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Flexibility-Based Congestion Management Considering Consumers' Inconvenience Cost of Demand Response Programs

V. Rahi[1], A. Abdollahi[1,], E. Heydarian-Forushani[2], M. Rashidinejad[1,3], A. Sheikhi Fini[4]*

[1] *Department of Electrical Engineering, Shahid Bahonar University of Kerman, Kerman, Iran*
[2] *Department of Electrical and Computer Engineering, Qom University of Technology, Qom, Iran*
[3] *Department of Electrical and Computer Engineering, Queen's University, Kingston, Canada*
[4] *Power System Planning and Operation Research Department, Niroo Research Institute, Tehran, Iran*

Abstract— *One of the most important challenges of smart grids is the congestion of transmission lines. A flexible smart grid with demand-side resources can be a suitable solution to manage transmission lines congestion. This paper proposes a multi-objective model with the aim of congestion management through generation rescheduling considering cost and emission purposes in a flexible smart grid. An inconvenience cost for consumers is defined to model the consumers' unsatisfactory as a consequence of participating in demand response programs (DRPs). Furthermore, a smart grid flexibility index (SGFI) has been presented to show the available flexibility of smart grid as a result of DRPs and gas turbine generators as fast response resources. The DRPs could increase the flexibility of the smart grids due to their impact on flattening the load curve, but this may cause some inconveniences for consumers. On the other hand, participation of consumers in DRPs and the power output gas turbine are associated with uncertainty. In this paper, the uncertainty of consumer's participation in the DRPs has been modeled by Fuzzy-Markov. The proposed multi-objective particle swarm optimization (MOPSO) has been implemented on the IEEE 30-bus system. The results show that the total operation cost including the generation cost, DRP cost, inconvenience cost of consumers, and pollution is reduced. In fact, the share of generation of expensive generators is reduced.*

Keywords—Congestion management, Consumer's unsatisfactory, Demand response programs (DRP), Generation rescheduling, Smart grid flexibility index (SGFI).

NOMENCLATURE

Abbreviations

DR	Demand response
DSM	Demand-side management
EE	Energy efficiency
ISO	Independent system operator
$MOPSO$	Multi-objective particle swarm optimization

Parameters

$(\alpha_p, \beta_p, \gamma_p)$	Coefficients of mth generators pollution
(a_p, b_p, c_p)	Generator cost coefficients
$\mu f_\alpha(par_\beta)$	Membership function for -th objective function
ρ, ρ_0	Electricity prices before and after the implementation of the DRP
N_b	Number of buses
N_g	Number of generators
N_L	Number of load buses
N_{br}	Number of transmission lines
N_{dr}	Number of responsive loads
$N_{g,s}$	Generation of gas turbine g in scenario s
N_{gas}	Number of gas turbines
N_{obj}	Number of objective functions
N_{par}	Number of optimization parameters
P_{Dq}	Active power demand of the bus q
$P_{g,s}^{max}, P_{g,s}^{min}$	Lower and upper bounds of active power of gas turbine g
P_{Gp}	The total penalty for d-th responsive demand
P_{Gp}^{max}	High limit of transmission power of generators of unit p
P_{Gp}^{min}	Low limit of transmission power of unit generators p
pen	The penalty factor
pen_d	The total penalty for d-th responsive demand
$Q_{Gp}^{max}, Q_{Gp}^{min}$	High and low limit of reactive power of unit generators p
V_{Gp}^{max}	Upper limits of voltage magnitude of the PV bus p
V_{Gp}^{min}	Lower limits of voltage magnitude of the PV bus p
V_{LN}	Voltage magnitude at the load bus N
W_α	Weighting coefficient of the α-th objective function

Sets

h	Index for hours
s	Index for scenarios
$SGFI$	Smart grid flexibility index

Variables

ΔT_d	Reduction in the responsive bus d
B	Profit in scenario s
B^T	The vector of control variables
$bpar_\beta$	The best solution for the β-th particle
cp_β	cumulative probability

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*Corresponding author:
E-mail: a.abdollahi@uk.ac.ir (A. Abdollahi)
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d_m, d_{0m}	The amount of load before and after the implementation of the DRP
E	Load sensitivity
Enc_d	Total incentives paid to the bus participating in the demand response
$gpar$	The best position for all particles
INC_d	Inconvenience of bus b to participate in the DRP
LR_d	The amount of load reduction requested by ISO
N_{rep}	The number of solutions available in the repository
$par_\beta(t)$	The location of particle β in time t
S_{LN}	apparent power flow of the transmission line n
$vel_\beta(t)$	Particle velocity β in time t

1. Introduction

Congestion management is one of the most important parts of electrical system performance in today's electricity markets. In this way, the congestion of transmission lines is reduced, leading to an increase in the security margin of the system and a reduction in power outages and equipment outages .The electricity industry in many countries is changing from a Vertically Integrated Power Systems to a competitive market [1]. This is in order to increase the demand for electricity at a reasonable price and cause possible problems such as congestion in the transmission lines of deregulated power plants [2]. Congestion refers to the overloading of transmission lines when the thermal bounds and line capacities are violated [3]. Congestion also occurs when power flow in the transmission lines is higher than the flow allowed by operational reliability limits [4]. The physical and systemic constraints of transmission networks are mentioned as one of the essential factors causing congestion in the transmission lines [5]. The physical constraints such as thermal restrictions of transmission lines or transformers can be effective in creating congestion. Node voltage limitations, transient stability, dynamic stability, and reliability constraints are some examples of transmission network limitations that have contributed to network congestion [6]. Congestion in power systems must be corrected immediately to ensure system security and prevent further failures. In the event of repeated system failures, congestion also occurs due to serious damage to power system components. It is not only the equipment that suffers from congestion, but also the quality of power supply [7]. The traditional solution is to construct new transmission lines that is not logical due to economic reasons. One of the methods for congestion management is to take advantage of nodal pricing basically, nodal pricing is a method of determining prices in which market clearing prices are calculated for a number of locations in the transmission network. Nodes Each node represents a physical location in the transmission system including generators and loads. [8]. In this type of pricing, the independent system operator (ISO) is able to inject electricity at one point and receives electricity from another point to eliminate congestion [9]. The pricing mechanism is one of the most important concepts of the electricity market. There are three categories of pricing mechanism: uniform marginal pricing, regional marginal pricing, and nodal marginal pricing [10]. In the regional marginal pricing method, if there is a network partitioning congestion, the network is divided into several regions. By implementing regional marginal pricing, effective price signals are provided under the assumption of accurate segmentation [11]. Areas are formed so that the possibility of congestion inside the area be low or and the probability of congestion between the areas be high [12]. A two-level optimization problem with the bidding strategy betterment approach is used in the problem of congestion management [13]. The problem of congestion management today is considered as a nonlinear problem with several constraints. To solve such problems, today use optimization algorithms such as genetics, particle swarm optimization (PSO), etc. [14–16]. In [15] This paper proposes a new structure for peak load in summer days. Two sub-services including solar Stirling engine and diesel power plant are considered to reduce consecutive network outages. this paper designs a new cooling, power and pure water production system for application in this region to alleviate the energy and water crisis [16]. In [17], the firefly algorithm is used to optimize the congestion problem. The proposed algorithm uses the pool-based electricity market based on rescheduling of active generators to reduce congestion. In [18], Congestion of transmission lines creates an obstacle that limits the most economical supply to meet the demand. In this work, the optimal capacities of distributed generation units (DG) are considered to relieve congestion in the transmission lines of the power system [19, 20]. The utilization of FACTS devices facilitates control of line flows with generation scheduling which could lead to system loss and cost reduction. Another method used in congestion management is generation rescheduling [21, 22]. In [23], a method for generation rescheduling and load reduction with voltage-dependent modeling is proposed. This paper takes into account the objectives such as reducing generation costs, reducing load and maximizing social welfare. In [24], in order to eliminate transmission congestion, an effective technique such as generation rescheduling is used so that a hydropower plant has been allocated within the network. It is noteworthy that, bus sensitivity and number of generators involved in congestion management determine the optimal location of the hydropower plant unit. In [25], a load management algorithm based on the load shifting capability of smart home appliances has been proposed. The obtained results reveal that a negligible amount of load shifting could greatly reduce the customer's convenience. A number of papers have discussed on customer unsatisfactory concept. Defining an appropriate model that could relate this unsatisfactory to the inconvenience cost of customers can be a good idea to investigate the behavior of customers [26]. The uncertainty of customer behavior in the demand response program (DRP) and renewable energy is investigated in [27]. In previous works, the uncertainty of customer's participation in DRPs has been investigated through quantitative models and stochastic methods such as Monte Carlo. In power systems, sudden events such as unexpected demand on hot summer days may lead to voltage drop and blackouts in large areas, which is why the use of load response programs is effective. Load response programs are implemented for the economic optimization of energy systems [28]. DRP can be used to manage the transmission lines congestion by reducing or shifting load according to the price of electricity [29]. DRP is recommended due to benefits such as improved reliability and cost reduction in the power system. DRPs are divided into two general categories, incentive-based programs and tariff-based methods [30]. In [31], a new method has been proposed in which the optimal locations and times for the implementation of the DRP are determined. Different electricity prices at different times cause consumers to change their consumption patterns. In [32], a new approach has been introduced to manage the congestion through smart grid platform. In this two-level structure, operator manages the electricity market irregardless of the limitations of the transmission network. According to the congestion of transmission lines, an exchange takes place between DRP and load shedding. In [33], The effect of quantifying the capacity of the energy storage system on the reliability of the power network and decongestion is analyzed. Reliability is also considered in the given problem. Flexible resources in power systems can play a fundamental role in improving congestion in these networks, while their ability to participate in energy markets can also be commercially important [34]. This article describes the flexibility of smart devices available in residential homes, whose flexibility varies throughout the day [35].

