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Integration of Smart Energy Hubs in Distribution Networks under Uncertainties and Demand Response Concept

Majid Majidi and Kazem Zare [1]

***Abstract*—Multi-energy systems are flexible energy systems that can benefit from energy resources to supply different energy demands. Due to the capabilities of multi-energy systems in generating different energy carriers, these systems have been rapidly expanded in power systems. After restructuring in power system in recent years and appearance of competent energy markets, energy systems operated within such environments have been usually exposed to uncertainties of various parameters such as price, demand and etc. In this paper, a novel optimization framework based on hybrid scenario-based/interval/information gap decision theory (IGDT) method is developed to investigate optimal operation of smart energy hubs (S. E. Hubs) subject to economic priorities, technical constraints of distribution network and uncertainties. Considering energy hubs equipped to smart facilities, demand side management programs (DSMPs) including price response and load response services have been available to motivate electrical consumers to revise their consumption pattern in order to satisfy economic priorities of energy hubs. By using the results of employed hybrid uncertainty modeling approach, the operator of S. E. Hubs can decide either to take risk-averse or risk-seeking strategy against the uncertainties. Uncertainty based integration of S. E. Hubs into distribution network is evaluated regarding the IEEE 33-bus test system and the results obtained from simulations are presented for comparison.**

***Index Terms*— Distribution network, smart energy hubs (S. E. Hubs), hybrid scenario-based/interval/information gap decision theory (IGDT) method, epsilon-constrained method, fuzzy decision making approach, demand side management programs (DSMPs).**

NOMENCLATURE

Indices

t	Index of time
c	Index of S. E. Hubs
i, j	Indices of distribution network buses

Parameters

η_{ge}^{CHP}	Gas to electricity efficiency of CHP units (%)
η^{B}	Efficiency of boiler units (%)
η^{CAC}	Efficiency of central air conditioning (CAC) units (%)
λ_t^{net}	Base hourly price of imported electric power from distribution network ($/MWh)
λ^{gas}	Price of gas ($/MWh)
λ_t^{LS}	Hourly charge of load curtailment ($/MWh)
α	Uncertainty parameter in IGDT
BN	Number of buses
C	Number of S. E. Hubs
CR	Critical cost for robustness function of IGDT
CO	Critical cost for opportunity function of IGDT
$DRP_{\max}$	Limitation of time-of-use (TOU) of DSMPs (%)
$H_{t,c}^{load}$	Hourly thermal load of S. E. Hubs (MW)
$H_{\min,c}^{B}$	Minimum generated heat by boilers (MW)
$H_{\max,c}^{B}$	Maximum generated heat by boilers (MW)
$I_{i,j}^{\max}$	Maximum current flow between the buses i and j (kA)
N_c^{CHP}	Number of CHP units in S. E. Hub c
N_c^{B}	Number of boilers in S. E. Hub c
N_c^{CAC}	Number of CAC units in S. E. Hub c
$P_{i,\min}^{net}$	Minimum active power of i^{th} bus (MW)
$P_{i,\max}^{net}$	Maximum active power of i^{th} bus (MW)
$P_{\min,c}^{CAC}$	Minimum consumed power by CAC units in S. E. Hub c (MW)
$P_{\max,c}^{CAC}$	Maximum consumed power by CAC units in S. E. Hub c (MW)
$P_{t,i}^{load}$	Hourly active load of i^{th} bus (MW)
$P_{t,c}^{load}$	Forecasted hourly electrical load of S. E. Hubs without DSMPs (MW)
$Q_{t,i}^{load}$	Hourly reactive load of i^{th} bus at time t (MVAr)
$S_{i,j}^{\max}$	Maximum power flow between the buses i and j (MVA)
T	Studied time period
U^{Min}	Lower level of uncertain parameter
U^{Max}	Upper level of uncertain parameter
$V_i^{\min}$	Minimum voltage of i^{th} bus (kV)
$V_i^{\max}$	Maximum voltage of i^{th} bus (kV)
$Y_{i,j}$	Admittance value between buses i and j (℧)
$\theta_{i,j}$	Admittance angle between buses i and j (Rad)

