Electrical Power and Energy Systems 97 (2018) 334–343

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Multi-objective dynamic economic and emission dispatch with demand side management

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ARTICLE INFO

Keywords:
Demand side management
Multi-objective optimization
Utility energy bill
Dynamic economic and emission dispatch
Load shifting

ABSTRACT

This paper proposes a combined model of Multi-Objective Dynamic Economic and Emission Dispatch (MODEED) with Demand Side Management (DSM) to investigate the benefits of DSM on generation side. This model considers a day ahead based load shifting DSM approach. In order to analyse the effect of DSM on the generation side, the objectives of dynamic economic and emission dispatch problem were minimized individually and simultaneously with and without DSM. A test system with six thermal generating units was considered for the validation of the proposed method. In this paper, authors used Multi-Objective Particle Swarm Optimization (MOPSO) algorithm to minimize the objectives of MODEED problem simultaneously. The simulation results of the MOPSO algorithm have also been compared with the non-dominated sorting genetic algorithm (NSGA-II). It is clear from the results that the proposed combined model is able to give benefits to both utilities and generating companies.

1. Introduction

Nowadays the electric power markets are showing more attention to the demand side management programs because of the exciting benefits such as system peak reduction, financial savings to the utilities and consumers, efficient utilization of network infrastructure, proper load profile improvement. DSM helps not only utilities and consumers but also provides impressive benefits to generating companies too [1,2]. DSM implementation in the existing electric power grids requires the latest information and communication technologies. By using these technologies, a two way communication is established between the power supplier and consumers. Central energy consumption controller and smart meters are the main devices for their dynamic communication [3,4].

Dynamic pricing policies like Time of Use (ToU) pricing, critical peak pricing, real time pricing, off peak low pricing and day ahead pricing are the smart pricing tools for the process of DSM implementation [5–7]. Incentive based DSM which involves more participants reduces the system peak demand and improves the load profile shape [8]. According to literature, the three DSM categories such as environmentally driven type, network driven type and market driven type are generally used. The environmental driven DSM mainly focuses on the social and environmental standards like reduction of greenhouse gas emission. The network driven type aims in maintaining the reliability of the system and the market driven type targets the financial savings of the utilities and consumers [9–11]. In [12], a day-ahead based load shifting DSM technique was implemented in a smart grid environment with the help of a heuristic algorithm. The real time pricing based energy control strategy was developed in [13] to manage the peak load demand. An energy management algorithm was proposed in [14] to achieve the pricing strategies and operating states of consumers.

The dynamic economic and emission dispatch (DEED) is a crucial optimization problem in the power system operation and control. DEED problem gives the on line generating schedules over a certain predicted load demand period by minimizing cost and emission simultaneously. The generation cost function with valve point loading effect is modelled as a non convex function which has multiple local minima. This dynamic optimization problem has to satisfy many constraints like equality, inequality and ramp-rate limits throughout the dispatch period [15–17]. DSM problem which handles the demand side is also considered as an optimization problem. DSM program should be implemented with a large number of controllable devices and each device has different consumption patterns. So, the evolutionary algorithms are preferably used to handle the such type of complexities [12].

In literature, many meta heuristic based optimization techniques have been proposed to solve the Dynamic Economic Dispatch (DED) problem. For example, the Enhanced Genetic Algorithm (E-GA) and Enhanced Differential Evolutionary (E-DE) algorithms were proposed for DED problems in [18]. In [19], the combination of GA and DE was used to solve the DED problem with different generating unit combinations like hydro-thermal, solar-thermal and wind-thermal. Enhanced PSO based DEED problem with wind uncertainties was proposed in [20]. Nowadays, the focus is mainly moving towards the combination of DED and DSM

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https://doi.org/10.1016/j.ijepes.2017.11.020
Received 7 July 2017; Received in revised form 22 October 2017; Accepted 19 November 2017
Available online 23 November 2017
0142-0615/

Nomenclature

$C_{g,t}(P_{g,t})$	fuel cost function during the time interval t
$E_{g,t}(P_{g,t})$	emission function during the time interval t
$P_{g,t}$	power output of g^{th} generating unit at the t^{th} time interval
G	total number of generating units
τ	total number of dispatch intervals
a_g, b_g, c_g	fuel cost coefficients of g^{th} generating unit
d_g, e_g	coefficients for the valve point loading effect of g^{th} generating unit fuel cost function
γ_g, β_g, α_g	emission coefficients of g^{th} generating unit
ξ_g, λ_g	coefficients for the valve point loading effect of g^{th} generating unit emission function
$P_{D,t}$	total load demand power at t^{th} time interval
$P_{L,t}$	total transmission power losses at t^{th} time interval
$P_g^{\min}$	minimum real power output of g^{th} generating unit
$P_g^{\max}$	maximum real power output of g^{th} generating unit
UR_g	ramp up limit of g^{th} generating unit
DR_g	ramp down limit of g^{th} generating unit
$\psi(t)$	load demand value after DSM scheduling at the time instant t
$\zeta(t)$	targeted load demand value at the time instant t
$\mathrm{FL}(t)$	forecasted load demand value at time instant t
$\mathrm{CL}(t)$	connected load demand at time interval t
$\mathrm{DL}(t)$	disconnected load demand at time interval t
N	total types of controllable appliances
X_{lit}	number of l type controllable appliances which are shifted from i to t time slot