Some other papers have discussed on the flexibility of smart grids, but most of them have expressed its concept and few of them have provided an appropriate index for flexibility of smart grids. Different viewpoints on flexibility have been investigated in different references. As a primary idea for flexibility concept, a flexible scheduling that can enable the utilities to change the grid's schedule and structure based on fast response resources based on regulatory conditions has been introduced in [36]. In [37], an overview of flexibility options for renewable energy resources integration in power system has been carried out. The authors have reviewed the techno-economic-environmental-socio impacts of the penetration of renewable energy resources on power systems. A flexibility plan for a smart microgrid with the aim of improving the voltage profile and congestion has been presented in [38]. This article has used the OpenDSS software for increasing the accuracy of the flexible scheduling model.

According to the literature, the impact of customer's inconvenience cost as a result of customer's participation in DRPs has been not addressed in congestion management problem with DR so far. Also, the influence of flexibility index for the quick response resources has been not considered. This paper addresses the problem of congestion management with respect to generation rescheduling, flexibility of generation dispatch, the uncertainty of customer's participation in the DRPs, and the inconvenience cost of customers who have participated in the DRPs. The goal of this paper is to maximize transmission line loading capability while minimize operation costs as well as emission. To this end, a multi-objective particle swarm optimization (MOPSO) model has been used to solve the generation rescheduling problem. Therefore, the main contributions of this paper are as follows:

- Defining a new index for flexibility of the smart grid named smart grid flexibility index (SGFI).
- Modelling the uncertainty of customer's participation in the DRPs by Fuzzy-Markov and considering the unsatisfactory of customers by inconvenience cost.

The rest of the paper is as follows. The proposed framework is presented in section 2. Section 3 assigns to problem formulation. The implementation procedure of the optimization method is discussed in section 4. The simulation and numerical results are expressed in section 5. Finally, the conclusion is expressed in section 6.

2. Congestion Management Based on Flexibility Energy Rescheduling (CMBFER)

The proposed framework for solving the CMBFER problem has been shown in Fig. 1. The proposed CMBFER framework is based on rescheduling and performing demand-side management programs such as DRPs and using high-ramp units such as gas turbines to provide the flexibility for the smart grid and reduce the congestion of transmission lines. Moreover, the uncertainty of customer's participation in the DRP has been modeled by Fuzzy-Markov. On the other hand, the unsatisfactory of customers due to participating in the DRP as inconvenience cost has been considered. A new index for the flexibility of the smart grid named smart grid flexibility index (SGFI) has been developed. Finally, the congestion management based on rescheduling has been solved by MOPSO method in different scenarios.

3. Model Formulation

3.1. The objective functions of the CMBFER problem

The objective functions of the CMBFER problem are as follows:

A) Minimizing loadability of congestion transmission line

In order to increase the loadability of the most congested transmission line, it is expressed as follows [39]:

$$\min \quad \max_{n} \ \{s_{l_n}\}; \quad n = 1, \ldots, N_{br} \tag{1}$$

B) Minimizing generation cost

The reduction in the total cost, which is mainly related to the cost of thermal units' generation, the cost of gas turbine generation, the cost of DRP, the cost of inconvenience of customers due to participating in DRP and the cost of flexibility, is expressed as follows [39]:

$$\min \left\{ \begin{array}{l} \sum_{P=1}^{N_G} a_p + b_p P_{Gp} + c_p {P^2}_{Gp} \\ + \sum_{g=1}^{N_{gas}} C_g P_{g,s} + \sum_{m=1}^{N_{DR}} Enc_d \\ + \alpha \sum_{n=1}^{B} \left(X_d - TP_d\right)^2 + C_F SGFI \end{array} \right\} \tag{2}$$

The cost coefficients of the generators are also indicated by $a_p, b_p \ and \ c_p$. C_f is the coefficient cost of flexibility. C_g is the generation cost of gas turbine g and $P_{g,s}$ is the power output of gas turbine g in scenario s, which is selected by the combination of Monte Carlo with K-Means method.

To create a scenario, the average of all clusters must be calculated. In the K-Means method, the number of clusters and the position of the center of each cluster must first be determined. Each scenario is assigned to the nearest center using Euclidean distance ($d_{eu_{ij}}$) as Eq. (3).

$$d_{eu_{ij}} = \sqrt{\sum_{v=1}^{V} (x_{iv} - c_{jv})^2} \tag{3}$$

where x_{iv} is the value of attribute *v* of the observation *i*, c_{jv} is the value of the attribute *v* of the center of the cluster *j*, and *V* is the number of total attributes involved in each observation.

Then the center of each cluster is updated and these steps have been repeated until all the centroids stop moving. The cluster quality can be calculated in order to determine the optimal number of clusters (*k*) by Eq. (4).

$$q_i = \frac{b_i - a_i}{\max(a_i, b_i)} \tag{4}$$

where a_i is the mean incompatibility of observing *i* with all other observations in the same cluster, b_i is the least incompatibility of observing *i* with all observations in other clusters.

The higher the value of q_i, the better the matching between the observation *i* and its cluster.

i. Minimizing pollution

The most important source of pollution in power plants is fuel combustion. Pollution reduction is expressed as follows:

$$\min \sum_{P=1}^{N_G} \propto_P + \beta_P P_{GP} + \gamma_P P_{GP}^2 \tag{5}$$

The pollution coefficients of the generators are indicated by $\propto_p$, β_p and γ_p.

C) Minimizing the cost of DR

The participation of subscribers in the DRP is not an easy task, because electricity has been provided to consumers easily and cheaply, and also the sale of electricity at a fixed rate has caused them to be separated from the restructured and localized market. As a result, they have no incentive to participate in consumption management programs. Two factors can cause Customers to participate in the DRP: first, change the price of electricity and second, implement incentive programs.

DRPs are divided into two general categories, incentive programs and time tariff methods. This paper also focuses on direct load control and emergency load response programs. To implement the demand response program, a set of buses are selected whose participation rate is modeled with Fuzzy uncertainty [40].

The uncertainty of the participation of customers in DRPs can be modeled based on historical data. First, the fuzzy-Markov model is explained and then its application in the participation of customers in DRPs modeling is discussed.

Table 1. Comparison of proposed method with other methods

	Objective function (s)	Single/multi objective	Solution method	FACTS device	Flexibility resources	uncertainty
[14]	Congestion cost	single	AANN and the modified PSO	Phase shifter transformers	DRP	–
[17]	Congestion cost	single	RTCM	–	DRP	–
[18]	Congestion cost	single	PSO	–	–	–
[18]	Fuel and emission cost	Single	Bacterial foraging and Nelder Mead	TCSC	–	–
[22]	Congestion cost	Single	Ant lion optimizer	-	–	–
[23]	Cost and load shedding	Multi objective	MOPSO	–	DRP	–
Current paper	Cost and pollution	Multi objective	MOPSO	–	DRP/Gas turbine	DRP/Gas turbine

