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RESEARCH ARTICLE

Integrated Electricity and Natural Gas Demand Response in Flexibility-Based Generation Maintenance Scheduling

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ABSTRACT Increasing emission concerns about greenhouse gases have led to an increasing tendency to use renewable energy sources (RERs) in the power system. Nevertheless, the probabilistic nature of RERs has led to an enhanced require to flexibility provision. Hence, it is necessary to implement a flexibility-based generation maintenance scheduling. For this purpose, it has used the flexibility index of the system in order to evaluate the flexibility of the power system. In flexibility studies, modeling and predicting the variability of renewable resources is important. In this paper, the uncertainties of wind are considered through forecasting by deep learning method in Python. Gas-fired power plants are one of the most important suppliers of flexibility in the supply-side. Therefore, the reliable operation of power system depends on the of natural gas availability. Furthermore, gas demand is subject to various uncertainties, especially in cold seasons, which will have significant effects on power system. in this paper, power-to-gas (P2G) technology as energy storages is modeled to mitigate the impact of wind output and gas demand uncertainty. Meanwhile, integrated natural gas and electricity demand response such as event-based and time-based model has been applied as a flexibility provision from demand-side point of view. In this paper, the objectives of reducing emission and costs, leveling the reserve margin and increasing flexibility are considered as the objectives of optimizing generation maintenance scheduling. In order to solve the multi-objective problem, the augmented Epsilon constraint method has been used. The proposed model has been implemented on a modified IEEE RTS 24 bus.

INDEX TERMS Flexible generation maintenance scheduling, natural gas uncertainty, P2G, energy storage, integrated natural gas, electricity demand response.

NOMENCLATURE

A. INDICES AND SETS

I	Index of generation units.
H	Index of scheduling time [hour].
T	Index of week.
Ut	Unexpected event time occurrence.

B. PARAMETERS

$a_{i,j}$	Constant coefficient of generation cost [$/h].
$b_{i,j}$	Linear coefficient of generation cost [$/MWh].
$c_{i,j}$	Quadratic coefficient of generation cost [$/MWh^2].
C_G^{st}/C^{P2G}	Operation cost of gas storages/ P2G [$/MBTU].
$EE_{h,h}$	Price elasticity of electricity demand.
$g_i^{\max}$	Maximum capacity of generation unit i [MW].
$g_i^{\min}$	Minimum power output of generation unit i [MW].
$G_{t,h}^D$	The gas flow (MBTU/hr).
GA_{event}	Committed gas usage limit [MBTU].
$GE_{h,h}$	Price elasticity of gas demand.

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$GP_{t,h}^{TOU}$	Natural gas price after TOU [$/MWh].
GP_h^0	Natural gas price before TOU [$/MWh].
$L_{t,h}^n$	Net load [MW].
M_i	Maintenance duration for generation [week].
N_i	Number of generating units.
N^{MN}	Maximum number of maintenance.
P_R	Rated power of wind turbine [MW].
$P_w^{real/forecasted}$	Generation of wind turbine for real data/forecasted data [MW].
PA_{event}	Limitation of committed power [MW].
Pnr	DRP penetration rate.
$\Pr_{t,h}^{TOU}$	Electricity price after TOU [$/MWh].
$\Pr_h^0$	Initial electricity price [$/MWh].
R_{min}	Minimum required reserve.
$RDR_{E/G}$	The incentive amount for electricity/gas DR[$/MWh or MBTU].
v_f^{DL}	Wind speed forecast through deep learning [m/s].
v_{in}^c	Cut-in speed of wind turbine [m/s].
v_{out}^c	Cut-out speed of wind turbine [m/s].
v_R	Rated speed of wind turbine [m/s].
η^{in}/η^{out}	Charge/Discharge efficiency of gas storages.
η^{P2G}	P2G efficiency.

C. VARIABLES

$C_{(i,h,ut)}^a$	Available capacity of unit i at time h [m/s].
CCL	Customer participation rate in RTP.
dr_h	Reduction of electricity supply.
$E_{t,h}$	Fuel energy level in gas storages.
$g_i^{t,h}$	Power generation of unit i at hour-h [MWh].
m_i	Cost assigned to maintenance of generating unit i [$/MW].
ng_h	Reduction of gas supply.
$P_{t,h}^D$	Peak demand in week t, hour h [MW].
$R^{t,h}$	Reserve capacity in week t, hour h [MW].
t_C	Maximum generation capacity time.
$U_{t,h}^{in}/U_{t,h}^{out}$	Charge/Discharge rate of gas storages.
$U_{t,h}^{P2G}$	Gas generation of P2G technology [MMBTU].
ω_i^t	Maintenance initial status; 1 if the unit's check starts at the beginning of period t, otherwise 0.
X_i^t	Maintenance strategy of generation unit i in week t (1 if the unit be on maintenance, otherwise = 0).

I. INTRODUCTION

The penetration rate of renewable energy resources (RERs) is rising in modern power systems due to their specific features such as zero-emission as well as low operation cost. The output of RERs and secure operation of power systems are interdependent when the penetration rate of RERs is high [1]. On the other hand, variable atmospheric parameters affect the output of RERs. Hence, flexibility analysis has become an important research topic. In [2], energy storages as flexibility supplier have been used as to handle the uncertainty of RERs. In [3], integrated demand response programs are modeled to provide flexibility in local energy systems. Incentive design for flexibility provisions is presented by the local distribution company that has been transformed residential demand to residential energy hub (REH) in [4].

Fast start gas-fired unit as flexible resource is used to mitigate variability of RERs. Secure operation of gas-fired units is depended on natural gas availability. In power system, one of a primary energy resources are the natural gas that is dramatically increased recently. Hence, the uncertainty of natural gas network such as gas demand is notable for secure operation in power system. Lack of attention to the penetration of various uncertainties and flexibility analysis in the generation maintenance scheduling (GMS) problem will lead to an insecure environment for power system operators and developers. Hence, it is necessary that published research in GMS is investigated.