optimization. The impacts of Demand Response (DR) program on the Unit Commitment (UC) problem were investigated in [21]. In [22], the UC problem with the economic and environment DR program was proposed. In [23], a GA based DED and DSM combination was proposed for an efficient energy management in a micro grid environment. A novel model of DED problem integrated with demand response in regional grids was proposed in [24]. In [25], a MODEED problem with game theory based DR model was presented. The DEED problem and DSM combination model incorporating high wind penetration was proposed in [26,27]. The main goal of DEED and DSM combination models proposed in the literature was to show the impacts of DSM on the supply side. From the overall literature, the DED problem is incorporated with either incentive based DR program or ToU based DSM method. In the incentive based DR program, the power supplier can control the customers' loads directly by providing impressive incentives. The ToU based DSM method introduces different prices for all individual time slots which make consumers move their loads to low pricing slots. In this paper, authors proposed a model which uses MODEED problem and a day-ahead based load shifting DSM program for residential loads. Compared to other DED and DR combinations in the literature, all necessary DSM constraints for the residential loads were considered in this paper without any load curtailment. In this proposed model, authors also considered the consumers' comfort by providing different delay times for all controllable loads based on their daily life style. The proposed combined model is mainly focusing on the benefits of DSM program towards the generation side with different residential participation levels. To the best of authors' knowledge, the proposed model has not been reported in the literature. The proposed combined model can be solved effectively by the evolutionary algorithms. In this paper, the proposed model uses non dominated sorting based MOPSO [28,29] algorithm with a fuzzy optimization tool for minimizing MODEED problem simultaneously and single objective PSO algorithm for minimizing the DSM technique. For a comparison purpose, the objectives of MODEED problem were minimized using NSGA-II and the results of both MOPSO and NSGA-II were also compared.

The organization of the paper is as follows. Section 2 explains the problem formulation and the DSM approach. The proposed combined model is explained in the Section 3. Section 4 explains the test system considered in this paper with different assumptions. The simulation results and their comparison are given in the Section 5. Section 6 gives the conclusion of the paper.

2. Problem formulation

2.1. Multi-objective dynamic economic and emission dispatch (MODEED) problem

The dynamic economic and emission dispatch is the most important optimization problem in the power system operation and control for satisfying the economic and social aspects. In this DEED problem, the total fuel cost and emission are the two different conflicting objectives which are to be minimized simultaneously. The mathematical formulation of the objective functions are shown as follows [2,29,30]

Minimize

$$F_1 = \sum_{t=1}^{\tau}\sum_{g=1}^{G} C_{g,t}(P_{g,t}), \tag{1}$$

$$F_2 = \sum_{t=1}^{\tau}\sum_{g=1}^{G} E_{g,t}(P_{g,t}), \tag{2}$$

where F_1 and F_2 are the total fuel cost and emission of G number of generating units over a τ total number of dispatch intervals. $C_{g,t}(P_{g,t})$ and $E_{g,t}(P_{g,t})$ are the fuel cost and emission functions respectively during the time interval t and $P_{g,t}$ is the g^{th} generating unit power output at the t^{th} time interval. The total amount of emissions such as NO_x and SO_x are modelled as a sum of quadratic and exponential terms in the emission function. The fuel cost function with valve point effect is modelled as a sum of quadratic and sinusoidal terms. The mathematical formulation of these functions are given in Eqs. (3) and (4).

$$C_{g,t}(P_{g,t}) = a_g P_{g,t}^2 + b_g P_{g,t} + c_g + |d_g \sin(e_g(P_g^{\min} - P_{g,t}))|, \tag{3}$$

$$E_{g,t}(P_{g,t}) = (\gamma_g P_{g,t}^2 + \beta_g P_{g,t} + \alpha_g) + \xi_g \exp(\lambda_g P_{g,t}), \tag{4}$$

where a_g, b_g, c_g are the g^{th} generating unit fuel cost coefficients and d_g, e_g are the fuel cost coefficients due to the valve point loading effect. γ_g, β_g and α_g are the g^{th} generating unit emission coefficients and ξ_g, λ_g are the emission coefficients due to the valve point loading effect.

2.1.1. Constraints

In DEED optimization problem, the objective functions are subjected to the following equality and inequality constraints:

1. Power balance constraint:

$$\sum_{g=1}^{G} P_{g,t} - P_{D,t} - P_{L,t} = 0 \ ,\forall \quad t \in \{1,2,\ldots,\tau\}, \tag{5}$$

where $P_{L,t}$ and $P_{D,t}$ are the t^{th} time interval total transmission power losses and total load demand power respectively. $P_{L,t}$ can be calculated by using B-loss coefficient method. The general mathematical form for the loss calculation is as follows

$$P_{L,t} = \sum_{g=1}^{G}\sum_{j=1}^{G} P_{g,t} B(g,j) P_{j,t}. \tag{6}$$

where $B(g,j)$ is the power transmission network loss coefficient value. $P_{g,t}$ and $P_{j,t}$ are the t^{th} time interval g^{th} and j^{th} generating unit real power outputs respectively.

2. Generation power limits:

$$P_g^{\min} \leqslant P_{g,t} \leqslant P_g^{\max}, \quad \forall \;\; g \in \{1,2,\cdots,G\}. \tag{7}$$

where $P_g^{\min}$ and $P_g^{\max}$ are the g^{th} generating unit minimum and maximum real power operating values, respectively.