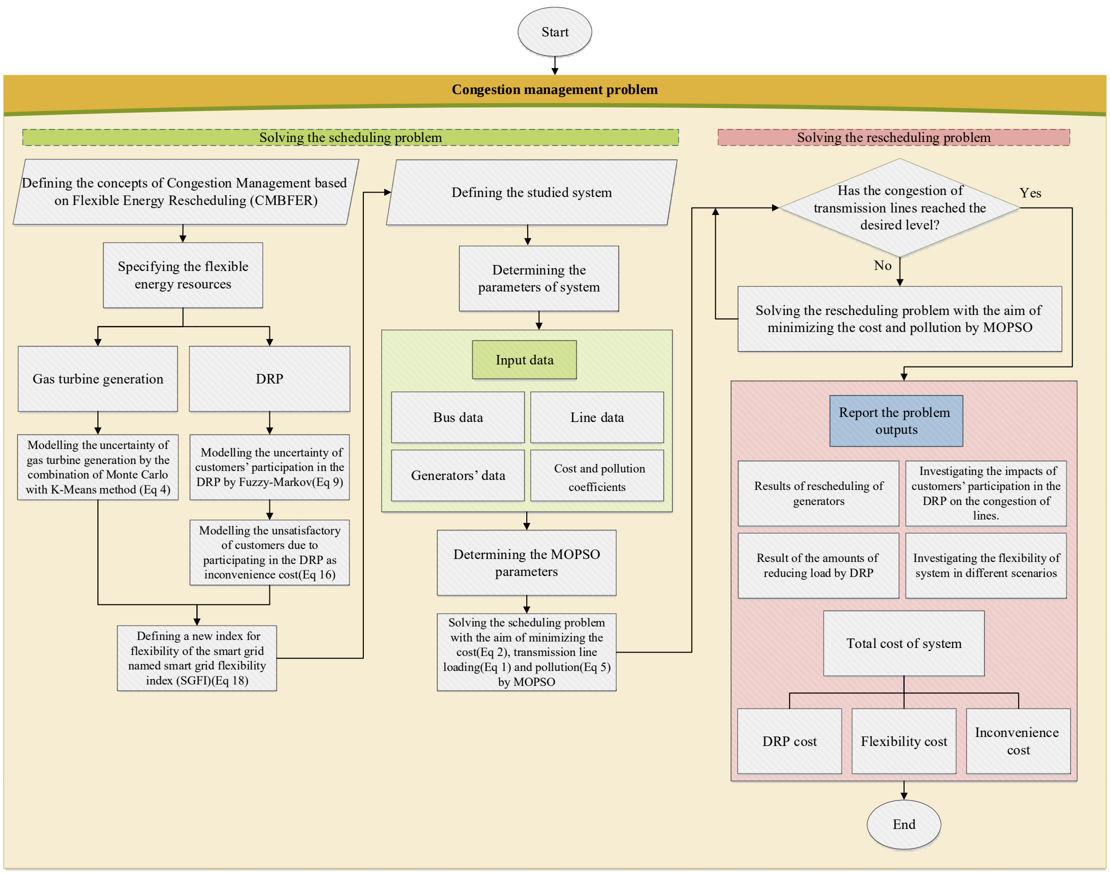

Fig. 1. The conceptual schematic of the proposed method

Suppose (P, Λ, Ω) is the standard probability space where Ω is a sample space, Λ is an algebra sum on Ω space and P is a probability value. Fuzzy set $\tilde{A}$ on Ω is called a fuzzy event. Assumption $\mu_{\tilde{A}}(\omega)$: $\omega \in \Omega$ is a function of event membership A. In this case, the probability of fuzzy events $\tilde{A}$ and the conditional probability of fuzzy events $\tilde{A}$ and B are as follows [40].

$$\begin{aligned} P(\tilde{A}) &= \sum_{\Omega} \mu_{\tilde{A}}(\omega) P_{\omega} \quad \mu_{\tilde{A}}(\omega) : \Omega \to [0,1] \\ P(\tilde{A}|\tilde{B}) &= \frac{P(\tilde{A}\cdot\tilde{B})}{P(\tilde{B})} \end{aligned} \tag{6}$$

The coefficient of two fuzzy events $\tilde{A}$ and $\tilde{B}$ is equal to the following expression.

$$\tilde{A}\cdot\tilde{B} \leftrightarrow \mu_{\tilde{A}\cdot\tilde{B}} = \mu_{\tilde{A}} \cdot \mu_{\tilde{B}} \tag{7}$$

Suppose X_t is the state of the system at time t. Consider a Markov chain with finite position whose probability transfer matrix is as follows.

$$P[p_{ij}] \quad \forall i, j \in \{0, 1, \ldots, N\} \tag{8}$$

Where it represents the probability of transition from state i to state j in one step and is defined as follows.

$$p_{ij} = P\{X_{t+1} = j | X_t = i\} = P\{X_1 = j | X_0 = i\} \tag{9}$$

Where, $\sum_{j=0}^{N} p_{ij} = 1$. Also, the probability matrix of its transfer in r step is equal to the following equation.

$$\begin{aligned} P^r &= [P^r_{ij}] \;\; P^r_{ij} \geq 0, \quad \forall i, j \in \{0, 1, \ldots, N\} \\ P^r_{ij} &= P\{X_{t+r} = j | X_t = i\} = P\{X_r = j | X_0 = i\} \end{aligned} \tag{10}$$

Also, $p_i = P\{X_0 = i\}$, $\forall i \in \{0, 1, \ldots, N\}$, i.e., p_i are the probabilities of the initial state of the Markov chain are and $\sum_{i=0}^{N} p_i = 1$.

The fuzzy membership function for the participation coefficient in the load response program is shown in equation (11). The fuzzy membership function for the participation rate of consumers in

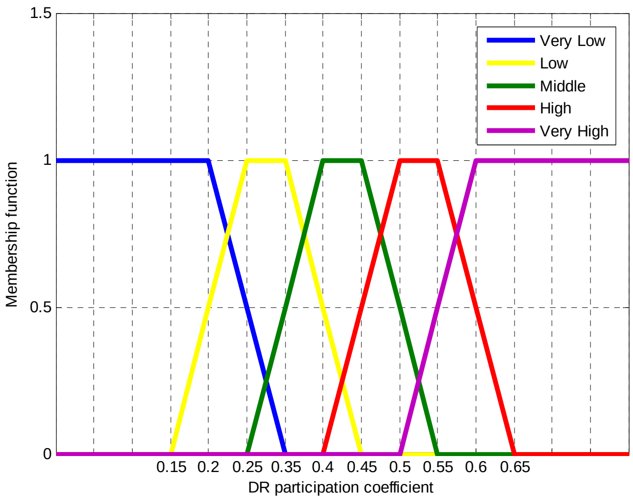

Fig. 2. Membership function for consumer participation rate in load response program

load response programs is shown in Fig. 2. According to Figure 2-3, if the participation coefficient of the load response program is less than 0.15, then it is placed in the fuzzy category. If the participation coefficient of the load response program is between 0.15 and 0.25, then it may be placed in each of the fuzzy categories. If the participation coefficient of the load response program is between 0.25 and 0.35, then it can be placed in very low, low and medium fuzzy categories, but it is more possible to be placed in the medium fuzzy category. If the participation coefficient of the load response program is between 0.35 and 0.4, then it can be placed in the low and medium fuzzy categories, and the possibility of being placed in both categories is equal. If the participation coefficient of the load response program is between 0.4 and 0.45, then it can be placed in the low, medium and high fuzzy categories, but the possibility of being placed in the medium category will be more. If the participation coefficient of the load response program is between 0.45 and 0.5, then it can be placed in medium and high fuzzy categories, and the possibility of being placed in both categories is equal. If the participation coefficient of the load response program is between 0.5 and 0.55, then it can be placed in the medium, high and very high fuzzy categories, but the possibility of being in the high fuzzy category is more. If the participation coefficient of the load response program is between 0.55 and 0.65, then it can be placed in the high and very high fuzzy categories. If the participation coefficient of the load response program is more than 0.65, then it is placed in the fuzzy category.

$$\mu(\lambda) = \begin{cases} \text{Very Low:} & \lambda \leq 0.35 \\ \text{Low:} & 0.15 \leq \lambda \leq 0.45 \\ \text{Middle:} & 0.25 \leq \lambda \leq 0.55 \\ \text{High:} & 0.4 \leq \lambda \leq 0.65 \\ \text{Very High:} & \lambda \geq 0.5 \end{cases} \tag{11}$$

In which, λ the coefficient of participation of consumers in the response program is the burden.

The diphase participation coefficient for the load response program is shown as equation (12).

$$\lambda = \frac{\mu}{e + \mu} \tag{12}$$

In which, λ the coefficient of participation of consumers in the response program is the load and the value of the membership function. For the very low category, the membership function is equal to 1, the low category is equal to 2, the average category is equal to 3, the high category is equal to 4 and the very high category is considered to be 5.

The proposed model for DR is based on incentives and penalties along with customer benefits as follows [39]:

$$\Delta T_d = L_{d0} - L_d \tag{13}$$

L_d *and* L_{d0} are the amount of bus load before and after the implementation of DR, respectively.