In recent years, extensive research has been published on GMS from different approaches such as emission reduction, reliability improvement and minimizing cost in power system. In [5], minimizing reliability index and operation cost is considered as the primary objectives in GMS by bi-level framework. A two-stage model based on non-cooperative game strategy has been presented in [6] for GMS in a restructured environment. A multi-objective coordinated procedure for GMS has been developed in [7] considering emission, reliability, and economic objectives. The lexicographic method has been employed to take into account the economic, emission, and reliability objectives in [8].

High speed, non-pollutant release and availability of energy storages (ESs) and demand response resources (DRRs) have led to their widespread utilize in modern power systems. one of the possible solutions to mitigate the impacts of RERs variability is utilize ESs and distributed energy resources (DERs) [9]. Different and emerging technologies of ESs have wide applications in the modern power system, which has caused significant effects. In recent studies, the effects of different types of ESs have been investigated. In [10], ES has been considered to mitigate the uncertainty and variability of RERs in flexible unit commitment. The water compressors and electrolyzes have been used for investigation hydrogen generation and storages from real PV/wind energy systems in [11]. In [12], DC-bus stability in a micro grid has been ensured with ESs. In [13], a hybrid energy storage system such as battery and super capacitor is provided for energy management in microgrid. In [14], a natural gas storage model is presented to reduce the impact of wind uncertainty in security-constrained unit commitment problem.

The authors in [15] have investigated the role of DRRs on reducing the variability of RERs and enhancing flexibility level of power system. In [16], an incentive-based DRRs has been applied with reconfiguration method for optimal energy management in a microgrid. In [17], an incentive-based DRRs has been implemented to reduce the emission and cost of operation. In [18], the impact of ESs and DRPs has been investigated on the effectiveness aspect of energy efficiency.

According to recent studies in the field of flexibility, the evaluation of flexibility in the field of short-term timescale is more important than long-term. The main contribution of this paper, a novel environmental techno-economic framework for uncertain based flexible GMS considering integrated DRRs ($\mathrm{UFGMS}^{\mathrm{IDRRs}}$) has been presented. On the other hand, the recent research demonstrates the emphasis of energy storage such as natural gas storages. In recent years, the power to gas (P2G) technologies as energy storages have been used to handle the uncertainties of natural gas network and variability of RERs. In this paper, the gas storage and P2G technologies is considered in the $\mathrm{UFGMS}^{\mathrm{IDRRs}}$ as flexible provision

The electricity demand response (EDR) is another approach of to mitigate the impact of power system uncertainties, which have been used extensively. On the other hand, the interdependencies between power systems, gas network, requires integrated decisions-making for two networks. The gas demand response (GDR) is the one of decision-making in the gas network that can have a significant impact on the power system. The lack of attention to integrating GDR and EDR leads to loss of opportunities in the power system. Another contribution of this paper, the integrated DRRs (IDRRs) such as time of use (TOU) and event programs have been applied to handle to variability of RERs and improved flexibility. It should be noted that the forecasting wind speed and gas demand have been conducted by deep learning and autoregressive integrated moving average (ARIMA), respectively.

The remaining parts of the paper are as follow. Section II assigns to formulation of the proposed $\mathrm{UFGMS}^{\mathrm{IDRRs}}$. The simulation results and numerical analysis are presented in Section III. Finally, Section IV concludes the paper.

II. MATHEMATICAL MODEL OF THE PROPOSED $\mathrm{UFGMS}^{\mathrm{IDRRs}}$

Figure 1 describes the framework of proposed $\mathrm{UFGMS}^{\mathrm{IDRRs}}$ associated with natural gas storage and the P2G technology. In Fig. 1 (a), the flexibility evaluation hierarchy is introduced. The flexibility of the system, the reaction time (RT) and maximum available capacity (MAC) are introduced for the evaluation of system flexibility considering unexpected events. The system flexibility index is obtained by aggregating MAC and RT. Then, two methods based upon time-series models are used to predict wind and natural gas uncertainty in Fig. 1(b). Here, the uncertainties of natural gas demand and the output of wind resources are considered by ARIMA and deep learning, respectively. In Fig. 1(c), the $\mathrm{UFGMS}^{\mathrm{IDRRs}}$ in combination with IDRRs, natural gas storage and the P2G technology is regarded as a multi-objective problem solving for cost, emission, reliability and flexibility. Several methods are deployed to handle multi-objective problems from the perspective of the system decision-maker [19]. In this paper, the augmented epsilon constraint is applied to solve multi-objective $\mathrm{UFGMS}^{\mathrm{IDRRs}}$ problem.

A. ELECTRICITY AND GAS DEMAND RESPONSE MODEL

The electricity DR (EDR) have potential to offer special features such as reliability improvement, reduction of operation cost, emission reduction, flexibility improvement. Disregarding to gas load is led to miss the chances of gas demand responses (GDR) utilization. In proposed model, both GDRs and EDRs have been implemented due to the maximum utilization of these resources. The TOU and event programs are considered in proposed $\mathrm{UFGMS}^{\mathrm{IDRRs}}$. In event-based electricity and gas DRRs, the customer receives incentive for reducing its consumption. Notice of gas and electricity curtailment event is supposed to be supervised in the moment. The total incentive payment for electricity DR curtailment is presented by equations (1) [20].

$$CE_{event} = \min\left\{0, dr_h\, RDR\,\left(P^{D}_{t,h+1} - PA_{event}\right)\right\} \tag{1}$$

The total incentive payment for gas DR curtailment is defined as given in Eq. (2) [19].

$$CG_{event} = \min\left\{0, ng_h\, GRDR\,\left(G^{D}_{t,h+1} - GA_{event}\right)\right\} \tag{2}$$

It should be noted, price-based DRRs depend profoundly on price signal. Participation in TOU involves no payment to the customers. However, customer is able to benefit from the reduction of utility bills. In this paper, TOU programs for gas and electricity customers are considered. In TOU programs the electricity price changes in three different time periods including valley, off-peak and peak in a daily horizon. Electricity and gas TOU programs are defined with Eq. (3) and Eq. (4), respectively [20], [21].