3. Ramp-rate limits of generating units:

$$P_{g,t}-P_{g,t-1} \leqslant \mathrm{UR}_g, \quad \forall \;\; g \in \{1,2,\ldots,G\}, \tag{8}$$

$$P_{g,t-1}-P_{g,t} \leqslant \mathrm{DR}_g, \quad \forall \;\; g \in \{1,2,\ldots,G\}, \tag{9}$$

So, Eq. (8) can be rewritten as

$$\max(P_g^{\min},P_{g,t-1}-\mathrm{DR}_g) \leqslant P_{g,t} \leqslant \min(P_g^{\max},P_{g,t-1}+\mathrm{UR}_g). \tag{10}$$

where UR_g and DR_g are the up and down ramp rate limits of g^{th} generating unit respectively. The ramp rate limits are the dynamic constraints in the economic dispatch problem. Practical thermal generating units take some time to increase or decrease their power outputs. These physical limitations of thermal units can be represented with the constrained generating capabilities [31].

2.2. Demand side management (DSM) approach

DSM methods are mainly required for the utilities to increase their financial savings and improve the system load profile shape. Usually the utility companies introduce attractive type DSM methods to encourage more number of consumers' participation. Due to this, the utility companies can easily succeed in achieving their goals. From the DSM literature, peak clipping, valley filling, load shifting, strategic conservation, strategic load growth and flexible load shape are the six basic load shaping methods. The first three methods are the basic level types and remaining three methods are advanced level types which control the overall load demand shape by either curtailing or extending with the help of system planning and operation [27,12]. The load shifting method is an aggregate of peak clipping and valley filling which is the most preferable method amongst all load management techniques. The load shifting method can be implemented with the help of controllable loads at the consumer side. In the load shifting method, the controllable loads are shifted from peak slots to off peak slots without changing any energy consumption. The six basic DSM load shape methods are shown in Fig. 1.

Day ahead based load shifting DSM technique [12] is used in this paper for investigating the effects of it on the generation side. In this paper the utility energy bill minimization is considered as the main objective for the DSM implementation. For that purpose, the forecast load demand curve is estimated according to the previous data. In order to do that the smart prices are assigned to each individual load hours and the utility creates a target load demand curve which is inversely proportional to individual slot prices. One day before, the central DSM controller receives the target load curve as an input entry and calculates the control actions of desired load consumption. According to the results, these control actions are executed in real time period. During real time operation, when a consumer sends a request for the device connection through an appliance ON button, the DSM controller will give either the connection permission or a new connection time. The whole real time process is effectively done by using two way communication and information technologies.

The wholesale electricity market prices of each individual slots are assigned by using ToU tariff method which is one of the smart pricing tool methods. In ToU tariff method the critical peak pricing and low price for off peak periods are considered [32,33]. Due to these pricing tools, the DSM participants will prefer to shift their devices in off peak periods. Since DSM has multiple controllable loads with different power consumption patterns, evolutionary algorithms are found to be suitable for minimizing this problem. In this paper the DSM objective is optimized by PSO algorithm to find a near global optimal solution.

2.3. Utility energy bill objective function

The main aim of the utility energy bill objective is to minimize the distance between the forecasted and targeted load demand curves with the help of controllable loads.The objective function is mathematically formulated as follows [12]

$$\min F = \sum_{t=1}^{\tau} (\psi(t)-\zeta(t))^2, \tag{11}$$

where $\zeta(t)$ and $\psi(t)$ are the targeted load demand value and load demand value after DSM scheduling at the time instant t respectively. τ is the total number of time instants available in the day load demand profile.

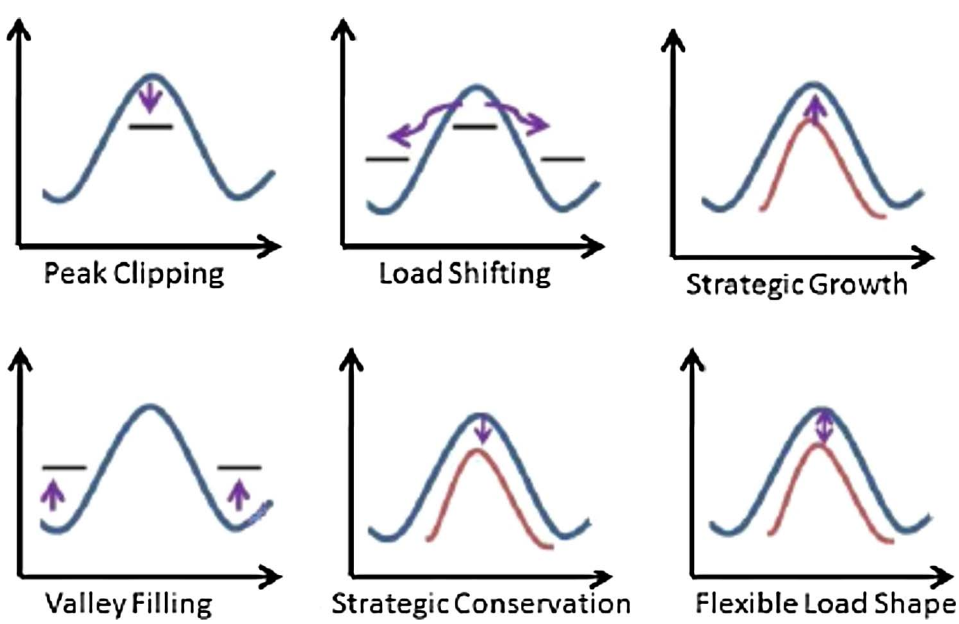

Fig. 1. DSM load shape methods.

