Flexibility Driven Generation Maintenance Scheduling in the Presence of Demand Response Resources to Attenuate Wind Output Variability Considering Gas Demand Uncertainty

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Generation maintenance scheduling (GMS) is one of the most important and influential programs on short-term scheduling. On the other hand, the variability nature of distributed renewable resources is led to the need for a power system to provide flexibility. In order to achieve a flexible operation, it is essential to develop a flexible GMS framework. 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. Gas-fired power plants are one of the most important suppliers of flexibility in the supply-side. Therefore, the reliable operation of electricity grids depend on the 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, the uncertainties of wind and gas load is considered through forecasting by ARIMA method in Python. In this paper, natural gas and electricity demand responses are implemented as flexibility provisions from demand-side resources. It is worth noting that the objectives of increasing flexibility, leveling the energy index of reliability and reducing emission and costs have been considered as the objectives of optimizing GMS . The proposed framework is implemented on a modified IEEE 24 bus. According to the results, the system flexibility has been improved without increasing costs. The flexibility index in proposed model has improved by about 19.11%, due to the use of DRRs.

keywords: *Generation maintenance scheduling, Gas load uncertainty, Augmented epsilon constraint method, Flexibility.*

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1. INTRODUCTION

A. Motivation and background

In recent years, the widespread penetration of gas-fired power plants has led to the importance of the gas network and the resulting uncertainties for the operators and developers of the power system. The natural gas system also has uncertainties in the amount of natural gas consumption, natural gas prices and so on. The unexpected increment in natural gas consumption is bounded the supply of fuel to gas-fired power plants. 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 is the natural gas that is dramatically increased recently.

B. Literature review

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 [1], the uncertain prices of natural gas and electricity are taken account into multi-stage mixed programming model that seeks optimal operations for accurate maintenance. In [2], the preventive maintenance schedule of multi-energy micro grids is introduced to increase the resilience of the system in unpredictable conditions. In [3], minimizing reliability index and operation cost is considered as the primary objectives in GMS by bi-level framework. A flexible GMS framework is presented considering the portfolio of demand response programs in [4].In [5], a GMS has been introduced as two-stage stochastic programming. The lexicographic method has been applied to consider the economics, emission, and reliability objectives in [6]. In [7], GMS is applied with minimizing operation and maintenance costs in multi-carrier energy systems. In [8], the operation cost, as well as demand reduction, has been minimized to ensure reliability constraints in GMS. In [9], GMS is integrally implemented with unit commitment with the aim of reducing costs. The flexibility analysis has become a thriving topic in research in the field of power systems. In [10], energy storages as flexibility supplier have been used as to handle the uncertainty of RERs. Reference [11] has been considered the transaction between gas and electricity system as a future flexible provision. In [12], resilient and flexible operation is applied considering plug-in electric vehicles (PEVs) as flexibility provisions. Incentive design for flexibility provisions is presented by the local distribution company that has been transformed residential demand to residential energy hub (REH) in [13].

Demand response resources (DRRs) are considered to be influential components of the power system due to their impact on security, environmental and economic as well as social parameters. In [14], the DRRs have been utilized to attenuate the variability of renewable resources as well as improving flexibility. In [15], an incentive-based DRRs has been applied with reconfiguration method for optimal energy management in a microgrid. DRRs have led to reduce costs and increase flexibility, as well as restore the system quickly in [12]. In [16], an incentive-based DRRs has been implemented to reduce the emission and cost of operation. In [17], the impact of energy storages and DRRs has been investigated on the effectiveness aspect of energy efficiency.

One of the significant characteristics in energy democracy policy is the customers welfare. Despite the willingness of consumers to participate in demand response programs (DRPs), consumers have little inclination to reduce consumption during peak hours, because the scheduling of the implementation of DRPs is determined by the ISO (usually implemented during peak hours). Hence, the implementation of DRPs causes consumer inconvenience [17]. In the smart society, the curtailment of demand in inappropriate time is led to enhance the customer inconvenience that should be noted in the scheduling of power system. The inconvenience of customers is a qualitative parameter, that has been modeled in cost function as a quantify parameter to evaluate their impact on power system.

To briefly demonstrate the contribution features of the proposed model as compared with the existing literature, Table 1 is added for more visual understanding. The considered factors for the following comparison are respectively:

- Factor 1: Generation maintenance scheduling.
- Factor 2: Flexibility analyses.
- Factor 3: Considering electricity network uncertainties (e.g. renewable generation or demand uncertainties).
- Factor 4: Considering gas network uncertainties (e.g. gas pipeline or gas load uncertainties).
- Factor 5: Electricity or natural gas DR participation.
- Factor 6: Considering inconvenience cost.
- Factor 7: multi-objective optimization method.

C. Model and contribution

As seen in Table 1, It should be mentioned that the previous researches have been evaluated the flexibility criteria in the power system studies with a short-term horizon. Regarding that GMS affects on short-term scheduling of power system, it is necessary to consider the flexibility in GMS to achieve a more flexible power system. Therefore, a novel environmental techno-economic framework for uncertain based flexible GMS considering DRRs (UFGMSDRRs) has been presented in this paper. The electricity demand response (EDR) is the another approach of to mitigate the impact of power system uncertainties ,which have been used extensively. On the other hand, the interdependencies between power system, 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 of integrating GDR and EDR leads to loss of opportunities in the power system. In this paper, the DRRs have been applied to handle to variability of RERs. It should be noted that the forecasting wind speed and gas demand have been conducted by autoregressive integrated moving average (ARIMA). In this paper, several analyzes have been implemented in UFGMSDRRs to evaluate the impacts of DRRs on objectives such as cost, emission, reliability, and flexibility, Here, to overcome the difficulties in solving the non-convex and mixed integer nature of UFGMSDRRs, the augmented epsilon constraint (AUGMECON) method is applied to find the optimal global solution.