$$EDR_{TOU}\,(h) = L^{n}_{t,h}\left(EE_{t,t}\left(\frac{\mathrm{Pr}^{TOU}_{t,h} - \mathrm{Pr}^{0}_{h}}{\mathrm{Pr}^{0}_{h}}\right)\right) \tag{3}$$

$$GDR_{TOU}\,(h) = G^{D}_{t,h}\left(GE_{t,t}\left(\frac{GP^{TOU}_{t,h} - GP^{0}_{h}}{GP^{0}_{h}}\right)\right) \tag{4}$$

B. UNCERTAINTY MODEL

The time-series analysis is an applicable approach for forecasting a continuous variable that is time-dependent [22]. In this paper, wind speed and gas demand are predicted by deep learning (DL) and auto ARIMA, respectively. The details of each forecasting method are given in the following.

- **Forecasting natural gas demand by ARIMA**

The ARIMA method is a type of statistical model that could be used for analyzing and forecasting time series data. It gives a simple and powerful solution for providing skilled time series predictions by explicitly catering to a set of common structures in time series data [22]. It's a more complex version of the autoregressive moving average, with the addition of integration.

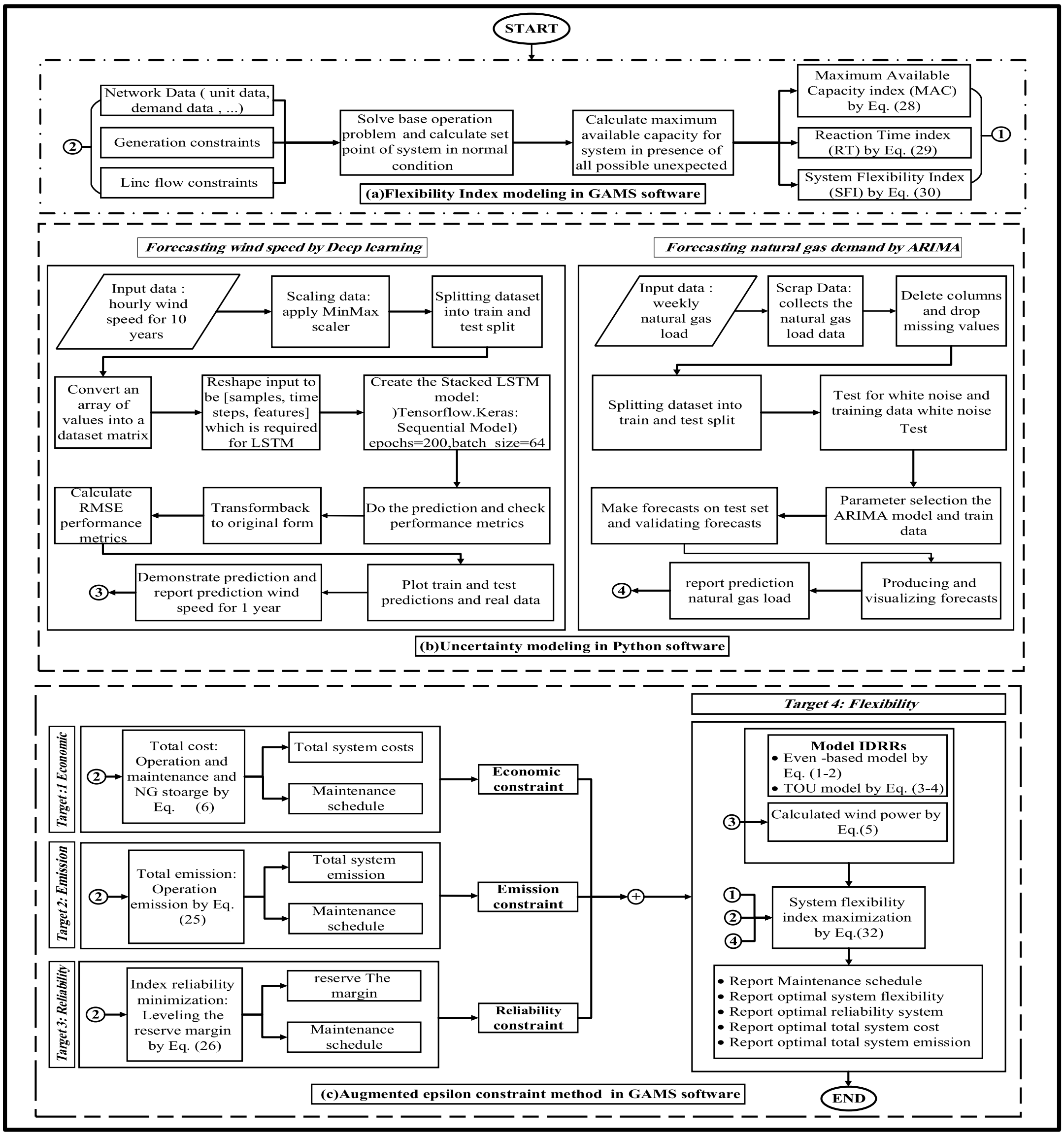

FIGURE 1. Structure of the proposed UFGMS$^{\text{IDRRs}}$.

The following are the parameters of the ARIMA model. The p is the lag order which indicates the number of lag observations incorporated in the model. The degree of differencing which refers to the number of times the raw observations are differed is depicted by d. The order of MA is illustrated by q which indicates the size of the MA window. In order to remove the trends and seasonal structures that may have negative impacts on regression model, the data is prepared by a degree of differencing to make it stationary. More details regarding this method could be found in [23]. The implementation of the ARIMA model in Python is illustrate in Fig. 1(b).