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Variables

$B_{t,c}$	Binary variable for load response services of DSMPs
$Cost$	Total operation cost of S. E. Hubs ($)
$f(X,U)$	Objective function of standard optimization problem with considering uncertainty
$f^{M}(X)$	Average cost of S. E. Hubs ($)
$f^{W}(X)$	Deviation cost of S. E. Hubs ($)
$f(X)$	Objective function of standard optimization problem without uncertainty
$f^{+}(X)$	Upper value of objective function of standard optimization problem without uncertainty
$f^{-}(X)$	Lower value of objective function of standard optimization problem without uncertainty
$g(X,U)$	Inequality constraint of standard optimization problem considering uncertainty
G_{t}^{net}	Imported gas by S. E. Hubs at time t (MW)
$G_{t,c}^{CHP}$	Consumed gas by CHP units at time t in S. E. Hub c (MW)
$G_{t,c}^{B}$	Consumed gas by boilers at time t in S. E. Hub c (MW)
$h(X,U)$	Equality constraint of standard optimization problem considering uncertainty
$H_{t,c}^{CHP}$	Generated heat by CHP units at time t in S. E. Hub c (MW)
$H_{t,c}^{B}$	Generated heat by boilers at time t in S. E. Hub c (MW)
$H_{t,c}^{CAC}$	Generated heat by CAC units at time t in S. E. Hub c (MW)
$I_{t,i,j}$	Current flow between the buses i and j at time t (kA)
$\hat{P}_{t,c}^{load}$	Actual hourly electrical load of S. E. Hubs without DSMPs (MW)
$P_{t,i}^{net}$	Injected active power to the substation at time t (MW)
$P_{t,c}^{CAC}$	Consumed power by CAC units at time t in S. E. Hub c (MW)
$P_{t,c}^{CHP}$	Generated power by CHP units at time t in S. E. Hub c (MW)
$P_{t,c}^{net}$	Imported power by S. E. Hubs at time t (MW)
$P_{t,i}^{wind}$	Active power of wind turbine's converter located in the i^{th} bus at time t (MW)
$P_{t,i}^{PV}$	Active power of photovoltaic system's (PV) converter located in the i^{th} bus at time t (MW)
$P_{t,c}^{load,DSM}$	Hourly electrical load of S. E. Hubs with DSMPs (MW)
$P_{t,c}^{LS}$	Curtailed load at time t in S. E. Hub c (MW)
$P_{t,c}^{ch}$	Charge power of battery storage at time t in S. E. Hub c (MW)
$P_{t,c}^{dis}$	Discharge power of battery storage at time t in S. E. Hub c (MW)
$V_{t,i}$	Voltage of i^{th} bus at time t (kV)
$V_{t,j}$	Voltage of j^{th} bus at time t (kV)
$Q_{t,i}^{net}$	Injected reactive power to the substation at time t (MVAr)
$Q_{t,i}^{wind}$	Reactive power of wind turbine's converter located in the i^{th} bus at time t (MVAr)
$Q_{t,i}^{PV}$	Reactive power of PV's converter located in the i^{th} bus at time t (MVAr)
$S_{t,i,j}$	Power flow between the buses i and j (MVA)
$S_{t,i}^{PV}$	Apparent power of PV's converter located in the i^{th} bus at time t (MVA)
$S_{t,i}^{wind}$	Apparent power of wind turbine's converter located in the i^{th} bus at time t (MVA)
TOU_{t}	Increased/decreased power in TOU of DSMPs at time t (MW)
U	Uncertain parameter in the standard optimization problem
$Z_{t,c}^{LS}$	Limitation of curtailed load in load response program at time t in S. E. Hub c (MW)
$\delta_{t,i}$	Voltage angle of i^{th} bus at time t (Rad)
$\delta_{t,j}$	Voltage angle of j^{th} bus at time t (Rad)

Functions

$\hat{\alpha}(C_{r})$	Robustness function of IGDT
$\hat{\beta}(C_{o})$	Opportunity function of IGDT

I. Introduction

Distribution networks can be challenged by various factors such as overload, energy losses and uncertainties. These issues can be handled by integration of local generation units into such networks. In this regard, the role of multi-energy systems can be important. Multi-energy systems or so called hub energies are energy systems equipped to electrical and gas networks to supply different types of energy demands. Integration of such flexible and efficient generation units can ensure economic and uncertainty-based performance of energy systems against the available challenges and issues.

Hub energy systems can benefit from higher flexibilities to interact with energy networks to satisfy demands in different levels [1]. This can leads to different models and concepts [2, 3] that can be designed for different applications. For instance, the energy management model based on hub energy concept has been proposed for industrial consumers equipped to communication facilities in [4] to satisfy their energy demands with respect to economic priorities. In another example, these systems have been integrated in neighborhood scales to supply building's energy demand with respect to technical barriers and available regulation [5]. Capable of coupling different types of energy carriers, these systems can provide demand management services for the corresponding end-users like integrated demand response [6]. The model introduced in [7, 8] enables each energy system to optimize its energy consumption while interacting with other energy systems. Different types of technologies used in these energy systems such as low carbon energy systems [9] including combined heat and power (CHP) systems, heat pumps [10, 11], electric vehicles [12], renewable generation units [10] and energy storage systems [13, 14] can provide a sensible condition for integrating different energy networks into each other to meet different energy demands [15, 16]. The low carbon technologies allows the operator of multi-carrier energy systems to consider environmental friendly decisions [17, 18]. Also, flexibilities of such mentioned local generation units can help the operators of distribution networks

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to configure the statues of lines and loads to achieve the desired performance [19] like improved voltage level or optimal power procurement plan. In addition to the grid-connected mode, these systems can also operate in islanded mode for specific purposes. As explored in [20, 21], local generation units within hub energy systems including electrical and thermal ones have the potential to meet energy demands without any need to the upstream network in remote areas. In fact, the presence of different energy resources allows different operating strategies to be applied in different operating conditions [22].