The total incentive paid to the bus participating in the DRP is calculated as follows [39]:

$$INC_d = Enc \times [L_{d0} - L_d] \tag{14}$$

Customers who participate in the DRP is penalized if they do not reduce their consumption according to the specified amount in the contract. The penalty for participating in the DRP is calculated as follows [39]:

$$Pen_d = Pen \times [LR_d - \Delta T_d] \tag{15}$$

The *pen* factor is considered zero and the *Enc* factor is considered to be 1 to 10 times the power price before the implementation of DR by ISO.

The following equation is used to obtain the power consumption of the customer participating in the DRP [39]:

$$d_d = d_{0d} \times \left[1 + E\frac{\rho - \rho_0 + Enc - pen}{\rho_0}\right] \times (1 - \lambda) \tag{16}$$

In equation (8), E the elasticity of the load, ρ represents the price before and ρ_0 represents the price after the execution of the DR program. The cost of the incentive paid to consumers who are participated in DRPs is expressed according to the following equation [39]:

$$\min \sum_{m=1}^{N_{DR}} Enc_d \tag{17}$$

D) The inconvenience cost of customers

Consumers' willingness to participate in a demand response program is considered an important factor in energy management. Prices change their load profile, causing their unsatisfactory, which is obtained according to the following equation [41]:

$$inc_d = \alpha \sum_{n=1}^{B} (X_d - TP_d)^2 \tag{18}$$

inc_d is inconvenience of bus d to participate in the DRP and α is bus sensitivity coefficient used to determine the customer's willingness to reduce or shift the load.

3.2. Control variables

Congestion in the power system is detected by measuring the following variables. The variables are shown in a set called B^T [41]:

$$B^T = \left[P_{G1}, \ldots, P_{G_{N_G}}, V_{L1}, \ldots, V_{L_{NL}}, Q_{G_1}, \ldots, Q_{G_{N_G}}, S_{L_1}, \ldots S_{L_{N_{br}}}\right] \tag{19}$$

A) The effect of flexibility on generation rescheduling

This paper presents a new flexibility index to demonstrate smart grid flexibility that improves transmission line congestion using fast response sources. The flexible resource used in this paper are the DRP and gas turbine. Implementing the DRP makes the load profile flatter and thus reduces the difference between the peak and the valley. On the other hand, using the generation of gas turbine as a fast response resource makes the system more flexible. However, the generation of gas turbine is associated with uncertainty. The SGFI has been used to express the effect of smart grid flexibility on generation rescheduling as Eq. (18).

$$SGFI = \frac{\left(\sum_{g=1}^{N_{gas}} \frac{P_{g,s}^{peak}}{Cap_g}\right)}{\left(\frac{\left(Ld_{peak} - \sum_{n=1}^{b}(p_{bus} \times dr_{red})\right)}{Ld_{peak}}\right)} \tag{20}$$

Ld_{peak}, and dr_{red} show the peak load and the amount of DRP contract, respectively, and p_{bus} shows the percentage of buses participating in the DRP. $P_{g,s}^{peak}$ and Cap_g are the total generation of gas turbine g at peak load considering the uncertainty and the capacity of gas turbine g, respectively.

B) The constraints of balancing the load and generation

The following constraint is stated to establish the equality of active and reactive power flow equations [39]:

$$P_{Gq} - (P_{Dq} - d_q) = V_q \sum_{a=1}^{N_g} Va(G_{qa} \cos\theta_{qa} + B_{qa} \sin\theta_{qa}) \quad q = 1, \dots, N_g \tag{21}$$

$$Q_{Gq} - Q_{Dq} = V_q \sum_{a=1}^{Ng} V_a (G_{qa} \sin\theta_{qa} - B_{qa} \cos\theta_{qa}) \quad q = 1, \dots, N_g \tag{22}$$

C) Inequality constraints

Controllable constraints and state variables are described with inequality constraints. The following constraints provide unequal constraints on different parts of the power system

D) Generator constraints

Each generator has a high and low limit for active, reactive and voltage power [39].

$$V_{Gp}^{min} \le V_{Gp} \le V_{Gp}^{max} \tag{23}$$

$$P_{Gp}^{min} \le P_{Gp} \le P_{Gp}^{max} \tag{24}$$

$$Q_{Gp}^{min} \le Q_{Gp} \le Q_{Gp}^{max} \tag{25}$$

$$P_{g,s}^{min} \le P_{g,s} \le P_{g,s}^{max} \tag{26}$$

E) Constraint on incentives paid to loads participating in the DRP

Paid incentives have a high and a low limit [39]:

$$in_m^{min} \le in \le in_m^{max} \tag{27}$$

F) Security constraint

The voltage and thermal limits of transmission lines are as follows [39]:

$$V_{lr}^{min} \le V_L \le V_{lr}^{max} \qquad r = 1, \dots, N_L \tag{28}$$

$$-S_{l_n}^{max} \le S_{l_n} \le S_{l_n}^{max} \tag{29}$$

4. Solving congestion management based on flexibility energy rescheduling (CMBFER) using 3 MOPSO

The multi-objective format of particle swarm optimization is called MOPSO. In solving problems by MOPSO, sorting out the answers is difficult. The methods used so far have turned multi-objective problems into single-objective ones. In multi-objective problems, there is a set of solutions called the Pareto optimal set. In this paper, a MOPSO algorithm is used to solve the CMBFER problem [42].

A) Implementation of MOPSO algorithm

Step 1. Calling information

In the first stage, the resistance and reactance of the lines, the thermal limit of the lines, the limitations of the generators, the cost coefficients and the pollution of the generators are called.

Step 2. Create an initial population

Like other algorithms, an initial population is created randomly to begin with random generation of particles location [38];

$$POP = [u_1^T, \dots, u_{Ns}^T]^2 \tag{30}$$

$$\begin{aligned} par_h^T = u_h^T &= \left[P_{G_{2_h}}, \dots, P_{G_{N_{Gh}}}, \dots, \Delta d_{1_h}, \dots, \Delta d_{N_{DR_h}}\right] \\ &= \left[par_{1_h}, \dots, par_{N_{par_h}}\right] \qquad h = 1, \dots, N_s \end{aligned} \tag{31}$$

$$par_{\eta h} = par_{\eta h}^{min} + rand \times \left(par_{\eta h}^{max} - par_{\eta h}^{min}\right) \quad n = 1, \dots, N_{par} \tag{32}$$

Random generation of particles velocity can be obtained as follows [38]:

$$VEL = [vel_1^T, \dots, vel_{N_s}^T]^T \tag{33}$$

$$vel_h^T = [vel_1^T, \dots, vel_{N_s}^T]^T \qquad h = 1, \dots, N_s \tag{34}$$

$$vel_{\eta h} = 0.1 \times \left[par_{\eta h}^{min} + rand \times \left(par_{\eta h}^{max} - par_{\eta h}^{min}\right)\right] \quad \eta = 1, \dots, N_{par} \tag{35}$$

Step 3. Control constraints

Due to the random generation of particles, the constraints on equality and inequality must be controlled.

Step 4. Run load flow and calculate objective function

For the objective functions (3), (5) and (6) the initial population is generated.

The value of the solution par_1 is less than or equal to par_2 in the objective functions. It is expressed mathematically as follows [38]:

$$\forall z \in [1, \dots, N_{obj}] \quad f_z(par_1) \le f_z(par_2) \tag{36}$$

For at least one objective function, the value of solution par_1 is less than the value of solution par_2 as follows [38]:

$$\forall v \in [1, \dots, N_{obj}] \quad f_v(par_1) < f_v(par_2) \tag{37}$$

If solution par_1 over par_2 prevails, par_1 is stored in the repository. The following conditions must be met to be in the repository:

- The repository is not full
- The selected solution does not fail with any of the solutions stored in the repository

Here, the Fuzzy clustering method is used to better select non-template solutions that are well compatible with the objective function.

Step 5. Determine Fuzzy member functions

Membership functions are obtained by the maximum and minimum values set. These values are obtained by the single-objective optimization method. The value obtained for the membership function indicates the satisfaction of the operator, so that if $\mathrm{M}_{f\alpha(par_\beta)} = 1$ it has the highest satisfaction and if it is equal to zero it has the lowest satisfaction. The calculation of $\mathrm{M}_{f\propto(par_\beta)}$ for $\propto th$ objective functions is expressed as the following equation [38]:

$$M_{\propto(par_\beta)} = 0 \qquad if, \qquad f_{\alpha(par_\beta)} > f_\alpha^{max} \tag{38}$$

$$M_{\propto(par_\beta)} = \frac{f_\propto^{max} - f_{\propto(par_\beta)}}{f_\alpha^{max} - f_\alpha^{min}} \quad if, \quad f_\alpha^{min} \leq f_{\alpha(par_\beta)\leq f_\propto^{max}} \tag{39}$$

$$M_{\propto(par_\beta)} = 1 \qquad if, \quad f_{\propto(par_\beta)<f_\propto^{min}} \tag{40}$$

After finding the membership functions for each objective function, it is normalized as follows [33]:

$$n_\mu(\beta) = \frac{\sum_{\alpha=1}^{N_{obj}} w_\alpha \times \mu_{f_{\alpha(par_\beta)}}}{\sum_{\beta=1}^{N_{rep}} \sum_{\alpha=1}^{N_{obj}} w_\alpha \times \mu_{f_{\alpha(par_\beta)}}} \quad \beta = 1, \ldots, N_{rep} \tag{41}$$

N_{rep} and $w_\propto$ show the number of solutions in the repository and the weight coefficient of the objective functions, respectively, and after normalization, the obtained answers are categorized in ascending order and are removed from the lowest based on the size of the repository.