- **Forecasting wind speed by DL method**

DL is a kind of machine learning and artificial intelligence that is designed to emulate how the human mind learns a topic. One of the most essential aspects of data science, which also encompasses statistics and predictive modeling, is this form of learning. Deep learning, on the other hand, is extremely effective for analyzing and understanding massive volumes of data, since it speeds up and simplifies the process. The LSTM model is used in the DL method to forecast wind speed for a year. The LSTM is a modified RNN model that solves long-term challenges by overcoming the limits of ordinary RNN. The gradient difficulties could be removed through using an additional particular hidden layer known as a memory unit. This unit has the ability to add or remove new input. By managing the data flow, the three control gates define the unit's performance. The structure of an LSTM unit is depicted in Fig. 2. More details about this method have been expressed in [24]. The implementation of DL in Python can be seen in Fig. 1(b).

The generation of wind units depends on a variety of factors including wind speed, direction and location of the wind farm. The output of wind farm is calculated based on

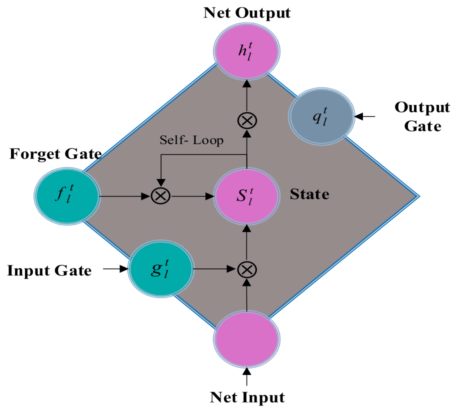

FIGURE 2. The LSTM unit structure.

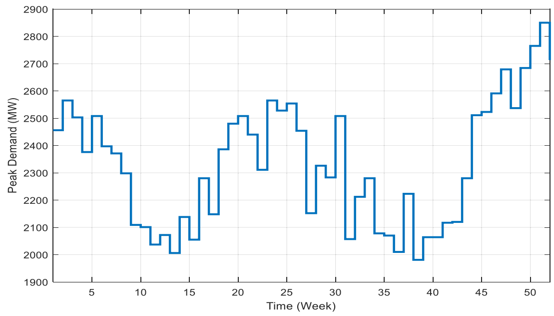

FIGURE 3. The weekly peak load.

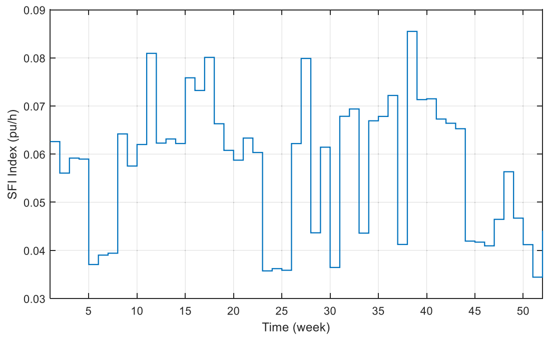

FIGURE 4. The flexibility index for Case 1.

equation (5) [25].

$$P_w = \begin{cases} 0 & v \leq v_{in}^c \ or \ v \geq v_{out}^c \\ \left(\frac{v - v_{in}^c}{v_R - v_{in}^c}\right) \times P_R & v_{in}^c \leq v \leq v_R \\ P_R & v_R \leq v \leq v_{out}^c \end{cases} \tag{5}$$

C. FORMULATION OF PROPOSED UFGMS$^{\text{IDRRs}}$

The GMS as a mid-term scheduling has been investigated from distinct perspectives such as emission reduction, reliability increment and minimizing cost as well as providing flexibility. Conflict of some scheduling objectives with each other complicates the GMS problem. In this section, each of these objectives is formulated separately.

- ***Objective 1: Economic***

The total system cost that must be minimized is modelled through Eq. (6). The first term in the objective function is conventional unit's operating cost, the next two terms are the incentive cost of IDRRs, the fourth term is gas storage cost,

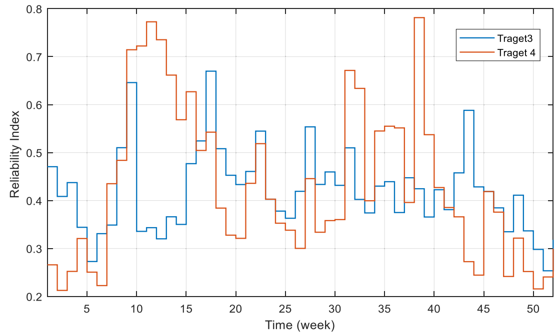

FIGURE 5. The reliability index for Case 1.

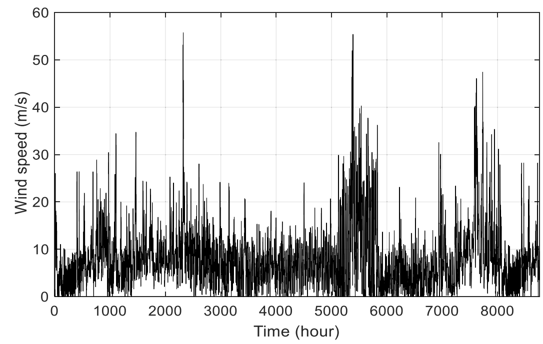

FIGURE 6. The forecasted wind speed by DL.

the fifth term assigns to the P2G operating cost, and the last term associates with the maintenance cost [8], [18].

$$Min \sum_{t=1}^{T} \sum_{h=1}^{H} \sum_{i=1}^{N} \times \left\{ \begin{array}{l} \left(a_i + b_i g_i^t + c_i g_i^{t2}\right)\left(1 - X_i^t\right) + CE_{event} + CG_{event} \\ + C_G^{st}(U_{t,h}^{out} + U_{t,h}^{in}) + C^{P2G} U_{t,h}^{P2G} + m_i g_i^{\max} X_i^t \end{array} \right\} \tag{6}$$

The economic objective in (6) is subjected to the following constraints.