With more emphasize on energy flows within energy networks in hub systems, several researches have been carried out about design and modeling of linkages in these systems. For instance, district heating network and the influence of its optimization on the performance of multi-carrier energy system has been studied in [23]. Also, optimal energy flow between several inter-connected hub energy systems has been optimized while variable efficiencies have been taken into account in [24]. In another study, the energy flows within hub energy system linked to both electrical and heat networks have been modeled in [25]. With respect to different energy flows in multi-carrier energy systems, optimal power flow of such energy systems is a complicated, nonlinear and non-convex problem. In order to handle such problems, different solutions have been innovated such as time varying acceleration coefficient- gravitational search algorithm [26] and mixed-integer linear programming [27-29] to convert such non-convex problems into linear problems to enhance flexibility and performance of system.

In order to ensure reliable operation of energy systems against the fluctuating behavior of input data and parameters, the uncertainty modeling is necessary [30]. For instance, one of uncertainty sources is the generation of renewable energy systems like PV units. In order to model the uncertainty of PV generation in a multi-carrier energy system in the presence of electric vehicles, two-point estimate method has been utilized in [31]. The other input data and info that may have fluctuating performance are demand and price which can belong to different sectors. The uncertainty-based optimal operation of multi-carrier energy system is studied under price and demand uncertainties in [32]. Also, the optimal operation of multi-carrier energy system is analyzed in [33] considering the uncertainties of wind generation and demand. The stochastic programming has been used in [34] to model the uncertainties of market price, demand and generation of wind unit in a multi-carrier energy system in which thermal energy market has been developed to enhance the performance of system in both deterministic and probabilistic operation modes.

In this paper, optimal integration of S. E. Hubs into distribution system is studied subject to economic priorities, technical constraints and simultaneous uncertainties through a mixed-integer non-linear programming (MINLP). The electricity consumers of energy hubs can participate in DSMPs. These consumers can either shift or reduce their electric consumption to flatten their consumption pattern and gain economic benefits. In this paper, uncertainty-based economic performance of S. E. Hubs is investigated under uncertainties of renewable units, electricity price and load through a hybrid uncertainty modeling approach with considering technical limitations of distribution network and energy hubs. Using stochastic programming for modeling the uncertainty of renewable units, the interval optimization method and IGDT are employed to model the uncertainties of price and electrical demand at the same time. By combining these methods, the operator can benefit from all available options to assess the optimal performance of operating hubs against uncertainties. So, the novelties and contributions of this paper can be expressed as following:

- S. E. Hubs are economically integrated into distribution network under technical constraints.
- Simultaneous uncertainties of price, load and renewable units are modeled through the hybrid interval/IGDT/scenario-based method.
- Economic operation and uncertainty-based performance of S. E. Hubs are strengthened under DSMPs.

Remained sections of this paper are categorized as follows: the mathematical presentation of studied model is addressed in Section II. Scenario-based method as well as IGDT and interval approach are explained in Section III. Case studies and results are presented in Section IV. Finally, this paper is concluded in Section V.

II. Problem Formulation

In this section, optimal uncertainty-based integration of S. E. Hubs into distribution network is formulated under DSMPs.

A. Objective function

Total cost of purchased energies as well as discomfort cost of electrical consumers whose loads are curtailed in DSMPs should be minimized as the objective function as:

$$Cost = \sum_{t}^{T} \left[\sum_{c=1}^{C} \left(\left(\lambda_t^{net} \times P_{t,c}^{net} \right) + \left(\lambda_t^{LS} \times P_{t,c}^{LS} \right) \right) + \left(\lambda^{gas} \times G_t^{net} \right) \right] \quad (1)$$

B. Distribution network constraints

Active and reactive power balance limitations of electric distribution system should be satisfied as follows [35]:

$$P_{t,i}^{net} + P_{t,i}^{wind} + P_{t,i}^{PV} - P_{t,i}^{load} = \sum_{j \in BN} V_{t,i} V_{t,j} Y_{i,j} \cos(\theta_{i,j} - \delta_{t,j} - \delta_{t,i}) \quad (2)$$

$$Q_{t,i}^{net} + Q_{t,i}^{wind} + Q_{t,i}^{PV} - Q_{t,i}^{load} = -\sum_{j \in BN} V_{t,i} V_{t,j} Y_{i,j} \sin(\theta_{i,j} - \delta_{t,j} - \delta_{t,i}) \quad (3)$$

