncertainty variable and M sample there is M^N scenario to qualify the stochastic operation of IPGS. Since the number of realization scenarios is high so the complexity, running time, and calculation burden of the problem increase, as well. To figure out this issue, the SCENRED applied by GAMS to reduce of scenario numbers [23]. SCENRED is a useful solver of GAMS which can reduce the number of scenarios for stochastic analyzing. The reduced scenarios specified by the new probabilities. To reach the small number of scenarios the SCENRED solver utilizes a fast backward/forward (FBF) technique which includes two algorithms i.e. backward reduction and forward selection [24]. The FBF method for scenario reduction is an iterative method in which, at each iteration, two computational stages are employed. In the first stage, FBF method sweeps all scenarios in the backward direction to eliminate similar or low probability scenarios. The scenario reduction in the first stage is proceeded by the predefined distance between scenarios and the acceptable probability value of each scenario. In the second stage, the accurate and desired number of realized scenarios is generated by sweep scenarios under the forward direction. Our approach to solve stochastic optimal operation of IPGS is illustrated as a flowchart in Fig.1.

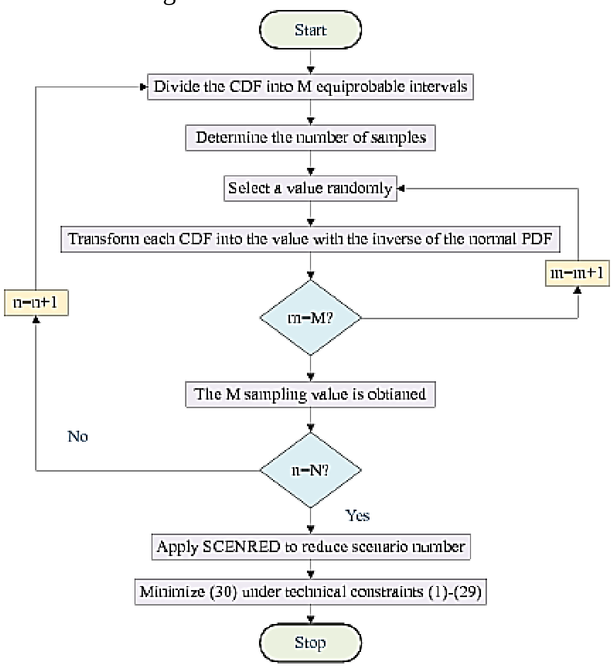

Fig. 1. Flowchart of proposed methodology

4. NUMERICAL RESULTS

In this section numerical results are provided in order to explain the integrated system of natural gas and electricity network performance based on the theoretical model in Eqns. (1)-(36). For this purpose, an IEEE 24-Bus electricity power system is selected by including

RESs such as WT and PV. Also, ES is used in order to store additional energy. The selected network for natural gas includes 7 nodes and 2 gas wells that are integrated by the power system through the P_2Gs and GTs as joint units (JUs). GTs of JUs has a maximum power of 220 MW, 100 MW, 20 MW for nodes 1, 2, 3, respectively. Fig.2 represents studied IPGS. As it can be seen, the natural gas network is connected to buses 3, 7, 19 of the power system by nodes 1, 2, 3 of the natural gas network. The mentioned buses utilize PtG units for supplying GTs as well as for storing electrical power in pipelines to reduce operation costs of IPGS. The values of ϕ and κ are 94.73 m^3=MWh and 0.01 MWh=m^3, respectively [25]. It must be mentioned that the studied period of determining integrated system performance is one day that is divided into 24 h.

The data of proposed IPGS are derived from ref. [1]. Uncertainty variables of system include $\upsilon(t), SR(t)$, and $P_d(t)$. To characterize uncertainty variables, scenarios are generated under normal PDF. The WTs are located in buses 8, 19, 21 that have $P_{r,WT}$ of 200 MW, 150 MW, 100 MW, respectively. The sets of PV and ES are installed in buses 6 and 22 that have $P_{PV}^{max}(t), P_{ch}^{max}(t), P_{dch}^{max}(t)$ and $\eta$of 50 MW and 100 MW, 0.5 MW and 90%, respectively. Other related data are presented as Fig.3 in which are utilized as mean values in uncertainty modeling.