$$\begin{aligned} \sum\nolimits_{i=1}^{N} g_i^{t,h} + P_w^{Real/forecasted} + \text{IDRR}_h & \\ = P_{D_{t,h}} + \text{loss}_h & \\ \text{IDRR}_h = \text{EDR}_h^{TOU} + GDR_h^{TOU} + EDR_h^{event} + GDR_h^{event} & \end{aligned} \tag{7}$$

$$g_i^{\min} \leq g_i^{t,h} \leq g_i^{\max} \tag{8}$$

$$\sum\nolimits_{t=1}^{T} X_i^t = M_i \tag{9}$$

$$X_i^t - X_i^{t-1} = \omega_i^t \tag{10}$$

$$\sum\nolimits_{t=1}^{T} \omega_i^t = 1 \tag{11}$$

$$\sum\nolimits_{i=1}^{N} X_i^t \leq N^{MN} \tag{12}$$

$$EDR_h^{TOU} \leq Pnr\, L_h \tag{13}$$

$$GDR_h^{TOU} \leq Pnr\, G_h^D \tag{14}$$

$$EDR_h^{event} \leq Pnr\, L_h \tag{15}$$

$$GDR_h^{event} \leq Pnr\, G_h^D \tag{16}$$

$$RDR_h^{\min} \leq RDR_h \leq RDR_h^{\max} \tag{17}$$

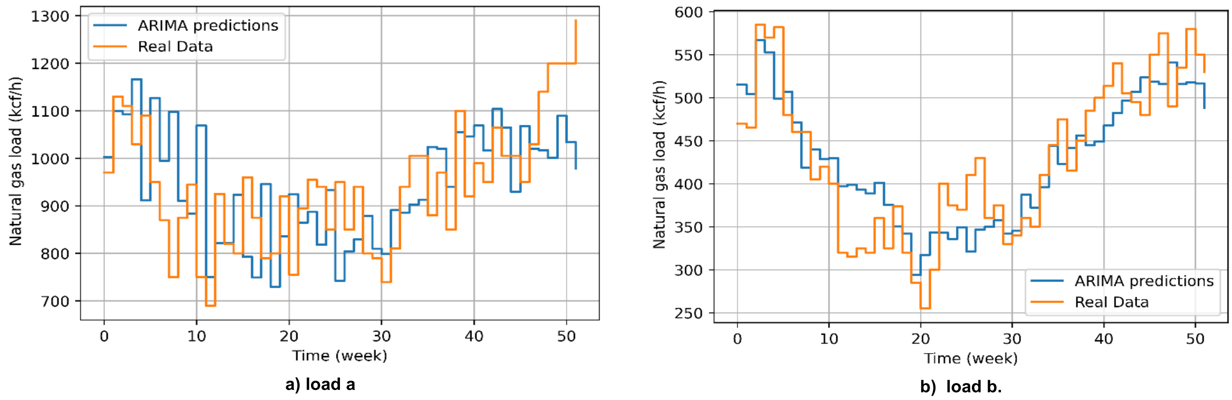

FIGURE 7. The forecasted natural gas by ARIMA.

$$GRDR_h^{\min} \leq GRDR_h \leq GRDR_h^{\max} \tag{18}$$

$$0 \leq U_{t,h}^{out} \leq U_{\max}^{out} \tag{19}$$

$$0 \leq U_{t,h}^{in} \leq U_{\max}^{in} \tag{20}$$

$$E_{t,h} = E_{t,h-1} + \eta^{in} U_{t,h}^{in} - \frac{U_{t,h}^{out}}{\eta^{out}} \tag{21}$$

$$E^{\min} \leq E_{t,h} \leq E^{\max} \tag{22}$$

$$E_0 = E_{NT} \tag{23}$$

$$U_{t,h}^{P2G} = \frac{P_{t,h}^{P2G} \eta^{P2G}}{HHV} \tag{24}$$

The power balance in each period is satisfied through Eq. (7) [26]. The limits for the output power of generation units are given in Eq. (8) [26]. The maintenance period of units is determined by Eq. (9). Eq. (10) covers consecutive periods of maintenance. Limit once being maintained in the planning horizon is guaranteed through Eq. (11). Eq. (12) has determined the maximum number to be maintain over a period of time. EDR and GDR participation have been limited by (13)-(16). The incentive rate for the EDR and GDR event in have been limited via (17) and (18), respectively. The maximum level of gas injection and release for gas storages are restricted via (19) and (20), respectively. The capacity of energy in h period is determined by Eq. (21). The energy level in storage is restricted via (22). The condition of initial has been determined via (23). Eq. (24) is shown gas generation of P2G technology.

- ***Objective 2: Emission***

The emission released from electricity generation is formulated as a quadratic function through Eq. (25) [7].

$$Min \left(\sum_{t=1}^{T} \sum_{h=1}^{H} \sum_{i=1}^{N} \left(\alpha_i + \beta_i g_i^t + \gamma_i g_i^{t2} \right) \left(1 - X_i^t \right) \right) \tag{25}$$

The maintenance constraints mentioned in Eq. (7) to (12) must be re-considered as previously explained.

- ***Objective 3: Reliability***

Fluctuations in output of RERs lead that the power system requires an appropriate level of reservation [27]. For reliability evaluation, the UFGMS$^{\text{IDRRs}}$ criteria is taken into account in this paper with the aim of leveling the reserve margin [7]. The objective function could be modelled as given in Eq. (26).