The current flow in the lines in distribution system should be within the rated values as:

$$0 \le I_{t,i,j} \le I_{i,j}^{\max} \quad (4)$$

The power flow within the lines is limited as follows:

$$0 \le S_{t,i,j} \le S_{i,j}^{\max} \quad (5)$$

As a basic rule in each distribution network, voltage of each bus should be within the predefined rated ranges as:

$$V_{t,i}^{\min} \le V_{t,i} \le V_{t,i}^{\max} \quad (6)$$

Also, total injected power to the substation of distribution network should be within the predefined values as:

$$P_{i,\min}^{net} \le P_{t,i}^{net} \le P_{i,\max}^{net} \quad (7)$$

C. Renewable generation units

Renewable generation units including PV systems and wind turbines are integrated into distribution network to satisfy active and reactive energy demands. The mathematical model of PV system is adopted from [36]. The reactive power received from converter of PV system can be calculated as:

$$S_{t,i}^{PV} = P_{t,i}^{PV} + Q_{t,i}^{PV} \quad (8)$$

Also, the model of wind units is adopted from [37]. The reactive power received from the converter of wind unit can be computed as:

$$S_{t,i}^{wind} = P_{t,i}^{wind} + Q_{t,i}^{wind} \tag{9}$$

It is noteworthy that the output powers of PV systems and wind units are expected values of these units which have been calculated based on scenario-based method.

D. Smart energy hubs (S. E. Hubs)

Concept of smart energy systems was first introduced to optimally coordinate smart electricity grid and gas network, storage technologies and local generation units to obtain an optimal operational solution for available sectors [38-41]. In this paper, 4 S. E. Hubs connected to both electrical and gas networks are operated to satisfy 4 local electrical and thermal energy demands. S. E. Hubs are divided into two groups. S. E. Hubs type 1 covering energy hubs 1 and 4 and S. E. Hubs type 2 covering energy hubs 2 and 3. Both S. E. Hubs are respectively depicted in Figs. 1-2. It should be noted that energy hubs 1, 2, 3 and 4 are connected to the buses 8, 13, 16 and 33, respectively [19].

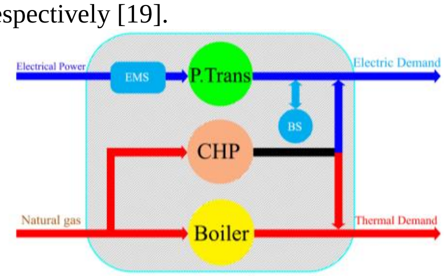

Fig. 1. S. E. Hubs type 1

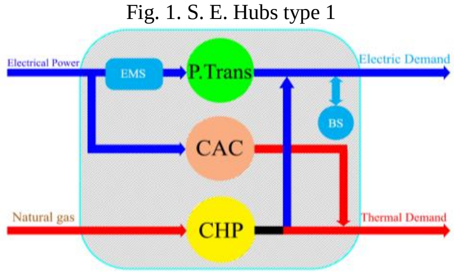

Fig. 2. S. E. Hubs type 2

Electrical demand balance limitation of S. E. Hubs type 1 is presented as:

$$P_{t,c}^{load,DSM} + P_{t,c}^{ch} = P_{t,c}^{net} + P_{t,c}^{CHP} + P_{t,c}^{dis} \tag{10}$$

Local thermal demand of S. E. Hubs type 1 should be supplied through the generated heat by CHP units and boilers:

$$H_{t,c}^{load} = H_{t,c}^{CHP} + H_{t,c}^{B} \tag{11}$$

Generated heat by boiler units is limited as:

$$H_{\min,c}^{B} \le H_{t,c}^{B} \le H_{\max,c}^{B} \tag{12}$$

Consumed gases by CHP units and boilers are respectively expressed in the following:

$$G_{t,c}^{CHP} = (N_c^{CHP} \times P_{t,c}^{CHP}) / \eta_{ge}^{CHP} \tag{13}$$

$$G_{t,c}^{B} = (N_c^{B} \times H_{t,c}^{B}) / \eta^{B} \tag{14}$$

Total consumed gas by the S. E. Hubs type 1 is calculated as:

$$G_{t,c}^{net} = G_{t,c}^{CHP} + G_{t,c}^{B} \quad \forall \ c = 1,4 \tag{15}$$

Electrical demand of S. E. Hubs type 2 should be satisfied through the generation of CHP units, battery storage and purchased power from upstream distribution network as:

$$P_{t,c}^{load,DSM} + P_{t,c}^{ch} = P_{t,c}^{net} + P_{t,c}^{CHP} - P_{t,c}^{CAC} + P_{t,c}^{dis} \tag{16}$$