D. Paper structure

The remaining parts of the paper are as follow. Section 2 assigns to formulation of the proposed UFGMSDRRs. The simulation results and numerical analysis are presented in Section 3. Finally, Section 4 concludes the paper.

2. METHODOLOGY

This study suggests a multi-objective framework in Fig. 1 to evaluate and reinforce a power system against variability of RERs. In Fig. 1 (a), the flexibility analyses hierarchy has been represented. 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 has been produced via dividing MAC to RT. Afterwards, a approach oriented upon time-series models is actuated to predict wind and natural gas uncertainty in Fig. 1 (b). In Fig. 1 (c), the $UFGMS_{DRRs}$ in combination with DRRs is regarded as a multi-objective problem solving for cost, emission, reliability and flexibility. Several approaches are deployed to manage multi-objective problems from the perspective of the decision-maker. In this paper, the augmented epsilon constraint is applied to solve multi-objective UFGMSDRRs problem. Here, the uncertainties of natural gas demand and the output of wind resources are considered by ARIMA.

The proposed model in this paper includes different goals as follows:

- Economic: Minimizing the total cost of operation, repair cost and incentives paid to subscribers in exchange for participation in load response programs is considered as an economic criterion.
- Environmental: due to the different value of producing a polluting unit in different areas of the power system, the

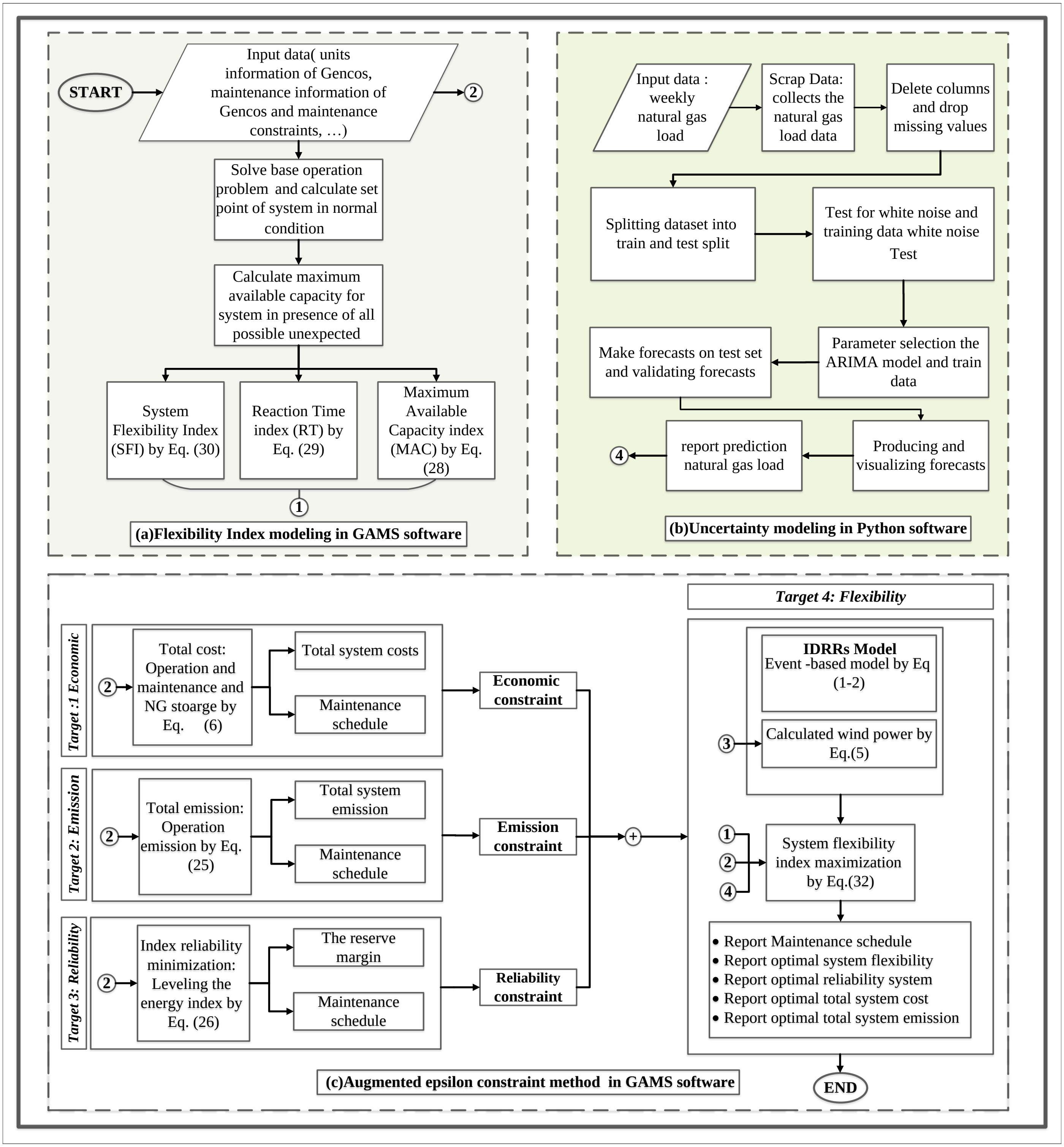


Fig. 1. The structure of $UFGMS^{DRRs}$

Table 1. Comparison of the proposed model with the recent research

Approach	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
[1]	✓	-	✓	✓	-	-	-
[2]	✓	-	✓	-	-	-	-
[3]	✓	-	-	-	-	-	✓
[4]	✓	✓	✓	-	-	-	✓
[5]	✓	-	✓	-	-	-	✓
[6]	✓	-	-	-	✓	-	✓
[14]	-	✓	✓	-	✓	-	✓
[17]	-	-	-	-	✓	✓	✓
Proposed	✓	✓	✓	✓	✓	✓	✓