Step 6. Update particle velocity and location

The velocity and location of the update is obtained by the following formula [38]:

$$vel_\beta(t+1) = w \times vel_\beta(t) + c_1 \times rand \times (bpar_\beta - par_\beta(t)) + c_2 \times rand \times (gpar - par_\beta(t)) \tag{42}$$

$$par_\beta(t+1) = vel_\beta(t+1) + par_\beta(t) \qquad \beta = 1, \ldots, N_S \tag{43}$$

Step 7. Investigate the constraints

In order to generate a new population, the constraints of equality and inequality must be examined at each stage.

Step 8. Update $bpar_\beta$ and $gpar$

For the populations obtained from the last step, the objective functions are calculated.

$bpar_\beta$ is updated as follows [33]:

- If solution $par_\beta(t+1)$ is defeated by solution $bpar_\beta$, then par is substituted
- If solution $bpar_\beta$ is defeated by solution $par_\beta(t+1)$, then $bpar_\beta$ is substituted
- If the two solutions $bpar_\beta$ and $par_\beta(t+1)$ cannot defeat each other, one of them is chosen randomly.

The $gpar$ is selected from the solutions in the repository and then the following steps are performed

The Fuzzy normalized vector is formed as follows [38]:

$$n_\mu^T = [n_\mu(1), \ldots, n_\mu(N_{rep})] \tag{44}$$

For the vectors obtained from the previous step, we obtain the cumulative probabilities [33]:

$$cp_1 = n_\mu(1) \tag{45.a}$$
$$cp_2 = cp_1 + n_\mu(2) \tag{45.b}$$
$$\vdots$$
$$cp_n = cp_{n-1} + n_\mu(n) \tag{45.c}$$

In the third stage, $gpar$ is selected using a roulette wheel. The roulette wheel consists of several parts, each part of which is related to the whole set and its environment is proportional to the probability of an event. As the wheel moves, the probability of placing the mark on each of the sections will be equal to the size of the sections. According to the mentioned relations, the cumulative probability for the first solution is equal to its normalized value and the last solution is equal to one. A number of random numbers between zero and one are generated and compared with the cumulative probability obtained, and the cumulative probability solution is considered as $gpar$.

Step 9. Stop condition

The maximum number of MOPSO iterations is considered as a stop condition.

Table 2. Coefficients of cost and pollution function

Case number	Case 1	Case 2	Case 3	Case 4	Case 5
Pollution function coefficient	1	0.75	0.5	0.25	0
Cost function coefficient	0	0.25	0.5	0.75	1

Table 3. Cost coefficients of generators

Gen.	a[$/h]	b[$/MWh]	c[$/MWh^2]	α[ton/h]	β[ton/MWh]	γ[ton/MWh^2]
G_1	0	2	0.02	0.040901	-0.05554	0.0649
G_2	0	1.75	0.0175	0.02543	-0.06047	0.05638
G_3	0	1	0.0625	0.04258	-0.05094	0.04586
G_4	0	3.25	0.00834	0.05326	-0.0355	0.0338
G_5	0	3	0.025	0.04258	-0.050904	0.04586
G_6	0	3	0.025	0.06131	-0.05555	0.05151

5. Numerical Results

The problem of CMBFER has been implemented on the IEEE 30-bus system.

5.1. The system under study

The system has 20 loads, 5 thermal generators, 1 gas turbine and 41 transmission lines. The generators are located on buses 1, 2, 13, 22, 23, and the gas turbine is located on bus 27. The data of cost and pollution coefficients of generators is given in Table 2. The information of buses, maximum and minimum active and reactive power generated by generators and transmission line information are taken from [18]. In the proposed congestion management problem, loads of buses 7, 8, 12, 17, 19, 21 and 30 are considered to participate in the demand response program [20]. The uncertainty of the extent of their participation is modeled with Fuzzy-Markov [40]. The price of electricity before and after the implementation of the DRP is set at 50 $/MWh [43]. Elasticity coefficient for the demand response is considered equal to -0.1 [20]. The weight coefficient of the cost function of generators has been given in Table 3. The coefficient cost of flexibility has been given from [44].

The data related to gas turbine with the capacity of 50MW are taken from [40]. The uncertainty of the gas input of gas turbine has been modeled by the combination of Monte Carlo simulation with K-Means method. Therefore, scenarios have been reduced by Monte Carlo simulation and one scenario has been selected among them by K-Means method as shown in Fig. 3.

The probabilities of each state of Fuzzy-Markov model for the participation of consumers in DRPs have been shown in Fig. 4. The total number of 5 states has been considered for the qualitative value of the participation of consumers in DRPs. Most of the data is in the very high state and then in the low state.

In this paper, to manage the congestion of the power system, the DRP and generation rescheduling in the form of 5 scenarios have been used. The maximum thermal limit of transmission lines for all scenarios is 32MVA.

The scenarios of the congestion management problem have been considered as follows:

- Scenario 1: congestion management regardless of the DRP and considering the uncertainty of gas turbine generation.
- Scenario 2: congestion management regardless of the DRP and without the uncertainty of gas turbine generation.
- Scenario 3: congestion management considering DRP associated with the uncertainty of the consumer's participation and with the uncertainty of gas turbine generation.
- Scenario 4: congestion management considering DRP associated with the uncertainty of the consumer's participation and without the uncertainty of gas turbine generation.

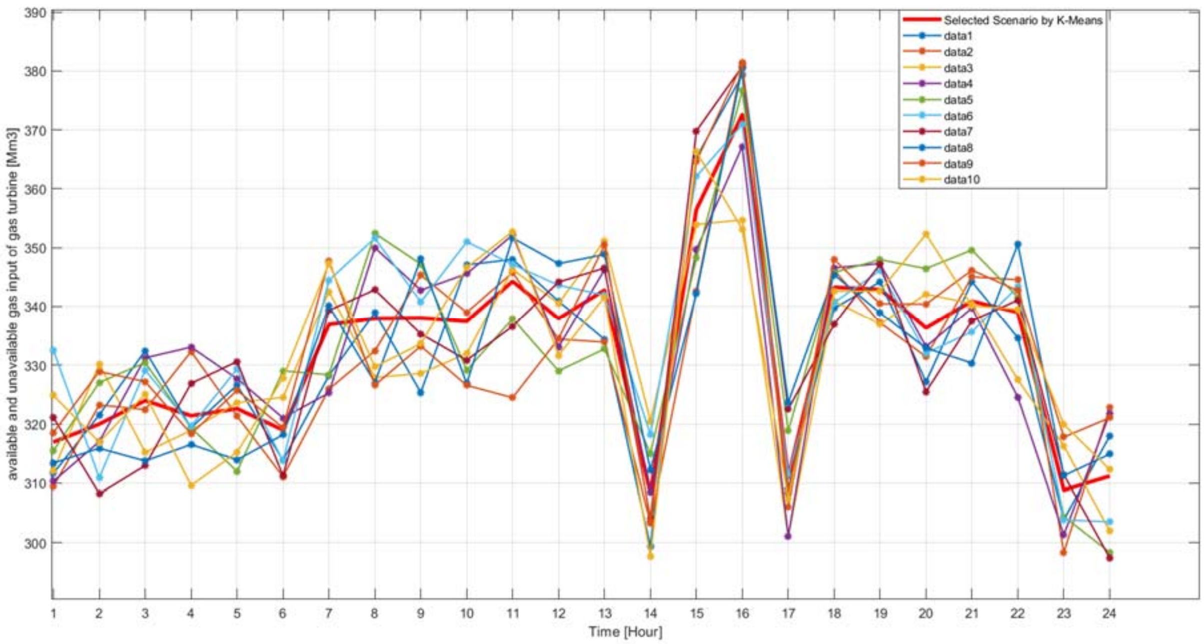

Fig. 3. Available and unavailable gas input of gas turbine in all scenarios and selected scenario by K-Means method.