Thermal load of S. E. Hubs type 2 is supplied through the generated heats by CHP systems and CAC units as:

$$H_{t,c}^{load} = H_{t,c}^{CHP} + H_{t,c}^{CAC} \tag{17}$$

The heat generated by CAC units is expressed as:

$$H_{t,c}^{CAC} = N_c^{CAC} \times P_{t,c}^{CAC} \times \eta^{CAC} \tag{18}$$

The consumed electric power by CAC units is limited as:

$$P_{\min,c}^{CAC} \le P_{t,c}^{CAC} \le P_{\max,c}^{CAC} \tag{19}$$

Gas consumption of CHP units in S. E. Hubs type 2 is calculated as:

$$G_{t,c}^{CHP} = (N_c^{CHP} \times P_{t,c}^{CHP}) / \eta_{ge}^{CHP} \tag{20}$$

Total consumed gas by S. E. Hubs type 2 is expressed as:

$$G_{t,c}^{net} = G_{t,c}^{CHP} \quad \forall \ c = 2,3 \tag{21}$$

Electrical generation and heat production of CHP units employed in S. E. Hubs are dependent to each other. Feasible region of mentioned CHP units is depicted in Fig. 3 [37]. Also, the linear model of these units is taken from [37].

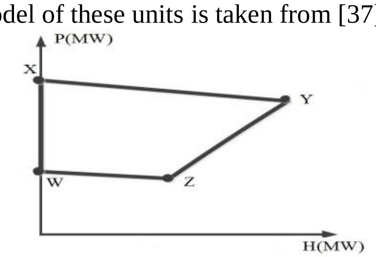

Fig. 3. Feasible region of CHP units

Considering the flexibility of S. E. Hubs, battery storage systems have been utilized to enhance performance of operating system. Model of storages is taken from [37].

E. Demand side management programs (DSMPs)

Recently, due to the significant improvements in the technologies used in power systems, in order to gain economic benefits, system operators can participate in demand side management programs like price response and load response programs. In this paper, shiftable loads as well as curtailable loads can participate in the mentioned programs.

1) Price response program

According to the price response program, the consumers are motivated to shift their electrical consumption from peak periods to off-peak periods. It is noteworthy that this program is assumed to be offered to the energy hubs 1 and 2. This program can be modeled as follows [42]:

$$P_{t,c}^{load,DSM} = P_{t,c}^{load} + TOU_t \quad \forall \ c = 1,2 \tag{22}$$

$$\left| TOU_t \right| \le DRP_{\max} \times P_{t,c}^{load} \tag{23}$$

$$\sum_{t=1}^{T} TOU_t = 0 \tag{24}$$

2) Load response program

In this program, the operator is allowed to curtail the load in some periods, preferably peak periods, to reduce the peak load. However, the operator should pay the consumers for the mentioned curtailment. This payment is appeared in the objective function as the discomfort cost of consumers. It is noteworthy that this program is offered to the energy hubs 3 and 4. This program can be modeled as follows [43]:

$$P_{t,c}^{load,DSM} = P_{t,c}^{load} - P_{t,c}^{LS} \quad \forall \ c = 3,4 \tag{25}$$

$$0 \le P_{t,c}^{LS} \le B_{t,c} \times Z_{t,c}^{LS} \tag{26}$$

III. UNCERTAINTY MODELING

1) Scenario-based method

In order to model the uncertainties of PV systems and wind units, Monte Carlo method is used to generate large number of scenarios. Using the scenario reduction method introduced in [44], the number of scenarios is reduced to 10. Then, the expected values of uncertain parameters are calculated and utilized in IGDT and Interval method. Probabilities of reduced scenarios are presented in Table I.

TABLE I
REDUCED SCENARIOS

Scenarios	Probability	Scenarios	Probability
S1	0.17	S6	0.14
S2	0.06	S7	0.07
S3	0.02	S8	0.20
S4	0.09	S9	0.08
S5	0.12	S10	0.05

2) Information gap decision theory (IGDT)

IGDT was firstly introduced by Yakov Ben-Haim [45]. The main feature of IGDT is that it doesn't need much data for uncertainty modeling. It benefits from two immunity functions namely robustness and opportunity functions to inform the operator about the negative and positive results of uncertainty [46]. Using these info, the operator can take the appropriate decisions against uncertainty. In this paper, the uncertainty of load is modeled by IGDT and the worst and the best possible conditions for load uncertainty are determined. Then the interval approach is applied to model the price uncertainty under the determined conditions. The robustness function of IGDT is modeled as:

$$\hat{\alpha}(CR) = Max\,\alpha \tag{27}$$

$s.t.$

$$Max\,\{Cost\} \le CR \tag{28}$$

$$\hat{P}_{t,c}^{load} \le (1+\alpha)P_{t,c}^{load} \tag{29}$$

$$Eqs.\ (1)\text{-}(26) \tag{30}$$

Also, the opportunity function is modeled as:

$$\hat{\beta}(CO) = Min\,\alpha \tag{31}$$

$s.t.$

$$Min\,\{Cost\} \le CO \tag{32}$$

$$\hat{P}_{t,c}^{load} \le (1-\alpha)P_{t,c}^{load} \tag{33}$$

$$Eqs.\ (1)\text{-}(26) \tag{34}$$

It is noteworthy that α (Alfa) is usually defined to be β (Beta) in the opportunity function for more clarification.