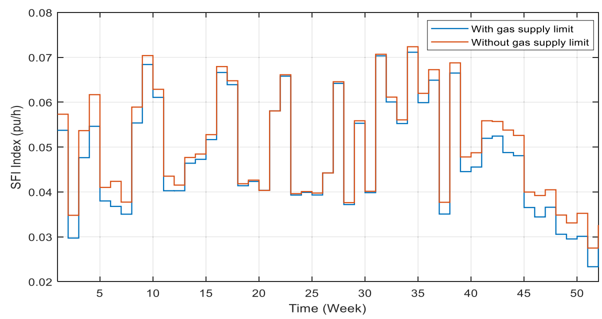

FIGURE 8. The flexibility results of Case 2.

$$Min \sum_{t=1}^{T} \sum_{h=1}^{H} \sum_{i=1}^{N} \left(\frac{\left\{ \sum_{i=1}^{N} P_{i,j}^{\max} \left(1 - X_{i,j}^t \right) - P_{D_{t,h}} \right\}}{P_{D_{t,h}}} \right)^2 \tag{26}$$

The constraint (27) ensures that the scheduled reserve is higher than a specified threshold for all periods.

$$R^{t,h} \geq R_{\min} \tag{27}$$

- ***Objective 4: Flexibility***

In this section, two sub-indicators such as RT and MAC have been applied to analyze flexibility. Hence, the RT and MAC have been defined in Eq. (28) and Eq. (29), respectively. Eventually, SFI is defined by combining RT and MAC to achieve the flexibility [10].

$$RT = \frac{1}{TN} \sum_{ut=1}^{T} \sum_{i=1}^{N} \left(t_{C_{(i,ut)}} - t_{(i,ut)} \right) \tag{28}$$

$$MAC = \frac{1}{TN} \sum_{ut=1}^{T-1} \frac{1}{T - ut} \sum_{h=1}^{H} \sum_{i=1}^{N} \frac{C_{(i,h,ut)}^a}{g_i^{t,h}} \tag{29}$$

$$\begin{aligned} SFI &= \frac{MAC}{RT} \\ &= \frac{1}{TN} \left(\sum_{ut=1}^{T-1} \frac{1}{T - ut} \left(\sum_{h=1}^{H} \sum_{i=1}^{N} \frac{C_{(i,h,ut)}^a \left(1 - X_i^t \right)}{g_i^{t,h} \left(t_{C_{(i,ut)}} - t_{(i,ut)} \right)} \right) \right) \end{aligned} \tag{30}$$

TABLE 1. Maintenance scheme results in Case 1.

Unit	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}
Target 1	9-14	38-42	9-12	27-30	34-37	3-5	7-9	18-20	15-17	18-19	31-32	13-14	42-43
Target 2	10-15	18-22	16-19	47-50	7-10	16-18	13-15	12-14	15-17	8-9	11-12	4-5	2-3
Target 3	31-36	38-42	10-13	38-41	11-14	24-26	8-10	27-29	14-16	31-32	15-16	21-22	8-9
Target 4	39-44	33-37	40-43	17-20	13-16	36-38	6-8	20-22	6-8	46-47	42-43	19-20	12-12
Unit	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}
Target 1	7-8	38-43	34-37	14-17	15-18	31-34	43-45	10-12	36-38	5-6	1-2	1-2	39-40
Target 2	6-7	44-49	6-9	47-50	43-46	2-5	3-5	50-52	42-44	51-52	51-52	45-46	1-2
Target 3	21-22	10-15	4-7	36-39	34-37	4-7	40-42	27-29	27-29	31-32	16-17	21-22	8-9
Target 4	1-2	1-6	26-29	47-50	24-27	28-31	17-19	27-29	13-15	51-52	1-2	51-52	21-22

TABLE 2. Maintenance scheme results in Case 2.

Unit	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}
Case 2	31-36	5-9	19-22	38-41	10-13	41-43	27-29	22-24	2-4	1-2	9-10	36-37	7-8
Unit	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}
Case 2	2-3	35-40	10-13	14-17	41-44	13-16	27-29	22-24	27-29	47-48	48-49	50-51	15-16

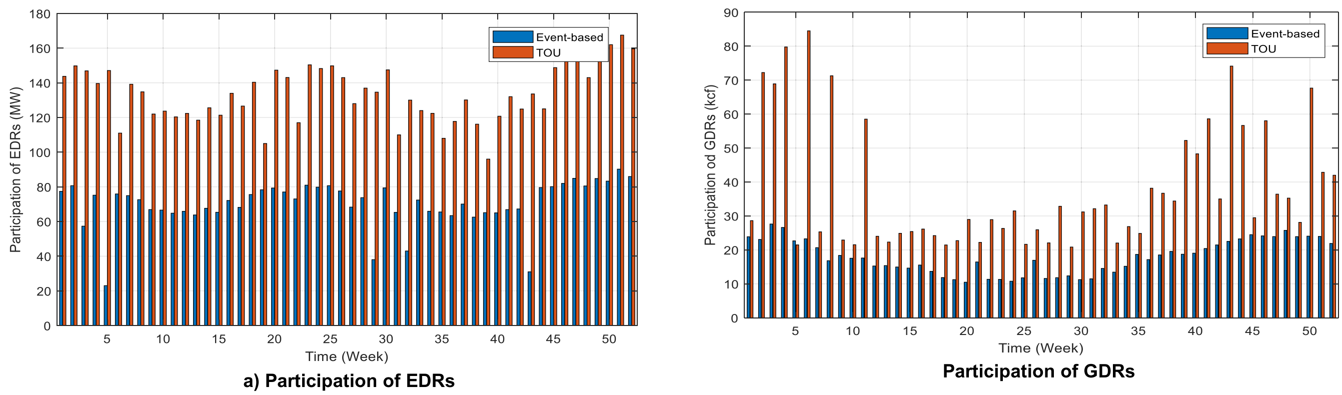

FIGURE 9. Result of IDRRs in UFGMS.

D. AUGMENTED EPSILON CONSTRAINT METHOD

The objectives of multi-objective problems (MOPs) may be at odds with one another. In MOPs, there is not a solution that could satisfy all goals simultaneously. Therefore, it is crucial to choose a solution that provides a trade-off between the objectives. The augmented epsilon constraint approach is utilized to manage MOPs in this paper [28].

The $UFGMS^{IDRRs}$ problem is formulated via (31), as shown at the bottom of the next page, follows.