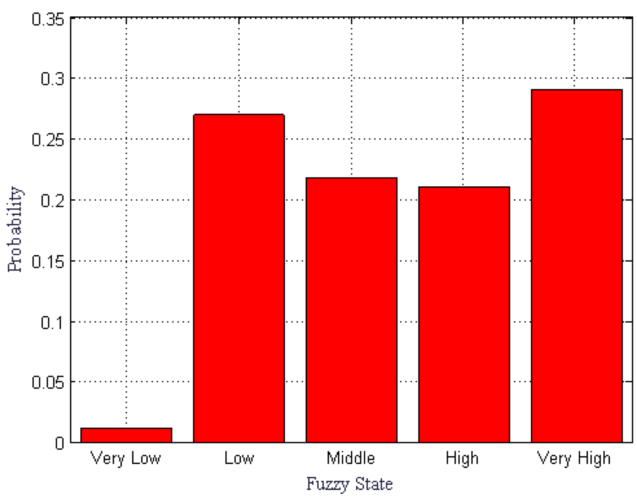

Fig. 4. The probabilities of each state of Fuzzy-Markov model for the participation of consumers in DRPs

- Scenario 5: congestion management considering DRP regardless of the uncertainty, with the participation coefficient of 10% and without the uncertainty of gas turbine generation.

The results of the transmission line flows without considering the thermal limit transmission lines are shown in Table 4. As the table shows, the power flow of transmission lines 10, 16 and 29 is equal to: 32.197 MW, 37.909 MW and 31.875.

According to the maximum thermal limit considered for the scenarios, at least one of these lines has a congestion.

Comparison of the results of scenarios 1 and 2 shows that the amount of pollution and cost of scenario 2 is less than scenario 1 and the comparison of scenario 1 with 3, 4 and 5 gives the same results. Comparison of the results shows that using a DRP reduces pollution so they can better achieve the goal of reducing

Table 4. Transmission line flow results regardless of maximum thermal limit

Line No.	Power flow			Line No.	Power flow		
	MW	MVAR	MVA		MW	MVAR	MVA
1	18.621	13.977	23.283	22	9.654	3.952	10.432
2	10.38	7.0869	12.569	23	6.341	2.853	6.954
3	7.108	3.673	8.001	24	3.191	0.584	3.244
4	7.888	5.9	9.851	25	5.419	1.338	5.582
5	9.254	4.58	10.325	26	3.701	6.813	7.753
6	10.179	5.827	11.729	27	7.299	8.613	11.29
7	15.1	11.565	19.02	28	6.777	6.67	9.509
8	9.194	5.709	10.823	29	26.868	21.94	34.687
9	9.194	5.709	10.823	30	14.709	23.665	27.864
10	22.149	23.368	32.197	31	7.793	2.39	8.151
11	0.597	3.144	3.201	32	7.374	15.287	16.973
12	0.342	1.802	1.835	33	9.625	5.66	11.166
13	0	0	0	34	3.546	2.349	4.253
14	0.604	3.154	3.211	35	13.325	2.985	13.655
15	7.717	3.786	8.596	36	19.79	11.301	22.789
16	37.862	1.8945	37.909	37	6.176	1.623	6.386
17	4.078	1.918	4.506	38	7.124	1.606	7.303
18	6.023	12.427	13.81	39	3.692	0.589	3.739
19	8.881	0.992	8.936	40	8.076	6.899	10.623
20	2.185	3.525	4.148	41	11.698	5.43	12.897
21	5.333	0.996	5.426	–	–	–	–

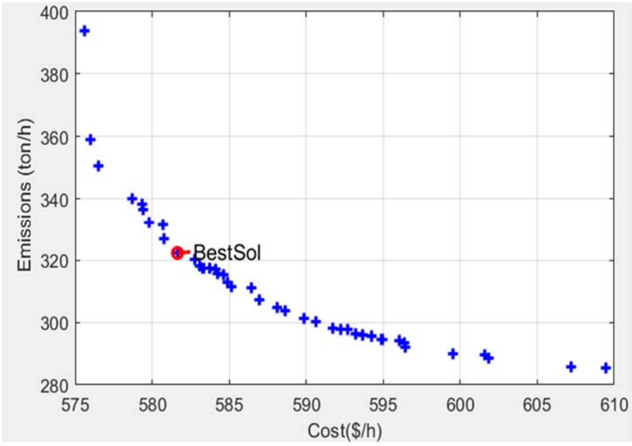

Fig. 5. Pareto curve for scenario 1

environmental pollution. The Pareto front for the optimal results of the CMBFER problem has been shown in Fig. 4. According to Fig. 5, the best solution has satisfied the reduction of the emission and cost value.

The numerical results of generation rescheduling, the effect of flexibility on generation rescheduling expressed with the participation of buses, as well as the reduction of bus load and the numerical value of pollution and cost objective functions in different modes are given in Tables 5-7.

The rescheduling results for each generator has been presented in Table 5. According to Table 5, the lowest amount of production for generators is occurred in scenario 5 because of performing DRP regardless of the uncertainty; also the greater amount of production for generators is occurred in scenario 1 because the DRP is not performed in this scenario and the generators should cover the demand of system.

Table 6 shows the amounts of reducing load of the system due to participating in DRPs for each bus. According to Table 6, the amount of reduced load due to performing DRPs in the scenario 5 is higher than other scenarios.

According to Figs. 6-10, a comparison of the results of Scenarios 1 and 2 shows that production costs are reduced when using demand response programs, but there is a small cost due to the use of flexible resources. On the other hand, a comparison of the results of scenarios 1 and 2 shows that pollution is reduced when using demand response programs due to less use of power plants. In fact, the use of demand response programs reduces the share of power plants in production and thus reduces pollution production. According to Figs. 6-10 and comparison of scenarios, it can be seen that transmission line congestion management using demand response programs and gas-fired power plants will have more flexibility. Also, according to Figs. 6-10, in scenarios and situations where demand response programs and high-ramp resources such as gas turbines have been used more, the network flexibility has increased and consequently the cost of flexibility has also increased.

According to Table 7, comparison of the results of scenarios 1 and 2 shows that the generation cost is reduced when using the DRP, but there is a slight inconvenience cost due to the load shift. On the other hand, comparison of the results of scenarios 1 and 2 shows that the cost of emission is reduced when using the DRP due to less use of power plants. The SGFI values for different scenarios are shown in Fig. 11. DRP and gas turbine are considered as fast response resources.

According to Fig. 11, the highest value of the SGFI is occurred in scenario 5 that is the congestion management by considering generation rescheduling, DRP and inconvenience cost and the maximum thermal limit of transmission lines is 35MVA as well as the gas turbine works in the highest value in 24 hours. The amount of SGFI changes in different scenarios of pollution coefficient, DRP value and gas turbine generation. In order to evaluate the proposed method, the obtained results have been compared with the results of literature [19], which shows that the cost of producing generators and the total cost have been greatly reduced in the proposed method, literature [19] has used TCSC for congestion management.

Table 5. Numerical results of rescheduling of generators in term of MW

Scenario no.	Case no.	P_{G1}	P_{G2}	P_{G3}	P_{G4}	P_{G5}	P_{G6}
Scenario 1	Case 1	45.21	57.96	23.20	31.18	15.67	18.38
	Case 2	36.03	55.18	24.005	36.10	18.49	21.59
	Case 3	34.49	44.28	24.84	39.77	22.63	25.31
	Case 4	29.12	33.57	27.74	42.09	29.7	29.09
	Case 5	24.58	29.62	30.32	46.60	38.30	30.85
Scenario 2	Case 1	36.59	48.88	24.14	27.89	17.064	27.06
	Case 2	38.919	51.5	27.19	28.97	16.31	22.43
	Case 3	30.17	53.02	18.44	41.66	19.74	20.28
	Case 4	36.58	35.7	22.11	34.51	24.94	27.79
	Case 5	28.32	34.207	30.57	46.98	29.64	15.36
Scenario 3	Case 1	36.71	53.47	18.77	51.456	16.07	16.39
	Case 2	40.58	46.63	27.23	41.81	17.15	18.31
	Case 3	38.99	42.21	23.92	47.61	18.31	20.56
	Case 4	27.22	33.71	28.93	43.66	27.94	30.09
	Case5	24.47	34.99	30.09	47.13	25.63	27.07
Scenario 4	Case 1	40.41	52.93	25.51	41.98	18.74	24.86
	Case 2	44.39	43.25	26.90	29.79	28.24	13.07
	Case 3	27.39	50.06	29.93	38.11	21.73	15.61
	Case 4	33.37	33.51	29.57	44.007	19.35	25.84
	Case 5	33.84	23.65	32.48	42.80	25.17	29.81
Scenario 5	Case 1	43.20	39.48	12.35	52.36	23.14	12.86
	Case 2	32.55	42.53	21.56	49.59	20.03	19.35
	Case 3	38.74	49.95	23.27	36.74	21.48	17.67
	Case 4	44.004	34.87	29.57	33.85	18.64	23.43
	Case 5	37.69	19.94	25.33	48.92	29.53	21.17