3) Interval optimization method

This approach was firstly introduced by Moore [47]. The upper and lower bonds of uncertain parameter are the only necessary info for uncertainty modeling in this approach. In this method, interval numbers are used to model the uncertainty [48]. This is while exact information of probability distribution is not required. In fact, using interval optimization method, uncertainty-based problem is converted into a deterministic multi-objective problem which can be easily solved by ε-constraint technique and fuzzy decision making algorithm.

For more clarification, a simple optimization problem is expressed in the following in which the objective function should be minimized subject to equal and unequal limitations and uncertainty of parameter U .

$$Min\ f(X,U) \tag{35}$$

$s.t.$

$$g(X,U) = 0 \tag{36}$$

$$h(X,U) \le 0 \tag{37}$$

According to this method, the uncertain parameter is expressed as an interval with upper and lower values equal to U^{Max} and U^{Min}, respectively. Then, the whole uncertainty limitations as well as uncertain objective function are converted into deterministic constraints and objective function including upper and lower values. The upper and lower values of objective function can be respectively calculated as:

$$f^{+}(X) = \max f(X) \tag{38}$$

$$f^{-}(X) = \min f(X) \tag{39}$$

Using the obtained upper and lower values, the average $(f^{M}(X))$ and deviation $(f^{W}(X))$ values can be calculated as:

$$f^{M}(X) = \left(f^{+}(X) + f^{-}(X)\right)/2 \tag{40}$$

$$f^{W}(X) = \left(f^{+}(X) - f^{-}(X)\right)/2 \tag{41}$$

According to interval method, the desired optimal value of objective function is expressed by $f^{M}(X)$ and the uncertainty level of objective function is expressed by $f^{M}(X)$. Both of these values should be minimized to reach the best possible economic performance and mitigate the impact of uncertainty. Since optimization of each one of mentioned values leads to degradation of other one, therefore, a trade-off solution satisfying both conflicting values should be determined. To do this, multi-objective optimization model can be employed. So, the deterministic objective function which should be minimized can be expressed as:

$$Min\ f(X) = Min\left(f^{M}(X) \quad f^{W}(X)\right) \tag{42}$$

In order to solve the multi-objective optimization problem, ε-constraint technique is employed and fuzzy decision making algorithm is used to select the trade-off solution between average and deviation costs of S. E. Hubs. These methods are explained step by step in [42].

For more clarification, flowchart of employed hybrid technique is presented step by step in Fig. 4.

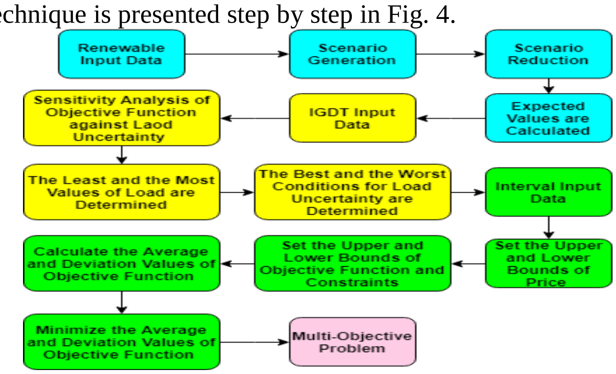

Fig. 4. Uncertainty modeling method

IV. NUMERICAL STUDY

In this section, optimal uncertainty-based integration of S. E. Hubs in an IEEE 33-bus distribution network under uncertainties of renewable generation units, load and upstream network price is simulated in the presence of DSMPs and the corresponding results are presented for comparison.

A. Input data

Data and info about prices, operation costs and technical constraints of battery storage systems as well as local units inducing CHP units, boiler units and CAC systems are taken from [19, 34 and 37] and the necessary data and info of IEEE test system are adopted from [49]. It is noteworthy that the upstream distribution network price is set to be variable within 0.80 and 1.20 of its nominal value. General algebraic modeling system (GAMS) is utilized to solve the studied model under MINLP. It is noteworthy that the scheduling process is considered to be done for a 24-hour time period.

B. Results

1) Deterministic scheduling results

In this case, optimal integration of S. E. Hubs into distribution network is studied without considering uncertainties. Considering/ignoring the participation of electrical demands in DSMPs, the economic results are obtained which are summarized in Table II. According to this Table, the economic performance of S. E. Hubs is enhanced under DSMPs.

2) Uncertainty-based scheduling results

In this case, S. E. Hubs are integrated into distribution networks under uncertainties of renewable generation units, upstream distribution network price and load. Using the IGDT, the most sustainable value of load is determined with and without DSMPs which is 1.069 and 1.0812 of base value, respectively. On the other hand, the least value of load is 0.929 and 0.849 of base value without and with DSMPs, respectively. These values are determined by the Alfa and Beta variables of IGDT which values are presented in Table II. In the next step, by applying interval method, the Pareto solutions are obtained in different cases which are depicted in Figs. 5-6.