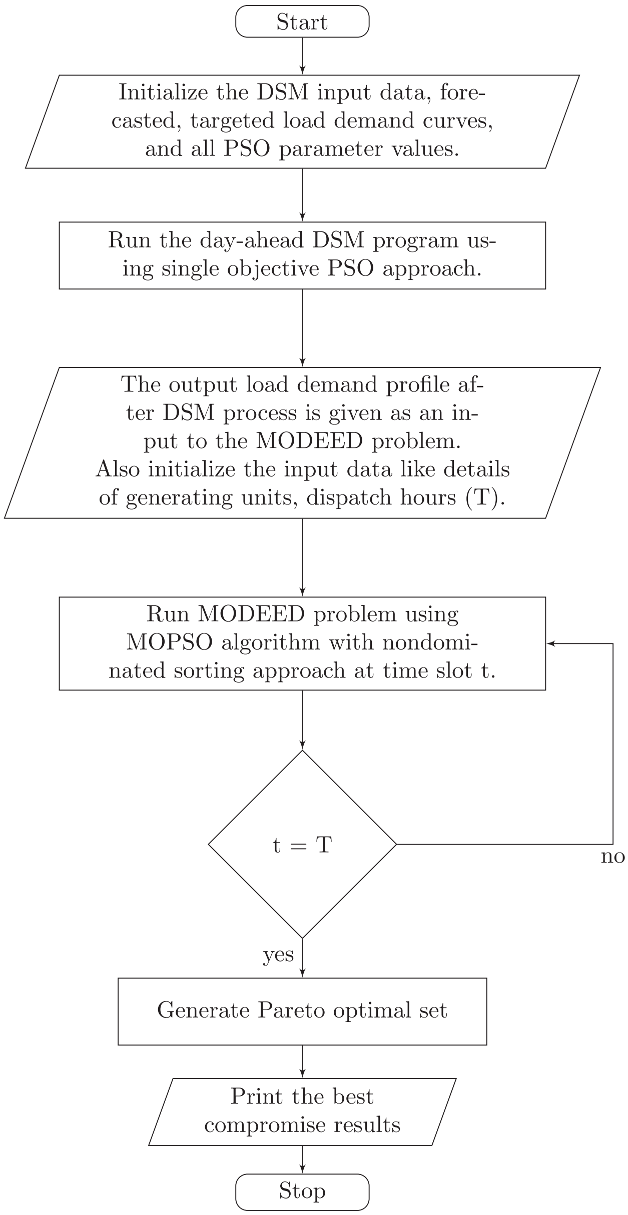

Fig. 2. Simplified flow chart of combined MODEED and DSM model.

2.4. Load shifting calculation and constraints

$\psi(t)$ can be calculated as follows

$$\psi(t) = \mathrm{FL}(t) + \mathrm{CL}(t) - \mathrm{DL}(t), \tag{12}$$

where $\mathrm{FL}(t)$ is the forecasted load demand value at time instant t, $\mathrm{CL}(t)$ and $\mathrm{DL}(t)$ are the connected and disconnected load demand values respectively during the load shifting operation at time interval t. These are formulated as follows:

$$\mathrm{CL}(t) = \sum_{i=1}^{t-1}\sum_{l=1}^{N} X_{lit}.\, P_{1l} + \sum_{j=1}^{t-2}\sum_{k=j+1}^{t-1}\sum_{l=1}^{N} X_{ljk}.\, P_{(t-k+1)l}, \tag{13}$$

where X_{lit} is the number of l type controllable appliances which are shifted from i to t time slot, N is the total types of controllable appliances, P_{1l} and $P_{(t-k+1)l}$ are the load power consumptions due to l type shifted device at 1 and $(t-k+1)$ time steps respectively. Here $(t-k+1)$ is the l type device power consumption time step at time instant t which is shifted from j to k.

$$\mathrm{DL}(t) = \sum_{q=t+1}^{t+m}\sum_{l=1}^{N} X_{ltq}.\, P_{1l} + \sum_{j=1}^{t-1}\sum_{k=j+1}^{j+m}\sum_{l=1}^{N} X_{ljk}\cdot P_{(t-j+1)l}. \tag{14}$$

where X_{ltq} is the number of l type controllable appliances which are delayed from t to q time slot and also have the maximum admissible m delay steps for the each controllable appliance.

For the load shifting process, the following conditions must be considered for proper load management. The number of shifted appliances at any time instant t must be non negative as shown in Eq. (15). The number of total shifted devices away from the time instant t cannot exceed the available controllable appliances at the particular time slot as given in Eq. (16).

$$X_{lit} > 0\,, \quad \forall \;\; l,i,t. \tag{15}$$

$$\sum_{t=1}^{\tau} X_{lit} \leqslant \mathrm{Ctrd}(i). \tag{16}$$

where $\mathrm{Ctrd}(i)$ is the total number of l type controllable appliances at time instant i. All other conditions are given as follows:

$$P_{(t-k+1)l} = 0\,, \quad \forall \;\; (t-k+1) > D. \tag{17}$$

$$X_{lit} = 0\,, \quad \forall \;\; i > t. \tag{18}$$

$$X_{lit} = 0\,, \quad \forall \;\; (t-i) > m. \tag{19}$$

where D is the total time duration of l type appliance power consumption. Eq. (18) shows that the DSM method has only delayed characteristic and not brought forward type. Eq. (19) represents the maximum allowable delay m for all appliances.