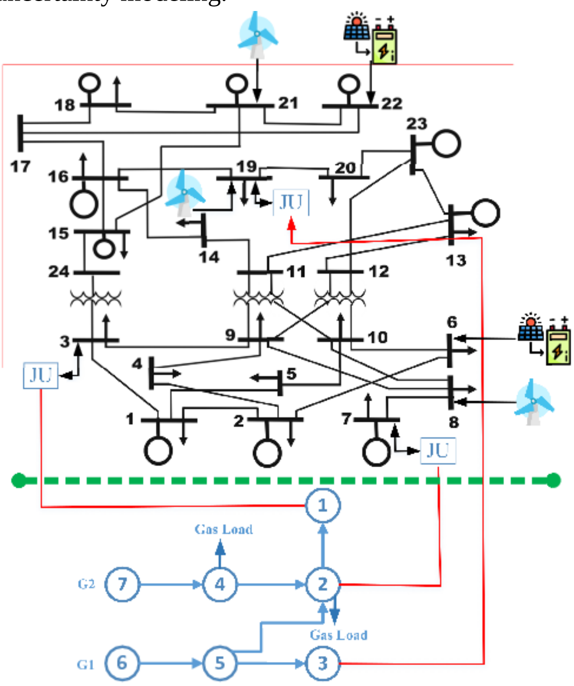

Fig. 2. Illustration of the under study IPGS

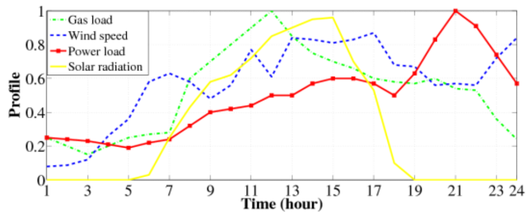

Fig. 3. The profile of gas load, electrical load, wind speed and solar radiation

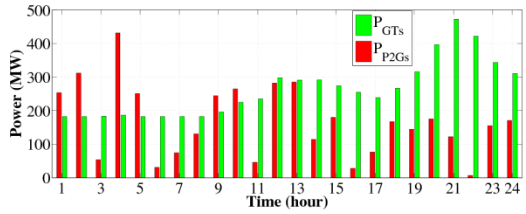

Fig. 4. Expected generated power from gas turbines and consumed power of power to gas units

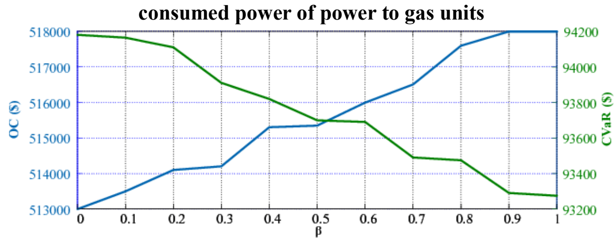

Fig. 5. Values of OC and CVaR for different values of risk factor

To analyze the optimal operation of JUs the generated power from GTs and consumed power of P2Gs are represented in Fig.4. The illustrated results are the average values of realized scenarios. Obviously, the power conversation process of GTs and P2Gs are almost inverse. Indeed, when the power system needs the backup of the gas network to supply electrical loads the generated power from GTs is high, however, P2Gs consume low power. In contrast, for time intervals with low PGTs the value of P2Gs increase significantly. As a result, the operation principle of JUs affected by various factors i.e. generated power from RESs as well as load profile. Thus, the data in Fig.3 has an important role in power exchange between the power system and the gas network. For example, at t=22 the electrical load is in peak, so, the operator receives power from the gas network through the GTs and interrupts consumed power by P2G units. Controversially, the time interval t=[1,5] is low load times, hence, consumed power by P2Gs efficiently increased. As well, for time interval t=[9,17] the generated power from RESs is high, so, the P2G (because of tight coordination between wind curtailing the power and cheap PV power) converts excess power to gas as well as power system utilize GTs to reduce the value of OC. Fig.5 shows the relation between the OC and CVaR in various values of risk factor. It is clear that the OC of the IPGS increase as well as the CVaR decreases as the risk factor increases.