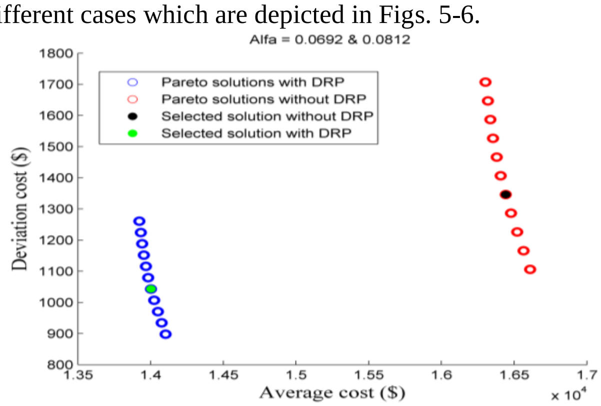

Fig. 5. Pareto solutions in the interval case with the max Alfa

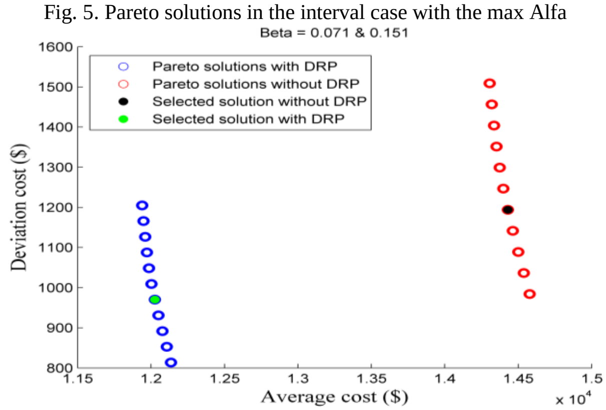

Fig. 6. Pareto solutions in the interval case with the min Beta

By using fuzzy decision making algorithm, the trade-off solutions are selected in different cases which are presented in Table II. According to the selected solutions in the interval method with the maximum Alfa, in order to tackle the uncertainties impact, the operation cost of S. E. Hubs is increased in both without/with DSMPs. Comparing these values with the results of deterministic case, it can be concluded that the increase rate of operation cost under DSMPs is less that the case in which DSMPs are ignored. In other words, the economic performance of S. E. Hubs under uncertainties is enhanced via DSMPs.

On the other hand, according to the selected solutions in the interval method with the minimum Beta, it can be seen that uncertainties are handled while the operation cost of S. E. Hubs is reduced in both without/with DSMPs. In fact, by taking risk-seeking strategy against the uncertainty of load, operator of S. E. Hubs can tackle price uncertainty while gaining economic benefit. In other words, the operator can overcome to the negative impact of uncertainties through taking risk-seeking decisions. Alike the former case, it can be seen from Table II that under DSMPs, the economic goals within uncertainties in the interval method with the minimum Beta are satisfied more in comparison with the case that DSMPs are not considered.

TABLE II
COMPARISON RESULTS

Case studies		Operation cost ($)	Deviation cost ($)	Alfa (%)	Beta (%)
Deterministic	No DSM	15375.636	1613.341	-	-
	With DSM	12995.069	1181.234	-	-
Interval with the most Alfa	No DSM	16441.415	1346.408	6.9	-
	With DSM	14002.234	1043.150	8.12	-
Interval with the least Beta	No DSM	14429.276	1194.078	-	7.1
	With DSM	12025.805	970.288	-	15.1

As a result of obtained solutions, the imported power and gas from upstream distribution and gas networks in different cases are illustrated in Figs. 7 and 8, respectively.