3. MODEED optimization algorithm approach

In this paper, the MODEED problem is implemented over a 24 h dispatch period by using non dominated sorting based MOPSO algorithm [29]. PSO is a population based evolutionary algorithm. Each population in this algorithm consists of controllable variables which move in the search space with a proper velocity for attaining the

Table 1
Six thermal generating units cost and emission coefficients data.

Power limits		Fuel cost coefficients					Emission coefficients					Ramp rate limits	
$P_g^{\min}$ (MW)	$P_g^{\max}$ (MW)	a_g	b_g	c_g	d_g	e_g	γ_g	β_g	α_g	ξ_g	λ_g	UR_g (MW/h)	DR_g (MW/h)
50	200	0.00375	2	0	18	0.037	0.0649	−0.05554	0.04091	0.0002	2.857	50	50
20	80	0.0175	1.75	0	16	0.038	0.05638	−0.06047	0.02543	0.0005	3.333	16	16
15	50	0.0625	1	0	14	0.040	0.04586	−0.05094	0.04258	0.000001	8	10	10
10	35	0.00834	3.25	0	12	0.045	0.0338	−0.0355	0.05326	0.002	2	7	7
10	30	0.025	3	0	13	0.042	0.04586	−0.05094	0.04258	0.000001	8	6	6
12	40	0.025	3	0	13.5	0.041	0.05151	−0.05555	0.06131	0.000001	6.667	8	8

Table 2
Six unit test system 24 h load demand profile.

Time (h)	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	166	196	229	267	283.4	272	246	213	192	161	147	160
Time (h)	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	170	185	208	232	246	241	236	225	204	182	161	131

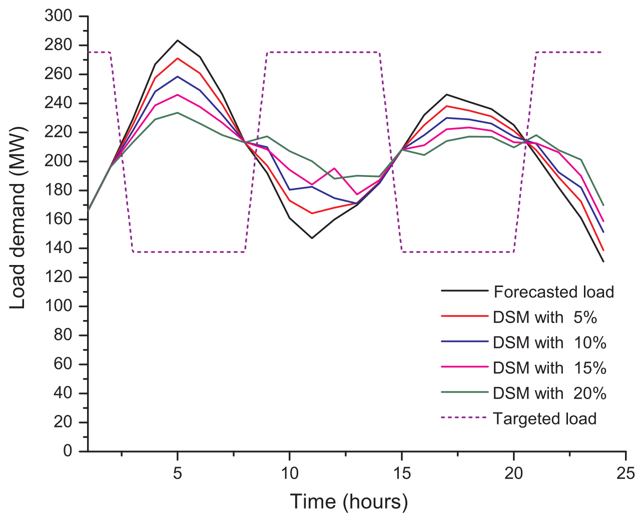

Fig. 3. Load demand curves after DSM with different participation levels.

optimal objective value. In this paper, the DSM technique is optimized first to get a modified load demand profile. After this step, the control variables of the MODEED problem are randomly generated between their minimum and maximum limits. After the initialization of control variables, their positions and velocities are updated by the following equations.

$$\vartheta_i^{k+1} = \omega^k * \vartheta_i^k + C_1 * \text{rand}()_1 * (\text{Pbest}_i^k - \chi_i^k) + C_2 * \text{rand}()_2 * (\text{Gbest}^k - \chi_i^k), \quad (20)$$

$$\chi_i^{k+1} = \chi_i^k + \vartheta_i^{k+1}. \quad (21)$$

where ϑ_i^{k+1} and χ_i^{k+1} are the i^{th} particle velocity and position vectors at the $(k+1)^{th}$ iteration respectively. C_1, C_2 and ω^k are parameters of PSO algorithm. All PSO parameters were modified and updated dynamically in this paper. The modified parameters and updating steps are adopted from the reference [29].

Table 3
Dynamic economic dispatch with different DSM participation levels.

Participation level	Without DSM	DSM with 5%	DSM with 10%	DSM with 15%	DSM with 20%
Fuel cost ($/day)	13,555	13,515	13,475	13,470	13,461
Emission (tons/day)	7.503	7.356	7.311	7.292	7.286

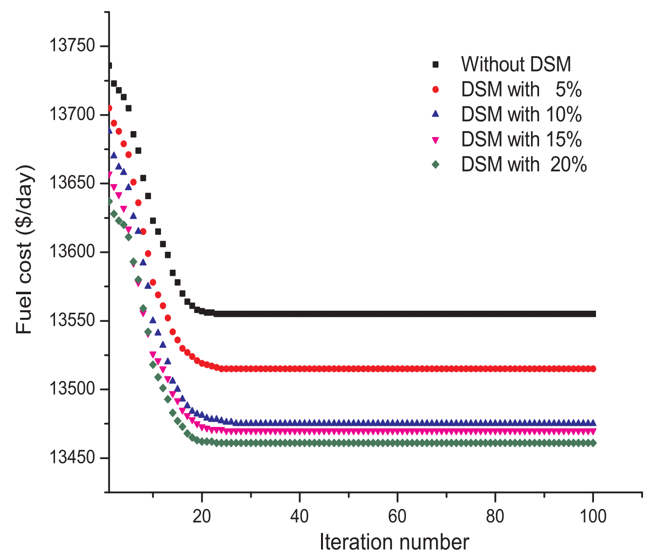

Fig. 5. Convergence characteristics of dynamic economic dispatch with different DSM participation levels.