environmental criterion is the minimization of the cost of emission of pollution.

- Reliability: Reliability energy index based on the expected unsupplied energy is considered as the index considered by the system operator to maintain reliability.

- Flexibility: The increase of the flexibility index based on the available free capacity and the reaction time for each area is considered as a flexibility evaluation criterion.

In order to establish a balance between the aforementioned goals, the augmented epsilon constraint method is used; It should be noted that, in this method, decision makers have freedom of choice. In the following, the enhanced epsilon constraint method is fully explained. The concept of the improved epsilon constraint method and the selected preferences of the decision maker, a structure consisting of four phases is presented as follows:

- The first phase: the costs incurred by the system, including the cost of operation, the cost of repairs, and the cost of maintaining the reservation, are minimized in the presence of the common constraints of the problem.

- Second phase: In this phase, the cost of pollutants released from the power sector is sometimes minimized; As long as the common constraints of the problem include maintenance constraints and production planning constraints. The production pattern of power plant units and the emission rate of pollutants are considered as the output of this phase.

- The third phase: the reliability criterion, which is considered as a reliability energy index during the study period, is leveled in the presence of the common constraints of the repair planning problem.

- Fourth phase: In this phase, the final answer to the problem is obtained. The objective function is to maximize the flexibility index in the planning period. Here, the results of the previous phases are applied as restrictions according to the payoff table so that other goals are also provided. In the rest of the section, the modeling of the problem will be discussed in detail.

A. Electricity and gas demand response model

The electricity DR (EDR) have potential to offer special features such as reliability increasment, reduction of operation cost, emission reduction, flexibility improvement. On the other hand, natural gas is also one of the most consumed energies in the world. 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 UFGMSDRRs. In event-based electricity and gas DRRs, the customer are obtained incentive for reducing their consumption. Notice of gas and electricity curtailment event is supposed to be supervised in the moment. The customers of participating in event-based DR programs will be notified before the event occurs. The total incentive payment for electricity DR curtailment is presented by Eq. (1) [18].

$$CE_{event} = \min \left\{0, dr_h.RDR.\left(P^D_{t,h+1} - PA_{event}\right)\right\} \quad \mathbf{(1)}$$

The total incentive payment for gas DR curtailment is defined via Eq. (2) [18].

$$CG_{event} = \min \left\{0, ng_h.GRDR.\left(G^D_{t,h+1} - GA_{event}\right)\right\} \quad \mathbf{(2)}$$

B. Uncertainty model

In order to predict the nature of the variability of RERs and gas load are applied a time series uncertainty method in this study. Herein, the ARIMA is applied to forecast wind generation and gas load. ARIMA as a type of statistical models could be predict and analyze time series data. ARIMA presents a potent method for developing expert time series predictions via providing a collection of joint structures [19]. ARIMA is an abbreviation for auto regressive integrated moving average. It's a more complex version of the autoregressive moving average, with the addition of integration. This abbreviation is descriptive, summarizing the model's major features. ARIMA are briefly defined follow as:

• Autoregression (AR): The dependent relationship between a set of lagged observations and an observation is used in this model.

• Integrated (I): To make the time series steady, differencing raw observations is used.

• Moving Average (MA): The dependency between a residual error and an observation from a moving average model is utilized to lagged observations. The following are the parameters of the ARIMA model:

• p: The lag order is the number of lag observations incorporated in the model. • d: The degree of differencing refers to the number of times the raw observations are differed. • q: The order of moving average (MA) is the size of the MA window.

The data is prepared by a degree of differencing in order to make it stationary, i.e. to remove trend and seasonal structures that negatively affect the regression model. A linear regression model is constructed with the specified number and type of terms, and the data is prepared by a degree of differencing in order to make it stationary, i.e. to remove trend and seasonal structures that negatively affect the regression model. The supplementary aspect about this approach is represented in [20]. The implementation of the ARIMA model in Python is illustrate in Fig. 1(b).