Table 6. Numerical results of reducing the load of buses participated in DRP in term of MW

Scenario no.	Case no.	Bus7	Bus8	Bus12	Bus17	Bus19	Bus21	Bus30
Scenario 2	Case 1	1.43	1.85	1.01	1.37	0.028	1.79	1.93
	Case 2	0.021	0.031	0.899	0.643	0.645	1.79	1.82
	Case 3	0.075	1.94	1.96	1.9	1.18	0.09	0.85
	Case 4	1.31	1.9	0.693	1.7	1.82	0.139	1.79
	Case 5	0.95	0.87	0.88	0.033	1.89	1.62	0.038
Scenario 4	Case 1	1.17	1.42	0.96	1.26	0.0004	0.79	1.18
	Case 2	1.31	1.311	1.02	0.14	1.22	0.13	0.86
	Case 3	1.11	1.91	0.66	0.66	1.47	1.59	0.87
	Case 4	1.05	0.13	1.43	0.004	0.062	1.4	1.47
	Case 5	1.13	0.061	0.708	0.091	0.105	0.83	0.702
Scenario 5	Case 1	1.38	1.72	0.13	1.56	0.12	1.97	1.79
	Case 2	1.33	0.98	0.076	1.3	0.062	1.708	1.08
	Case 3	1.66	0.030	0.074	0.048	0.137	1.62	0.72
	Case 4	1.33	1.43	0.72	1.62	0.93	1.67	0.106
	Case 5	1.45	1.48	1.64	1.22	0.061	1.42	1.92