In this paper, the multi-objective optimization problem was handled by the non dominated sorting approach with a fuzzy optimization tool. The membership and decision making concept of the fuzzy optimization tool are shown as follows.

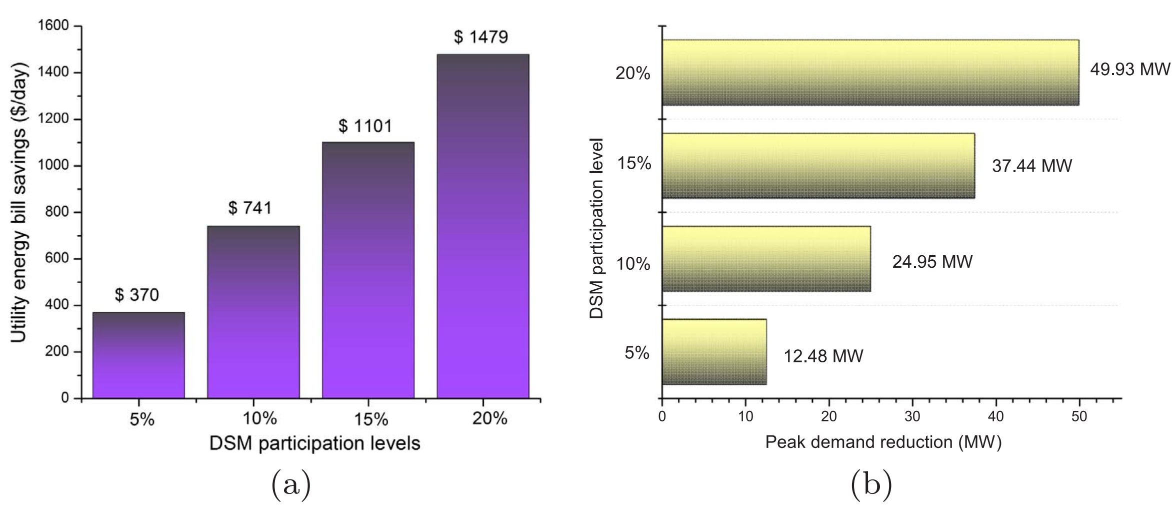

Fig. 4. Utility energy bill savings and peak demand reduction with the different levels of DSM participation.

Table 4
Dynamic emission dispatch with different DSM participation levels.

Participation Level	Without DSM	DSM with 5%	DSM with 10%	DSM with 15%	DSM with 20%
Fuel cost ($/day)	15,959	15,978	15,986	15,994	15,983
Emission (tons/day)	4.938	4.913	4.895	4.884	4.877

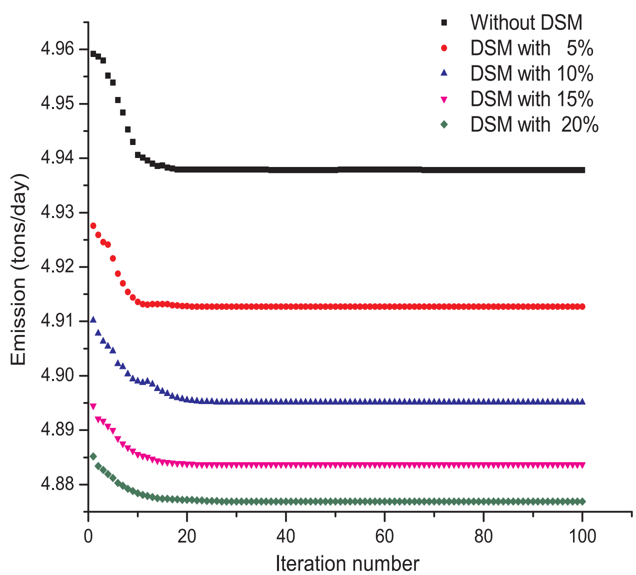

Fig. 6. Convergence characteristics of dynamic emission dispatch with different DSM participation levels.

Table 5
Dynamic economic and emission dispatch with the different DSM participation levels.

Participation Level	Without DSM	DSM with 5%	DSM with 10%	DSM with 15%	DSM with 20%
Fuel cost ($/day)	14,404	14,341	14,312	14,229	14,167
Emission (tons/day)	5.774	5.745	5.720	5.705	5.656