In the power system, wind resources are one of the most prevalent and significant RERs. The production of wind resources is determined by a variety of factors, including wind speed and direction, as well as the location of the wind turbines. Wind speed has a significant impact on the production of wind resources. The output of wind farm output is determined via Eq. (3) [21].

$$P_w = \begin{cases} 0 & v \le v_{in}^c \ or \ v \ge v_{out}^c \\ \left(\dfrac{v - v_{in}^c}{v_R - v_{in}^c} \right) \times P_R & v_{in}^c \le v \le v_R \\ P_R & v_R \le v \le v_{out}^c \end{cases} \tag{3}$$

C. Phase1: Economic

The total costs of system including maintenance, operation DRPs incentive and inconvenience cost have been minimized in this section [18].

$$Min \left(\sum_{t=1}^{T} \sum_{h=1}^{H} \sum_{i=1}^{N} \left\{ \begin{array}{l} \left(OC_i^{t,h}\right).\left(1 - X_i^t\right) + C_{IDRR}^{t,h} + \\ + inc_{DRP}^{t,h} + m_i.g_i^{\max}.X_i^t \end{array} \right\} \right) \tag{4}$$

where:

$$OC_i^t = a_i + b_i.g_i^t + c_i\left(g_i^t\right)^2 \tag{5}$$

$$inc_{DRP}^{t,h} = \sum_{j=1}^{N^{dr}} \kappa^{inc}\left(DR_i^{up} + DR_i^{Dn}\right) \tag{6}$$

The economic objective has been subjected to the following constraints:

$$\textstyle\sum_{i=1}^{N} g_i^{t,h} = L_{t,h}^n + \text{loss}_h - \text{IDRR}_h, \ \ \forall t \in T, \forall h \in H \tag{7}$$

$$L_{t,h}^n = P_{D_{t,h}} - P_w^{\mathrm{Re}\,al\,/\,forecasted} \tag{8}$$

$$IDRR_h = EDR_h^{event} + GDR_h^{event} \ \forall h \in \mathrm{H} \tag{9}$$

$$g_i^{\min} \le g_i^{t,h} \le g_i^{\max} \ \forall i \in N, \forall t \in T, \forall h \in H \tag{10}$$

$$\textstyle\sum_{t=1}^{T} X_i^t = M_i, \forall i \in N, \forall t \in T \tag{11}$$

$$X_i^t - X_i^{t-1} = \omega_i^t, \ \forall i \in N, \forall t \in T \tag{12}$$

$$\textstyle\sum_{t=1}^{T} \omega_i^t = 1 \ , \forall i \in N, \forall t \in T \tag{13}$$

$$\textstyle\sum_{i=1}^{N} X_i^t \le N^{MN}, \forall i \in N, \forall t \in T \tag{14}$$

$$EDR_h^{event} \le Pnr.L_h, \forall h \in \mathrm{H} \tag{15}$$

$$GDR_h^{event} \le Pnr.G_h^D, \forall h \in \mathrm{H} \tag{16}$$

$$RDR_h^{\min} \le RDR_h \le RDR_h^{\max}, \forall h \in \mathrm{H} \tag{17}$$

$$GRDR_h^{\min} \le GRDR_h \le GRDR_h^{\max}, \forall h \in \mathrm{H} \tag{18}$$

The power balance in each subperiod has been satisfied via Eq. (7); Eq. (10) have limited units' generations. Eq. (11) determine the maintenance period of units. Eq. (12) covers consecutive periods of maintenance. Limit once being maintained in the planning horizon is guaranteed via Eq. (13). Eq. (14) has determined the maximum number to be maintain over a period of time. EDR and GDR participation have been limited by Eq. (15) and Eq. (16). The incentive rate for the EDR and GDR event in have been limited via Eq. (17) and Eq. (18), respectively.

D. Phase2:Emission

The emission has been represented as the quadratic function in the power system. The greenhouse gases released from electricity generation are minimized by Eq. (19) [22].

$$Min \left(\sum_{t=1}^{T} \sum_{h=1}^{H} \sum_{i=1}^{N} \left(\alpha_i + \beta_i g_i^t + \gamma_i \left(g_i^t\right)^2 \right).\left(1 - X_i^t\right) \right) \tag{19}$$

E. Phase3:Reliability

The appropriate reliability index should be apply to attain the reliable system .The energy index of reliability (EIR) as probabilistic reliability index is considered to satisfy the system reliability.

$$Min \left(\sum_{t=1}^{T} \sum_{h=1}^{H} \underbrace{\left(1 - \frac{EENS(h)}{TE(h)} \right)^2}_{EIR} \right) \tag{20}$$

The reliability index is based on the expected energy not supplied (EENS). The higher value of EIR is the more suitable for the system operator, but it is obvious that increasing reliability requires high cost. The the system operators seeks to achieve a suitable and standard level. Therefore, it has been tried to make the EIR index at the same level by using leveling during the planning horizon.

Eq. (21) satisfies a reserve above a determined level.

$$R^{t,h} \ge R_{\min}, \forall t \in T, \forall h \in H \tag{21}$$

F. Phase 4: Flexibility

The operating status of the system should be clear in the assessment of flexibility. Therefore, it should be noted that to what extent, at what speed and with what acceleration, the system has the ability to go out of balance and reach its maximum capacity. Therefore, only the maximum power generation capacity cannot be relied upon as a measure to check the degree of flexibility of the system; Rather, the response time and reaching the maximum capacity and acceleration of the system in reaching this goal are important parameters in the level of flexibility. In fact, it is a system with more flexibility to obtain more capacity in less time and with more acceleration. Moreover, two sub-indicators such as RT and MAC have been applied to analyze flexibility in this phase. Hence, the RT and MAC have been defined in Eq. (22) and Eq. (23), respectively. Eventually, SFI is defined by combining RT and MAC to achieve the flexibility as in Eq. (24) [23].