III. NUMERICAL ANALYSIS

The $UFGMS^{IDRRs}$ is implemented on the modified IEEE 24-bus test system including wind resources with 300 MW and 26 dispatchable units (U_1-U_{26}) that 300 MW of hydro generation removed. All the economic and technical data of generation units has been extracted from [8]. The weekly peak load is illustrated in Fig. 3 and the peak load of system is 2850 MW [29]. In this study, the *eps* and reserve criterion are considered 10^{-6} and 20%, respectively [30]. The maintenance scheduling and flexibility evaluation horizons are assumed 52-week and 8736 hours, respectively. The slopes of emission function and the startup emission of conventional generating units are the same as those for related unit fuel cost curves, all multiplied by conversion factors of 0.2 and 0.5 for SO_2 and NO_x emission, respectively [31]. The $UFGMS^{IDRRs}$ problem is solved by BARON in GAMS software environment.

One of the main purposes of this paper is to evaluate the effects of renewable RERs uncertainty on system flexibility. Hence, various cases are conducted to reveal the effectiveness of the proposed model. The flexibility of system has been investigated disregarding to uncertainties of gas and wind as well as without considering the participation of IDRRs in Case 1. The flexibility of system has been evaluated with considering uncertainties of gas demand and wind speed in Case 2. In Case 3, the effectiveness of IDRRs and energy storage on flexibility is evaluated eventually.

- **Case 1: Flexibility analysis disregarding to uncertainties of gas and wind as well as the participation of IDRRs**

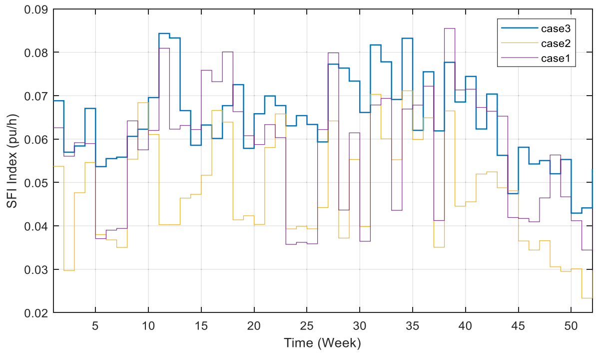

FIGURE 10. Comparison of flexibility index between all cases.

The UFGMS^{IDRRs} model seeks to achieve a comprehensive maintenance scheme with the goals of reliability, flexibility, environmentally and economic. Hence, maintenance and operation costs as the costs of system have been minimized. In objective 4, the amount of obtained from the first objective, 238.39M\$, assume as a limitation. The greenhouse gas emissions and reservation criteria as the reliability objective are minimized in objective 2 and objective 3, respectively. The amount of greenhouse gas emissions and reserve level are considered as constraints in objective 4. The SFI as objective 4 is maximized with considering pervious objectives as constraints. In Table 1, the maintenance schemes of all objectives are presented. In Fig. 4, reliability results of all targets are shown. According to Fig. 5, the best level of reliability is achieved by objective 3. The reserve of objective 4 could not attain reserve of objective 3, but it has reached the acceptable level Note that the total emission of Case 1 is 123.435 Mlbs, which is a good level compared to the total emission of objective 2 (120.221 Mlbs).

In Fig. 4, the SFI index for each week is illustrated. The lowest flexibility occurs in weeks of 23-31 and 46-52. According to Fig. 3, the peak demand is happened at these weeks. Also, in the weeks when the peak load occurs, the fast ramp units have not been maintained so as not to reduce the flexibility of the system.

- **Case 2: Flexibility analysis regarding to uncertainties of gas and wind speed**

The value of root mean square error (RMSE) and mean absolute percentage error (MAPE) for the forecasted wind power generation are 0.16% and 2.82%, respectively. Forecasted wind speed is depicted in Fig. 6. The climate data is extracted from [32]. The forecasted natural gas demands by ARIMA are illustrated in Fig. 7. The maximum capacity of gas pipeline 1 is 7000 kcf/h that it is supplied four units (U4, U5, U18 and U19) and the natural gas load a. The maximum capacity of gas pipeline 2 is 6000 kcf/h that it is supplied three units (U3, U16 and U17) and the natural gas load b. 1 kcf of gas is assumed could produce 1 MBtu of energy [33].

In Table 2, the maintenance schemes of Case 2 are reported. It should be noted that a maximum of 3 units in a week have been maintained due to the limitations of the number of units under repair in a week. Also, the schedules to repair fast ramp units are distributed over a period of time so that they can be accessed throughout the year. In Table 2, the maintenance schemes of Case 2 are reported. It should be noted that a maximum of 3 units in a week have been maintained due to the limitations of the number of units under repair in a week. Also, the schedules to repair fast ramp units are distributed over a period of time so that they can be accessed throughout the year. A comparison of the SFI between with and without gas supply restriction is shown in Fig. 8, that The level of flexibility decreases with limited gas supply, due to lack of access to maximum gas-fired resources capacity. On the other hand, the existing capacity of dispatchable sources has decreased due to the variability of wind resources, which has

$$\mathrm{Max}\left\{\begin{array}{l}\underbrace{\frac{1}{TN}\left(\sum_{ut=1}^{T-1}\frac{1}{T-ut}\left(\sum_{t=1}^{T}\sum_{i=1}^{N}\frac{C^{a}_{(i,t,ut)}\cdot\left(1-X_i^t\right)}{g_i^{t,h}\times\left(t_{C_{(i,ut)}}-t_{(i,ut)}\right)}\right)\right)}_{\text{Flexibility Objective}}\\ +eps\times(s_2+s_3+s_4)\end{array}\right\},$$

$$s.t.:\ \underbrace{\sum_{t=1}^{T}\sum_{h=1}^{H}\sum_{i=1}^{N}\left\{\begin{array}{l}\left(OC_i^{t,h}\right).\left(1-X_i^t\right)+C^{t,h}_{IDRR}\\ +inc^{t,h}_{DRP}+m_i.g_i^{\max}.X_i^t\end{array}\right\}}_{\text{Economic Objective}}+s_2=e_2.$$

$$\underbrace{\sum_{t=1}^{T}\sum_{h=1}^{H}\sum_{i=1}^{N}\left(\alpha_i+\beta_i g_i^t+\gamma_i\left(g_i^t\right)^2\right).\left(1-X_i^t\right)}_{\text{Emission Objective}}+s_3=e_3.$$

$$\underbrace{\sum_{t=1}^{T}\sum_{h=1}^{H}\sum_{i=1}^{N}\left(\frac{\left\{\sum_{i=1}^{N}P_{i,j}^{\max}\left(1-X_{i,j}^t\right)-P_{D_{t,h}}\right\}}{P_{D_{t,h}}}\right)^2}_{\text{Reliability Objective}}+s_4=e_4. \quad (31)$$