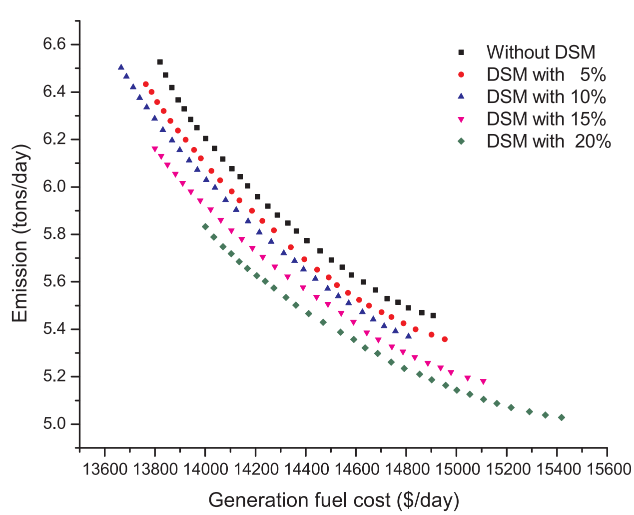

Fig. 7. Pareto sets of MODEED problem with different DSM participation levels.

$$\mu_k(X) = \begin{cases} 1 & \text{if } F_k(X) \leqslant F_k^{\min} \\ \frac{F_k^{\max} - F_k(X)}{F_k(X) - F_k^{\min}} & \text{if } F_k^{\min} < F_k(X) < F_k^{\max} \\ 0 & \text{if } F_k(X) \geqslant F_k^{\max}, \end{cases} \tag{22}$$

$$N_{\mu_j} = \frac{\sum_{k=1}^{\ell} \mu_k(j)}{\sum_{j=1}^{M} \sum_{k=1}^{\ell} \mu_k(j)}. \tag{23}$$

where $F_k^{\min}$ and $F_k^{\max}$ are the k^{th} objective function $F_k(X)$'s minimum and maximum values respectively, $\mu_k(X)$ is the k^{th} objective function membership value. N_{μ_j} is the j^{th} non dominated solution's normalized membership function value, M is the total number of non dominated solutions and ℓ is the total number of objective functions. The maximum N_{μ_j} value decides the multi objective problem final solution. The flow chart of the proposed combined model is shown in Fig. 2. The pseudo code of the proposed model is also given in Algorithm 1.

Algorithm 1. MOPSO optimization for the combined model of MODEED problem and DSM program.

Require: Forecasted load, targeted load, all controllable device's data, DSM participation level, all generating units data and the total number of dispatch intervals ($\tau = 24$).
Ensure: Assign the all PSO parameter values - ω, C_1, C_2, pop and MaxIter
1: Initialize a random population to minimize DSM objective (Eq. (11))
2: While iter < MaxIter **do**
3: **for** Each population i **do**
4: Update velocity and positions by using Eqs. (20) and (21)
5: **end for**
6: Check all constraints (Eqs. (15)–(19)) and calculate the fitness value of each population
7: Now update the Pbest and Gbest values
8: **end while**
9: Print the Gbest value of utility bill and load demand curve after DSM
10: Use this final load demand data as an input for MODEED problem
11: **while** t < τ **do**
12: Initialize the t^{th} hour random population for economic and emission objectives (Eqs. (1) and (2))
13: Check all equality and inequality constraints (Eqs. (5)–(10)), delete which are not satisfied and replace with the new satisfied populations
14: Apply non dominated sorting approach to initial random population and save those non dominated solutions in the repository
15: Calculate the crowding distance and rank for each non dominated solution
16: Select the Gbest value randomly from the top 10% of non dominated repository
17: while iter < MaxIter **do**
18: Repeat the steps from 3 to 5
19: Add updated population to the saved non dominated repository and apply non dominated sorting approach
20: Repeat the steps from 15 to 16
21: **end while**
22: Update generator's minimum and maximum values by using ramp rate limits and t^{th} hour best generation values
23: **end while**
24: Apply fuzzy member ship function and decision making tools (Eqs. (22) and (23))
25: Print the best compromised values and plot the Pareto optimal set.

Table 6
Generator's 24 h optimal power outputs with and without DSM integration.

Time slot	MODEED without DSM						MODEED with 20 % DSM					
	Pg_1	Pg_2	Pg_3	Pg_4	Pg_5	Pg_6	Pg_1	Pg_2	Pg_3	Pg_4	Pg_5	Pg_6
1	59.08	43.65	21.62	14.43	15.72	13.47	65.34	38.47	20.63	10.82	16.66	16.15
2	66.53	41.18	23.10	15.41	25.32	26.91	99.19	37.63	20.33	12.36	14.69	15.38
3	78.39	50.13	29.90	19.85	27.21	26.79	91.11	43.39	24.45	18.97	16.87	21.71
4	130.08	58.17	25.51	16.98	21.04	21.73	94.69	44.16	25.91	22.48	21.73	23.83
5	159.05	55.51	24.44	15.33	17.30	20.34	126.97	41.56	22.61	17.70	13.15	16.88
6	169.58	44.31	23.38	15.31	14.27	13.83	82.16	47.62	28.88	19.28	22.07	29.37
7	146.23	39.10	21.32	14.14	16.21	15.51	70.50	46.22	28.32	21.84	24.45	29.63
8	99.08	48.46	22.77	17.47	15.07	14.11	57.87	46.15	26.90	24.74	27.57	32.26
9	75.91	41.89	22.35	19.07	17.66	17.78	62.47	47.93	27.51	26.25	25.01	30.64
10	64.63	34.97	18.35	14.86	14.93	15.20	62.47	40.93	25.41	24.76	26.04	29.81
11	54.22	34.85	19.65	10.00	15.04	14.81	67.62	44.83	23.16	22.06	22.89	22.10
12	56.89	34.59	22.27	11.61	18.11	18.23	63.44	37.51	24.27	20.84	21.35	22.88
13	75.87	36.78	19.04	15.23	12.01	13.48	67.55	42.23	23.71	21.79	19.81	17.33
14	70.27	40.25	23.44	19.05	14.51	19.88	62.11	38.93	24.93	21.03	23.13	21.64
15	84.59	46.15	24.13	20.55	17.67	18.12	82.32	45.77	23.66	23.17	16.32	19.97
16	114.34	47.42	22.33	15.89	17.81	19.11	101.91	42.29	22.21	13.54	13.41	14.82
17	141.39	40.91	20.68	15.51	17.06	16.82	107.28	46.18	19.79	14.96	15.25	14.91
18	143.11	45.61	19.34	12.99	12.29	14.31	87.61	46.73	27.68	18.02	20.69	19.73
19	113.96	43.10	25.89	19.13	16.63	22.04	72.36	49.98	25.22	22.18	24.92	25.16
20	86.51	44.74	26.25	26.50	18.37	26.07	78.24	42.93	25.11	21.63	22.83	21.67
21	83.44	46.91	21.27	21.83	17.01	16.69	68.97	46.78	28.27	27.52	24.01	25.21
22	77.51	38.99	21.52	16.96	12.26	17.35	55.44	44.73	31.69	24.76	25.32	27.92
23	57.57	37.83	21.26	12.06	15.82	18.25	66.47	44.22	23.75	23.66	23.80	21.73
24	51.54	30.93	17.50	10.00	10.36	12.00	52.25	39.36	22.39	19.23	19.32	18.92