$$RT = \frac{1}{TN}\sum_{ut=1}^{T}\sum_{i=1}^{N}\left(t_{C_{(i,ut)}} - t_{(i,ut)}\right) \tag{22}$$

$$MAC = \frac{1}{TN}\sum_{ut=1}^{T-1}\frac{1}{T-ut}\sum_{h=1}^{H}\sum_{i=1}^{N}\frac{C^{a}_{(i,h,ut)}}{g_i^{t,h}} \tag{23}$$

$$SFI = \frac{1}{TN}\left(\sum_{ut=1}^{T-1}\frac{1}{T-ut}\left(\sum_{h=1}^{H}\sum_{i=1}^{N}\frac{C^{a}_{(i,h,ut)}\cdot\left(1-X_i^t\right)}{g_i^{t,h}\times\left(t_{C_{(i,ut)}} - t_{(i,ut)}\right)}\right)\right) \tag{24}$$

The objectives of multi-objective problems (MOPs) may be at odds with one another. In MOPs, there is no one best solution that can achieve all the targets at once. As a result, it is necessary to choice one solution to compromise between the targets. The augmented epsilon constraint approach has been implemented for solving MOPs in this paper. provides a quick overview of the optimization technique. According to the mentioned method, economic, environmental, reliability and flexibility goals are solved separately. Then, lower and upper bounds (lb_k and ub_k) are calculated for economic, environmental and reliability purposes. In the following, the range of changes of the objective functions (r_k) except for the calculated flexibility of specifying the desired points (g_k) is created to create values on the right side. using the upper edge of the objective functions, created the values on the right side ($e_k = ub_k - (i_k \times r_k)/g_k$). At the end, solving the main problem (flexibility) is done by considering other functions as limitations. s_k is the optimization surplus variable. The more detail about this method has been expressed in [24].The main objective function of the proposed method is formulated as follows:

$$Max\left\{\begin{array}{l}\underbrace{\frac{1}{TN}\left(\sum_{ut=1}^{T-1}\frac{1}{T-ut}\left(\sum_{t=1}^{T}\sum_{i=1}^{N}\frac{C^{a}_{(i,t,ut)}\cdot\left(1-X_i^t\right)}{g_i^{t,h}\times\left(t_{C_{(i,ut)}} - t_{(i,ut)}\right)}\right)\right)}_{\text{Flexibility Objective}}\\ +eps\times\left(s_2+s_3+s_4\right)\end{array}\right\} \tag{25}$$

$s.t.$

$$\underbrace{\sum_{t=1}^{T}\sum_{h=1}^{H}\sum_{i=1}^{N}\left\{\begin{array}{l}\left(OC_i^{t,h}\right)\cdot\left(1-X_i^t\right)+C_{IDRR}^{t,h}\\ +inc_{DRP}^{t,h}+m_i.g_i^{\max}.X_i^t\end{array}\right\}}_{\text{Economic Objective}}+s_2=e_2 \tag{26}$$

$$\underbrace{\sum_{t=1}^{T}\sum_{h=1}^{H}\sum_{i=1}^{N}\left(\alpha_i+\beta_i g_i^t+\gamma_i\left(g_i^t\right)^2\right)\cdot\left(1-X_i^t\right)}_{\text{Emission Objective}}+s_3=e_3 \tag{27}$$

$$\underbrace{\sum_{t=1}^{T}\sum_{h=1}^{H}\underbrace{\left(1-\frac{EENS(h)}{TE(h)}\right)^2}_{EIR}}_{\text{Reliability Objective}}+s_4=e_4 \tag{28}$$

3. RESULTS

The $UFGMS^{DRRs}$ is implemented on IEEE 24-bus. The modified IEEE 24-bus including wind resources with 300 MW and 26 dispatchable units (U1-U26) are listed in Table 2 [6].The weekly peak load is illustrated in Fig. 2 and the peak load of system is 2850 MW [25]. The reserve criteria and eps are considered 20% and 10-6, respectively [26]. The maintenance scheduling and flexibility evaluation horizons are assumed 52-week and 8736 hours, respectively. The emission function slopes and the startup emission of generating units are the same as those for corresponding unit fuel cost curves, all multiplied by conversion factors of 0.2 and 0.5 for SO_2 and NO_x emission [27]. The $UFGMS^{DRRs}$ problem is solved by BARON in GAMS.

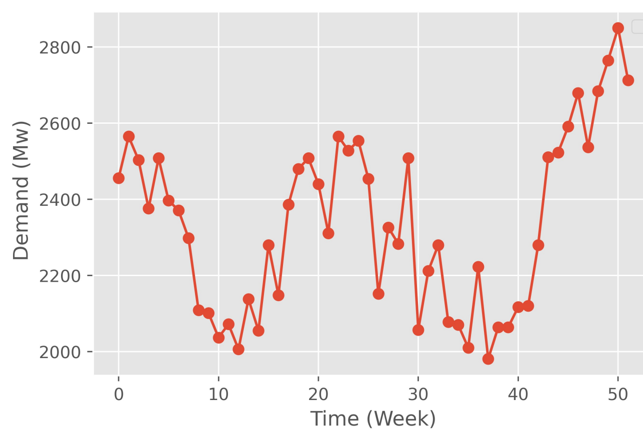


Fig. 2. The weekly peak load.

In this section, three cases have been implemented to investigate the impact of the $UFGMS^{DRRs}$ model on the level of system flexibility, the details of which are as follows:

• Case 1: Flexibility analysis disregarding to uncertainties of gas and wind as well as the participation of DRRs.

• Case 2: Flexibility analysis regarding to uncertainties of gas and wind speed.

• Case 3: Flexibility analysis considering DRRs. In the following, the results related to each case will be examined separately. Eventually, the results of all cases will be compared with each other.