Table 1. Operation cost of various components in ipgs with different standard deviation and $\beta=\circ$ $(\$\times10^5)$

	Determin	$\sigma=4\%$			$\sigma=8\%$			$\sigma=12\%$		
		Worst Scen	Opt	Best Scen	Worst Scen	Opt	Best Scen	Worst Scen	Opt	Best Scen
$P_{\varepsilon}(\%)$	100	0.113	-	0.119	0.127	-	0.118	0.134	-	0.111
P_{TG}	5.113	5.712	5.712	5.712	5.712	5.712	5.712	5.712	5.712	5.712
P_{GT}	0.819	0.946	0.930	0.925	0.962	0.946	0.939	1.725	1.589	1.478
P_{P2G}	0.067	0.085	0.089	0.093	0.81	0.085	0.09	0.078	0.08	0.081
TOC	5.999	6.743	6.731	6.73	7.484	6.74	6.741	7.515	7.381	7.271

Correspondingly, the risk-averse operator solutions want to achieve less CVaR as much as possible. Inversely, the risk-taker operator solves its operation problem to achieve the less OC. According to Fig.5, the value of the OC is 513022 $ for the risk-taker scheduling, while, this quantity for the risk-averse scheduling problem is equal to 517910 $. In addition, the optimal value of CVaR for β=0 and β=1 is 94171 $ and 93297 $, respectively. It is worth noting that β=0 demonstrates the risk-taker operator and β=1 represents the risk-averse operator to solve the optimal operation problem of IPGS.

Different parts of the IPGS illustrated in Fig. 2 are discussed in Table 2. To have a comprehensive analysis the operation cost of different components is calculated for different standard deviations of the uncertainty variables. Accordingly, the increase in TOC has a direct relationship with an increase in the standard deviation. For example, the value of optimal TOC under the deterministic framework for σ=4 %, 8 % and 12 % has 12.2 %, 12.3 % and 23 % growth, respectively. As shown in Table 2, for each σ the calculated OC for the best-scenario and optimal are lower than OC of worst-scenario. Besides, the operation costs of GTs for the worst-scenario are higher than in other scenarios. The main task of the power system's operator is to satisfy the load demand (P_d). Thus, the operation cost of the P2G units in the best-scenarios is more than other scenarios for each σ. Additionally, for each σ .the operation cost of P2G units in the worst-scenario is less than in other scenarios. Because in the best scenario more power is generated from RESs and P_d is less. Also, because of compensating the random behavior of load and RESs by different power sources, the operation costs of TGs are the same in different standard deviations.

Table 2. Comparison of ipgs's cost regarding different uncertainty variables modeling

	Case1		Case2	
β	0	1	0	1
OC(s)	513022	517910	497154	501340
CVaR (s)	94171	93297	95172	97960

To make a balance between power generators and load demand as well as to decrease the shaded load, the operation cost of GTs is increased, and the operation cost of P2G units is declined. Therefore, the power system flexibility and robustness are improved against uncertainty variables by joint units.

As a comparison, the effect of the uncertainty modeling method is discussed for different PDFs. Indeed, to handle random data Beta, Weibull, and normal PDFs are implemented for solar radiation, wind speed, and load, respectively [1]. These considerations are studied as Case2 and compared with the above analysis as Case1. Accordingly, Table 2 is obtained for OC and CVaR for minimum and maximum values of β under each case study. As shown in this table, in the point of risk analysis method view the optimum value of CVaR in Case1 for β=1 is about 5% lower than the CVaR in Case2. In contrast, with neglecting CVaR (β=0), the minimum value of OC in Case2 is lower than the OC in Case1. Hence, regarding different PDFs for each uncertainty variable, the calculated minimum value for OC is better than performing the same PDF. Inversely, the results of CVaR with higher values of β by applying the same PDF are appropriate than modeling uncertainty variables by different PDFs.

5. CONCLUSION

We present a risk-focused model of the IPGS optimal operation problem. The problem was solved using a scenario-based stochastic optimization technique that ensures the solution to the IPGS problem meets a pre-defined desired confident level of operation cost. The outputs of the IPGS optimal operation problem address the challenge of analyzing the steady-state coordination between the power system and gas network with considering that the generated power from RESs and load demand are uncertain. In addition, to reach the optimal operation under the stochastic framework financial risk analysis is cosidered to demonstrate the risk- taker and risk – averse operators' solutions.

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