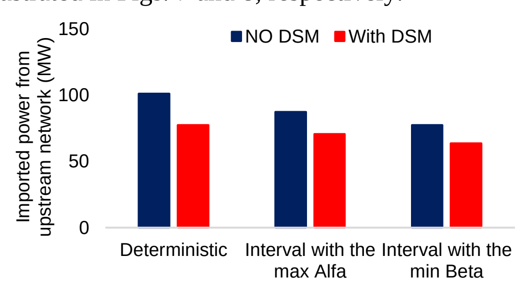

Fig. 7. Imported power from upstream distribution network

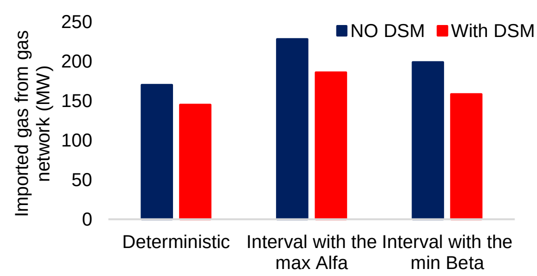

Fig. 8. Imported gas from gas network

According to Fig. 7, in order to mitigate the negative impact of price uncertainty in the interval cases (uncertain price with the max Alfa/min Beta), the imported power is reduced in comparison with deterministic case. It should be noted that by taking risk-seeking strategy against the uncertainty of load which is determined by the opportunity function of IGDT, the reduction of purchased power becomes more sensible. On the other hand, in order to make up the reduction in the imported power in the interval cases, imported gas from gas network is increased. As depicted in Fig. 8, by taking risk-seeking strategy against the load uncertainty, imported gas is increased less in comparison with the case that risk-averse strategy is taken. It is noteworthy that due to flexible nature of hub energy systems, the shares of electricity and gas networks in supplying demand are optimally adjusted under DSM programs to gain the maximum possible economic benefit.

Considering these results, total produced power by CHP units in different cases is depicted in Fig. 9.

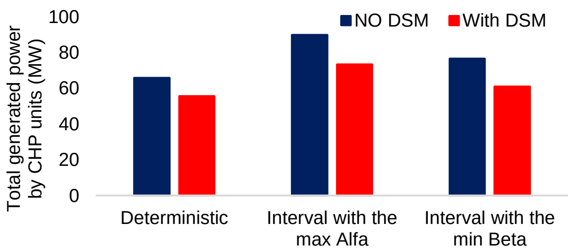

Fig. 9. Total generated power by CHP units

As a result of reduction of distribution network power in the interval cases, generated power by CHP units in these cases is increased to supply demands. By taking risk-averse strategy, the possible negative consequences of load uncertainty are taken into account and therefore total generated power by CHP units is increased more in comparison with the case that risk-seeking strategy is taken. Also, due to the available uncertainties in the electrical sectors, total consumed power by CAC units in the interval cases is reduced and therefore generated heat by CAC units in these cases is reduced which is depicted in Fig. 10.

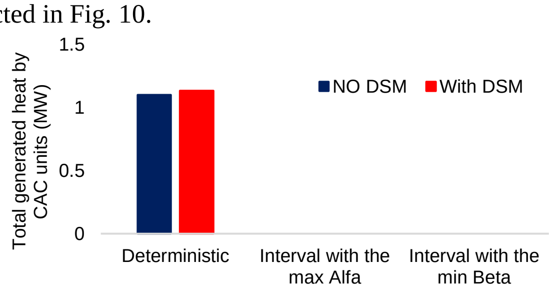

Fig. 10. Total generated heat by CAC units

With respect to these results, total generated heat by CHP units in different cases can is depicted in Fig. 11.

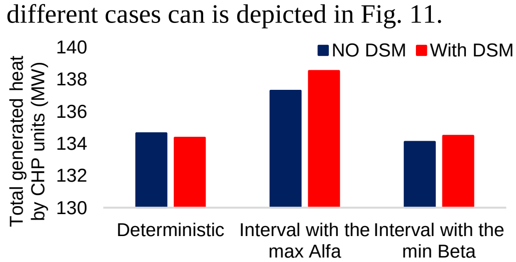

Fig. 11. Total generated heat by CHP units

V. Conclusion

In this paper, uncertainty-based optimal integration of S. E. Hubs into distribution network is investigated under DSMPs. Optimal integration of S. E. Hubs into distribution network under load response and price response programs is studied as a MINLP while the uncertainties of distribution network price, renewable units and local energy demands of S. E. Hubs are modeled through a hybrid interval/scenario-based/IGDT method. Calculating the expected values of generation of PV units and wind turbines, the maximum and minimum possible values of local loads are determined using robustness and opportunity functions of IGDT. Then, interval optimization method is applied to model the uncertainty of price with respect to the results of IGDT. Solving the multi-objective optimization problem resulted by interval method through epsilon-constrained method, optimal Pareto solutions are obtained for different cases. According to the selected trade-off solutions by fuzzy decision making algorithm, it can be seen that by taking risk-averse strategy against the uncertainties, total operation cost of S. E. Hubs is increased to tackle the mentioned uncertainties. According to the results, the robustness level of S. E. Hubs against uncertainties is strengthened under DSMPs. On the other hand, when the operator of S. E. Hubs takes risk-seeking strategy, uncertainties are handled while total operation cost of S. E. Hubs is reduced. In fact, negative economic impacts of uncertainties are mitigated through the taken risk-seeking decisions. It should be noted that alike the risk-averse operation mode, economic performance of S. E. Hubs within uncertainties is improved under DSMPs.

So, by analyzing the obtained results it can be concluded that by taking the provided appropriate strategies by the developed hybrid method under DSMPs through MINLP: 1) S. E. Hubs can be optimally integrated into energy networks under available technical constraints 2) Economic priorities can be satisfied 3) Negative impacts of uncertainties can be mitigated as much as possible.

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