A. Case 1: Flexibility analysis disregarding to uncertainties of gas and wind as well as the participation of DRRs

The $UFGMS_{DRRs}$ model seeks to achieve a comprehensive maintenance scheme with the goals of reliability, flexibility, environmentally and economic. Hence, maintenance and operation

Table 2. Generation units information of IEEE 24-bus

Unit	g^{max}/g^{min}	FOR	M_i	a_i (\$)	b_i ((\$/MWh)	c_i (\$/MWh^2)	HR_i ($MBtu/MWh$)	RU_i ($1/MWh$)
1	400/100	0.12	6	311.91	7.503	0.00195	10	10
2	350/140	0.08	5	177.05	10.862	0.00153	9.5	36
3	197/68.9	0.05	4	260.17	23.200	0.00263	9.6	78
4	155/54.3	0.04	4	143.59	10.758	0.00487	9.7	78
5	155/54.3	0.04	4	143.31	10.737	0.00481	9.7	78
6	100/25	0.04	3	218.77	18.200	0.00598	10	31
7	100/25	0.04	3	218.33	18.100	0.00612	10	31
8	76/15.2	0.02	3	81.626	13.407	0.00932	12	36
9	76/15.2	0.02	3	81.464	13.381	0.00910	12	36
10	20/4	0.10	2	118.82	37.890	0.01433	14.5	104
11	20/4	0.10	2	118.45	37.777	0.01359	14.5	104
12	12/2.4	0.02	2	24.888	24.888	0.02855	12	42
13	12/2.4	0.02	2	24.761	24.761	0.02842	12	42
14	12/2.4	0.02	2	24.638	24.638	0.02801	12	42
15	400/100	0.12	6	310.00	7.492	0.00194	10	10
16	197/68.9	0.05	4	259.13	23.100	0.00260	9.6	78
17	197/68.9	0.05	4	259.13	23.000	0.00259	9.6	78
18	155/54.3	0.04	4	143.02	10.715	0.00473	9.7	78
19	155/54.3	0.04	4	142.73	10.694	0.00463	9.7	78
20	100/25	0.04	3	217.89	18.000	0.00623	10	31
21	76/15.2	0.02	3	81.298	13.354	0.00895	12	36
22	76/15.2	0.02	3	81.136	13.327	0.00876	12	36
23	20/4	0.10	2	118.10	37.664	0.01261	14.5	104
24	20/4	0.10	2	117.755	37.551	0.01199	14.5	104
25	12/2.4	0.02	2	24.411	25.675	0.02649	12	42
26	12/2.4	0.02	2	24.389	25.547	0.02533	12	42

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 3, the maintenance schemes of all objectives are presented. 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. 3, the SFI index for each week is illustrated. The lowest flexibility occurs in weeks of 23-31 and 46-52. According to Fig. 2, 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.

B. Case 2: Flexibility analysis regarding to uncertainties of gas and wind speed

The availability of natural gas for electricity generation depends on the demand for natural gas, which if not considered can disrupt the operation of the power system. In this section the variability of wind speed anad gas uncertainty has been modeled by ARIMA. ARIMA as a time series method is a suitable method for forecasting time based-data. Therefore, the foretasted gas loads and wind speed by ARIMA has been presented in Fig. 4 and Fig. 5, respectively. The historical data for wind speed gas demand are extracted from [28] and [29], respectively. 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

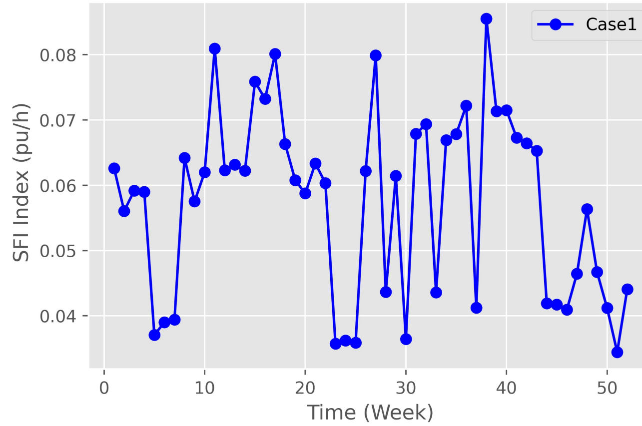


Fig. 3. The flexibility index in Case 1.

energy [29].

In Fig. 6, the SFI index for Case 2 is presented with respect to the natural gas supply limitation and without the natural gas supply limitation. According to Fig. 6, the flexibility index has decreased significantly compared to Case 1, which is due to the modeling of wind power plant production changes. On the other hand, the level of SFI has decreased due to the constraint of gas supplies, which is due to the reduction of the available capacity of gas-fired units. Also, the reduction in the production of gas-fired units has worsened other goals, such as cost, reliability, and the environment of the system compared to Case 1. The maintenance schedule of units is presented in Table 4.