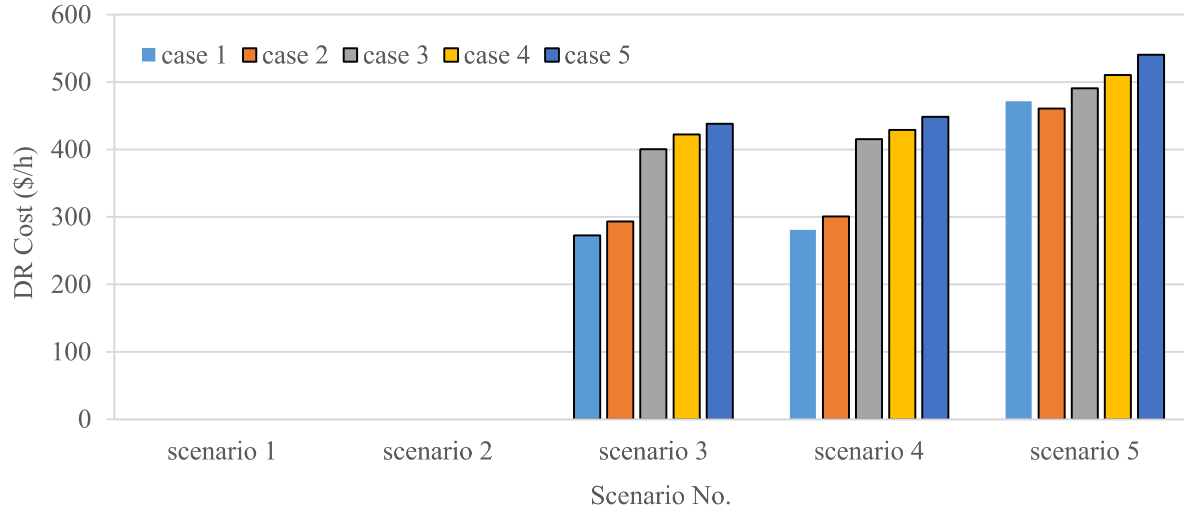

Fig. 6. The DR cost values for scenario and cases different

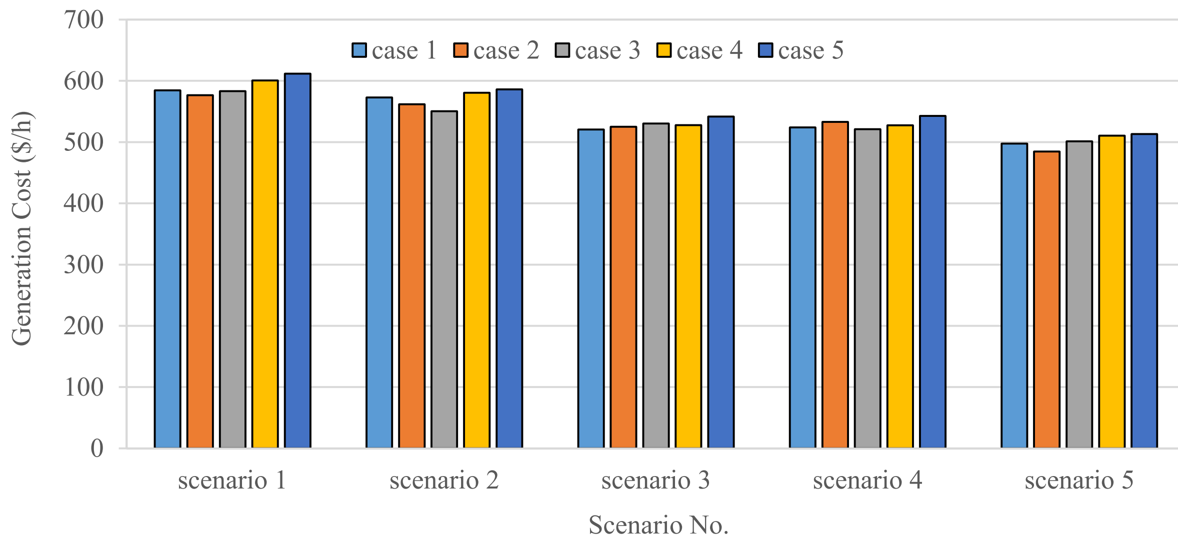

Fig. 7. The generation cost values for scenario and cases different

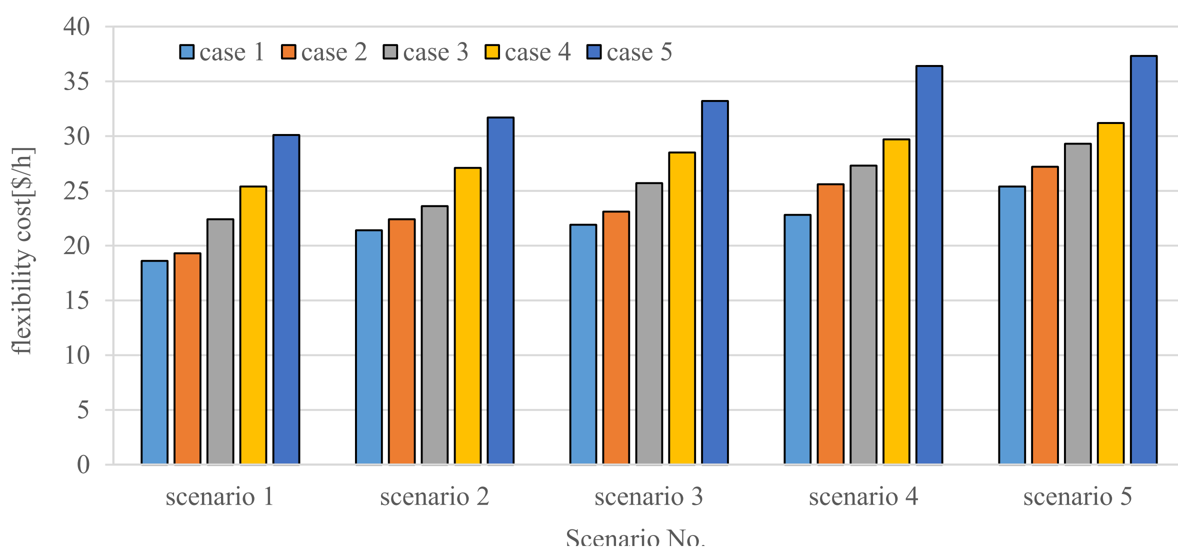

Fig. 8. The flexibility cost values for scenario and cases different

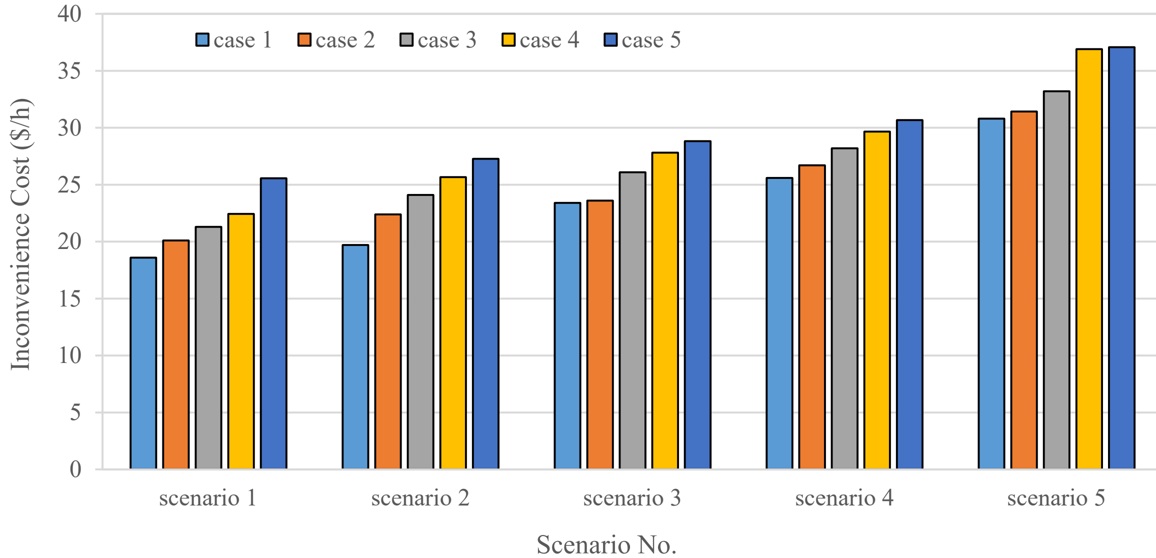

Fig. 9. The inconvenience cost values for scenario and cases different

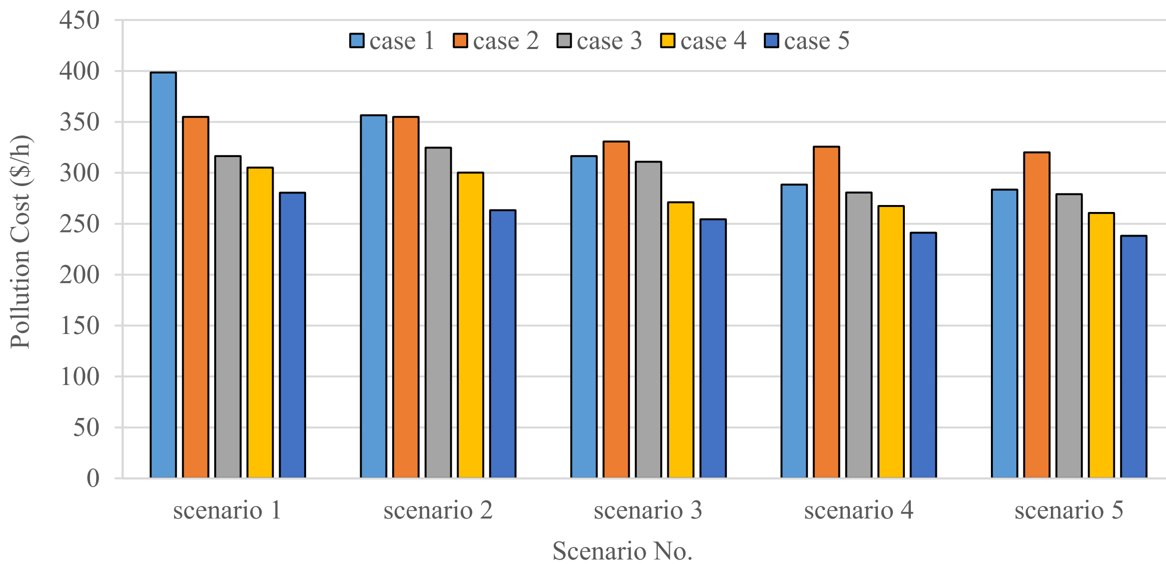

Fig. 10. The pollution values for scenario and cases different

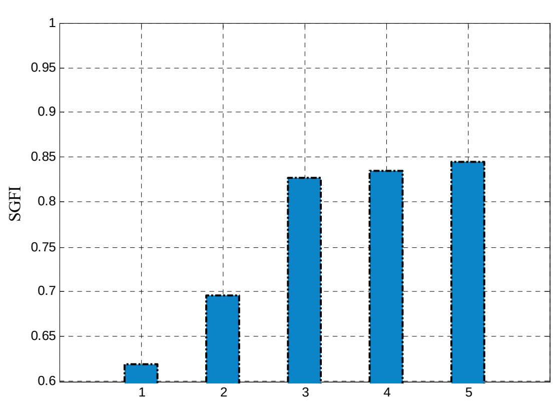

Fig. 11. The SGFI values for different scenarios

6. Conclusion and future work

This paper has introduced a flexible smart grid as well as investigated the impacts of DRP on the generation scheduling and transmission lines congestion. The objective functions of this problem are to minimize the total cost of DRP and pollution and to maximize the loadability of transmission lines. Comparison of the results of scenarios 1 and 2 shows that the production costs and pollution have decreased by 4.79 and 3.18 percent, respectively. According to the scenarios, the more fast response sources are used, the more flexibility index and consequently the congestion of transmission lines decreases. As the results also show, it is inevitable not to use load response resources in transmission lines that have high congestion. Of course, participation in load response programs also causes dissatisfaction for subscribers, but subscribers who participate in load response programs receive incentives, and the cost of subscriber dissatisfaction is very small compared to the incentives paid. Therefore, a MOPSO is used for congestion management. The uncertainty of consumer participation

Table 7. Numerical results power flow of more congested transmission lines in term of MVA

Scenario No.	Congestion lines	Case 1	Case 2	Case 3	Case 4	Case 5
Scenario 1	Line 10	34.01	33.84	33.41	33.05	32.82
	Line 16	23.12	24.61	27.85	29.67	33.45
	Line 29	27.41	28.94	30.52	32.97	34.78
Scenario 2	Line 10	34.12	33.45	33.12	32.45	31.84
	Line 16	23.45	25.78	26.97	29.38	33.45
	Line 29	27.65	28.78	29.61	32.53	33.41
Scenario 3	Line 10	31.95	31.94	31.93	31.93	31.92
	Line 16	30.21	30.45	30.52	30.78	31.45
	Line 29	29.25	29.68	30.14	31.12	31.68
Scenario 4	Line 10	31.91	31.88	31.57	31.25	30.96
	Line 16	24.67	25.69	27.45	29.31	30.51
	Line 29	30.31	30.68	31.11	31.27	31.47
Scenario 5	Line 10	29.98	29.98	29.96	29.96	29.95
	Line 16	24.15	25.42	27.45	28.81	29.05
	Line 29	29.14	29.25	29.78	29.81	21.89

Table 8. Comparison of the proposed method with the literature method [19]

Solution Algorithm	**Generation[MW]**						**Costs[$/h]**		
	P_{G1}	P_{G2}	P_{G3}	P_{G4}	P_{G5}	P_{G6}	Fuel	other	total
GA [19]	44.33	53.27	37.43	19.21	16.64	22.82	1021.8	48.8	1070.6
DE [19]	59.55	54.04	34.37	14.39	12.84	17.66	1028.7	44.9	1073.6
PSO [19]	44.31	52.92	37.83	18.96	18.27	20.33	1017.9	47.8	1065.7
BFA [12]	45.55	64.46	29.45	10.83	14.32	27.66	1022	53.4	1075.4
BFA-NM [19]	45.99	59.93	23.79	32.38	14.66	18.43	972.49	78.9	1051.4
MOPSO(SC4)	40.41	52.93	25.51	16.42	18.74	18.74	600.73	1.3	601.76
MOPSO(SC5)	43.20	39.48	12.35	10.25	23.14	12.86	611.87	0	611.87

in the DRP and customer' inconvenience to participate in the DRP are investigated. The Fuzzy-Markov is used to model the uncertainty of the participation of customers in DRP. The SGFI is presented to analyze the flexibility of smart grid. The lower the uncertainty of consumer participation in DRP and the output power of the gas turbine, the higher the flexibility index. The method has been tested on the standard system and the results show the fast response sources could reduce the generation cost and Pollution generation cost of power plants, but an inconvenience cost may occur due to the load shift.

In the future, congestion management can be used in buses, such as the use of electrical energy storage devices and the use of more rapid response resources to make the system more flexible.

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