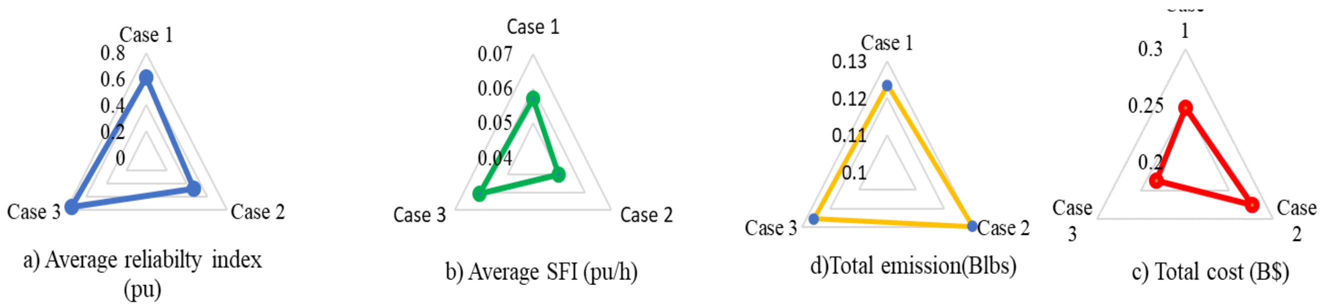

FIGURE 11. Comparison of different objectives.

TABLE 3. Maintenance scheme results in Case 3.

Unit	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}
Case 3	31-36	7-11	26-29	23-26	21-24	15-17	22-24	17-19	1-3	18-19	1-2	21-22	7-8
Unit	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}
Case 3	8-9	37-42	12-15	10-13	31-34	48-51	18-20	15-17	1-3	11-12	13-14	9-10	6-7

TABLE 4. Comparison of optimization results for defined cases.

	The incentive of IDRRs (m$)	The operation cost of GS (m$)	Total emission (Mlbs)	Average SFI (pu/h)	Total cost (m$)
Case1	-	-	123.435	0.0571	247.97
Case2	-	-	129.712	0.0497	275.26
Case3	2.4	1.78	121.52	0.0607	232.34
[8]	-	-	133.443	-	245.99

led to a decrease in system flexibility. It should be noted that due to decrement in utilization of wind resources, system costs and emission rates have increased.

- **Case 3: Flexibility analysis considering IDRRs and gas storage**

In this Case, EDRs, GDRs and gas storage based on P2G technology have been used to reduce the limitations of the gas supply and the variability of wind resources. The results of IDRRs in $UFGMS^{IDRRs}$ are illustrated in Fig. 9. The participation of EDRs for all types is presented in Fig. 9-a. As it is clear, the EDRs have been more participated during peak load which leads to an improvement in the reliability index (increasing the level of reservations) and reducing operating costs (due to the use of expensive power plants in the peak load). According to the flexibility index figures for case 2 with gas limitation (Fig. 8), It can be seen that the flexibility criteria has decreased significantly in the range of 20 to 30 weeks. In order to provide flexibility, flexible resources have been used on the demand side. Fig. 9-b represents the amount of the portfolio of GDRs consisting of Event based and TOU. Performing the portfolio of GDRs is applied during weeks with the lowest flexibility criteria due to gas limitation. It is clear, Event based have been more involved than TOU. According to Fig. 1, the portion of each DRPs in flexible generation maintenance scheduling has been identified, which can be a roadmap for power system developers.

In Table 3, the maintenance schemes of Case 3 are reported. It should be noted that a maximum of 3 units in a week have been maintained due to the limitations of the number of units under repair in a week. Also, the schedules to repair fast ramp units are distributed over a period of time so that they can be accessed throughout the year. A comparison of the SFI among all cases is shown in Fig. 10, which reveals the level of flexibility increases in Case 3. On the other hand, due to the presence of fast response such as IRRs and energy storage, it has improved system flexibility. In fact, the EDRs, GDRs and gas storage based on P2G technology have led to mitigate the gas supply limitation and variability of wind resources.

The flexibility, cost, reliability and emission objectives in various cases are compared with each other as shown in Table 4 and Fig. 11. The flexibility index in case 2 has decreased by about 12.96% compared to case1. The flexibility index in case 3 has improved by about 22.32% compared to case 3, due to the use of IDRRs (flexibility resources) and P2G-based gas storage (reduction of gas supply limitation). Emission level, reliability and cost in Case2 have the worst and in Case 3 the best value. Due to the use of IDRRs, the level of demand has decreased significantly and the production of fossil fuel power plants has decreased. According to Fig. 1, Case 3 has the best results compared to other cases due to the presence of IDRRs and energy storage. It is clear, comparing the total cost of the proposed model system with the results of [8], it can be seen that about 12.35 m$ per year has been saved.

IV. CONCLUSION

In recent years, the interdependence of gas and electricity system has increased. Hence, the limitation of natural gas supply is notable for secure operation in power system. On the other hand, lack of attention to the penetration of RERs and flexibility analysis in the GMS will lead to an insecure environment for power system operators and developers. In this paper, an environmental techno-economic framework for uncertain based flexible GMS considering integrated DRRs has been applied. In the proposed model, the EDRs, GDRs and gas storage based on P2G technology have been used to mitigate the limitations of the gas supply and the variability of wind resources. The obtained results revealed that higher penetration of RERs decreases the SFI. It has been concluded that the system flexibility and reliability have been improved tangibly by considering the IDRRs and gas storage while the total costs and emission over the horizon have not been increased.

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