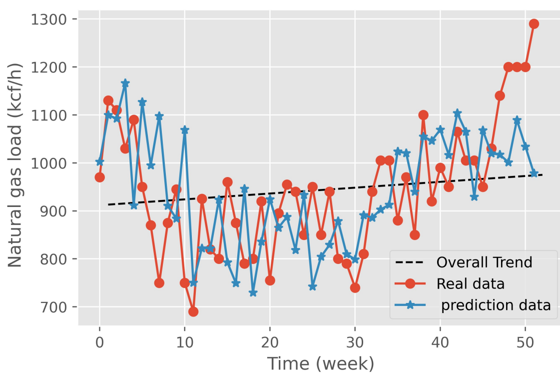
C. Case 3: Flexibility analysis considering DRRs

In this Case, EDR and GDR have been used to reduce the limitations of the gas supply and the variability of wind resources. The results of DRRs in UFGMSDRRs are shown in Fig. 7. Fig. 7a depicts the participation of EDRs of all categories. The participation of each GDR in flexible GMS has been determined in Fig. 7b, According to Fig. 7a, EDR program is implemented throughout the year. But in the weeks when the system peak occurred, participation is more significant. Fig. 7b shows that the participation of the GDR program is greater in the weeks when gas consumption is higher and has limited the production of gas-fired power plants, which can serve as a road-map for power system operators. The flexibility index of all three cases is shown in Fig. 8 for better comparison. In Case 3, implementing EDR and GDR programs have led to reduce the effects of wind farm output changes and gas supply constraints. As a result, it has a favorable acceptance level compared to other cases. The maintenance schedule of units for Case3 is presented in Table 5.

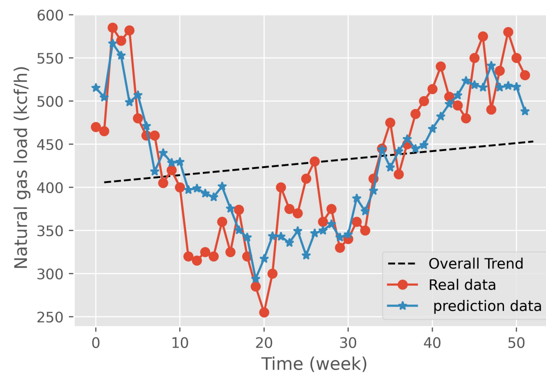
The flexibility, cost, reliability and emission objectives in various cases are compared with each other as shown in Table 6 and Fig. **??**. The flexibility index in case 2 has decreased by about 12.96% compared to case1. The flexibility index in case 3 has improved by about 19.11% compared to case 2, due to the use of DRRs (flexibility resources and 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 DRRs, the level of demand has decreased significantly and the production of fossil fuel power plants has decreased. According to Fig. 9, Case 3 has the best results compared to other cases due to the presence of DRRs.

Table 3. Maintenance scheme results for 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



(a) Load a



(b) Load b

Fig. 4. The forecasted natural gas demand.

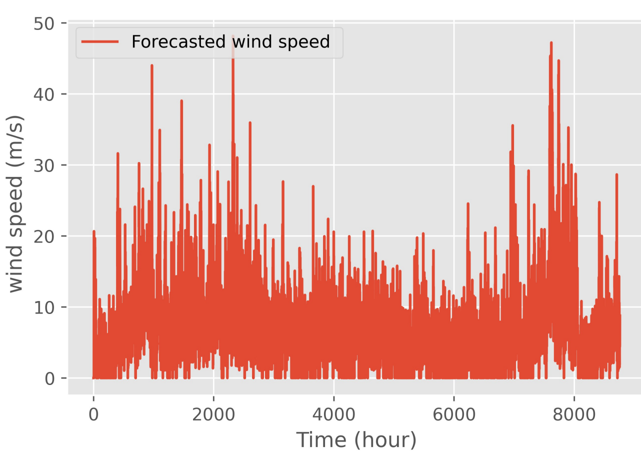


Fig. 5. The forecasted wind speed by ARIMA

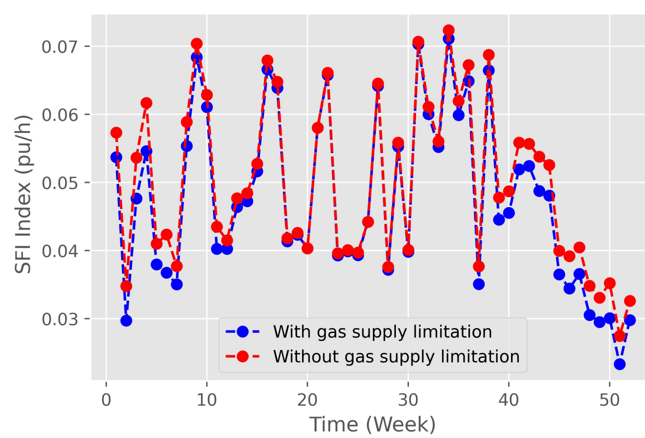
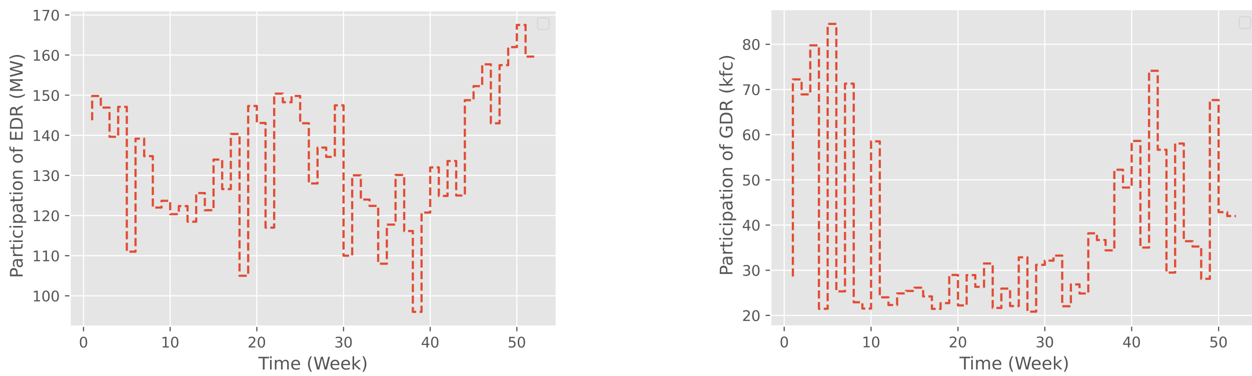


Fig. 6. The flexibility index for a year in case2

Table 4. Maintenance scheme results for Case 2

Unit	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13
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	U14	U15	U16	U17	U18	U19	U20	U21	U22	U23	U24	U25	U26
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



(a) Participation of EDR **(b)** Participation of GDR

Fig. 7. Result of DRRs in UFGMS.

Table 5. Maintenance scheme results for Case 3

Unit	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13
Case 3	33-38	12-16	30-33	4-7	34-37	44-46	13-15	40-42	19-21	31-32	44-45	4-5	33-34
Unit	U14	U15	U16	U17	U18	U19	U20	U21	U22	U23	U24	U25	U26
Case 3	36-37	9-14	22-25	28-31	39-42	6-9	15-17	26-28	10-12	7-8	50-51	5-6	9-10

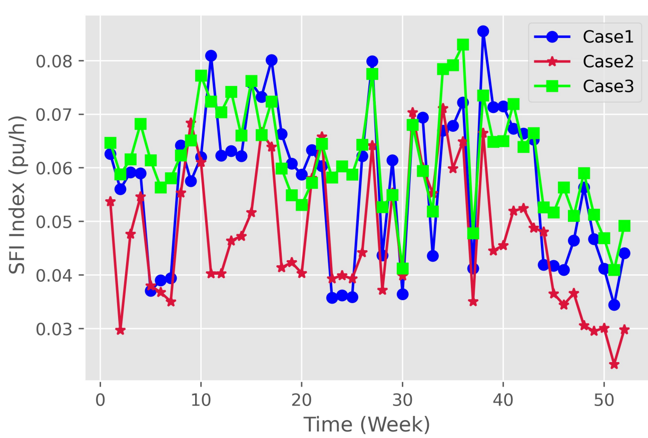


Fig. 8. The flexibility index for all cases.

Table 6. Comparison of different objectives.

	Total emission (Mlbs)	EIR	Average SFI (pu/h)	Total cost (m$)
Case1	123.435	0.9942	0.0571	247.97
Case2	129.712	0.9923	0.0497	275.26
Case3	122.02	0.9951	0.0592	236.67

4. 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 EDR and GDR have been used to mitigate the limitations of the gas supply and the variability of wind resources. The obtained results revealed that extensive presence of wind power plant attenuates the flexibility index. In this paper, it is illustrated that both price-based programs

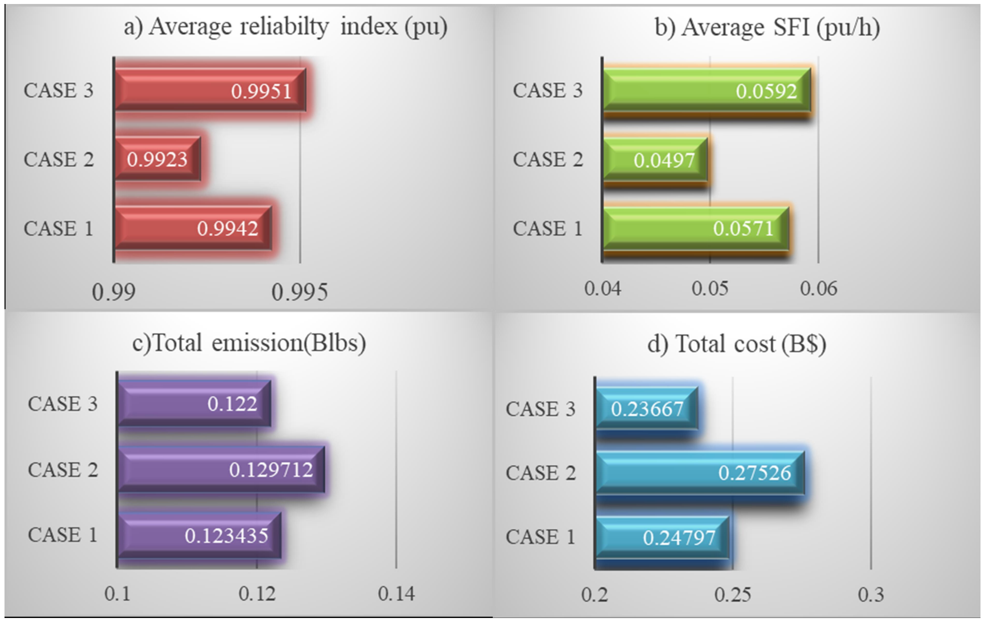


Fig. 9. Comparison of different objectives.

and incentive-based DR programs entail notable benefits to improve techno-economic indices. The level of participation and impact of any type of DRRs on system flexibility can also be an applicable roadmap for investing on demand-side resources in future power system. The results are shown that reliability and flexibility are ameliorate significantly via the DRRs as well as the total cost and emission are reduced. In future research, it should be necessary to consider load and price uncertainties as well as additional constraints to apply the proposed structure on real systems.

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