4. Test system data

In this paper, a test system with six thermal generating units is considered for all case studies. The generator's fuel cost coefficients, emission coefficients, ramp rate limits, 24 h forecasted load demand profile and corresponding all other system data are taken from Refs. [29,34,35] and also given in Tables 1 and 2. The transmission loss coefficient matrix of six generating unit test system is given in Eq. (24). Generally the load of any interconnected power system is a combination of residential, commercial and industrial sector loads [36]. Due to this, authors considered 30% of the total energy demand as the residential load. The residential area has several controllable appliances like dish washers, washing machine, kettle, ovens and other appliances which can be easily managed in the load shifting process when compared to commercial and industrial loads. Therefore, in this paper the day ahead based load shifting DSM technique was applied to residential loads only.

In the DSM implementation process, the four different participation levels 5%, 10%, 15% and 20% of the total residential load demand were considered. The utility's wholesale electric market prices of each individual hour was assigned by ToU tariff. According to this, two different prices namely critical peak pricing and low off peak price, are considered with the values of 10 \$/MWh and 5 \$/MWh respectively, for the whole dispatch period. In this analysis, the power consumption of all controllable appliances are assumed to be 2 kW with different power consumption patterns. In this approach, the maximum delay steps of each controllable devices were assigned according to the consumer's daily life style. For example, two or three maximum delay steps are allowable for the high priority devices like kettle, oven and hair dryers which are considered here. Similarly, twelve maximum delay steps were considered for low priority devices like tumble dryer, iron and vacuum cleaners.

$$B = \begin{pmatrix} 2.2 & 1.1 & -0.1 & -0.1 & 0.1 & 0.4 \\ 1.1 & 1.6 & 0 & -0.1 & 0 & 0.3 \\ -0.1 & 0 & 2.4 & -1 & -1 & -0.7 \\ -0.1 & -0.1 & -1 & 1.9 & 0.7 & 0.4 \\ 0.1 & 0 & -1 & 0.7 & 1.6 & 0 \\ 0.4 & 0.3 & -0.7 & 0.4 & 0 & 2.6 \end{pmatrix} \times 10^{-4} \quad \text{per MW} \tag{24}$$

5. Simulation results and discussion

In this paper, the impacts of DSM on both utility and generating companies were studied. Both DSM and DEED optimization problems were implemented in MATLAB platform. In each optimization algorithm, number of populations $NP = 30$ and number of iterations MaxIter=100 were considered. In order to find out the best solution, 30 different trials were made.

5.1. DSM effects on the utility side

The primary goal of the paper is to analyse the impacts of the DSM implementation on the generation side. However, the impacts of DSM on the utility side were considered too. In order to achieve this, the DSM problem was implemented with the minimization of utility energy bill as a main objective. Fig. 3 shows the forecasted load demand curve, targeted load demand curve and load demand curves after the DSM implementation with different residential participation levels. From the load demand curves, it is clear that the better load demand profile was achieved at higher participation levels. It was seen the DSM load curves move towards the targeted load curve at higher participation levels. So, the utility company has achieved the attractive benefits due to the implementation of DSM which are shown in Fig. 4(a) and (b). According to the simulation results of this DSM program, the utility company's per day energy bill savings are \$370, \$741, \$1101 and \$1479 respectively for the participation levels of 5%, 10%, 15% and 20% of the total residential load demand. Similarly, the system peak load demand was also reduced to 12.48 MW, 24.95 MW, 37.44 MW and 49.93 MW respectively for the above participation levels.

5.2. DSM effects on the generation side

To study the impacts of DSM on the generation side, the three different case studies were considered with different DSM participation levels. In case 1 and case 2, the dynamic economic dispatch and emission dispatch problems were individually minimized along with the DSM technique, respectively. Case 3 explains the proposed model of MODEED with the DSM technique.

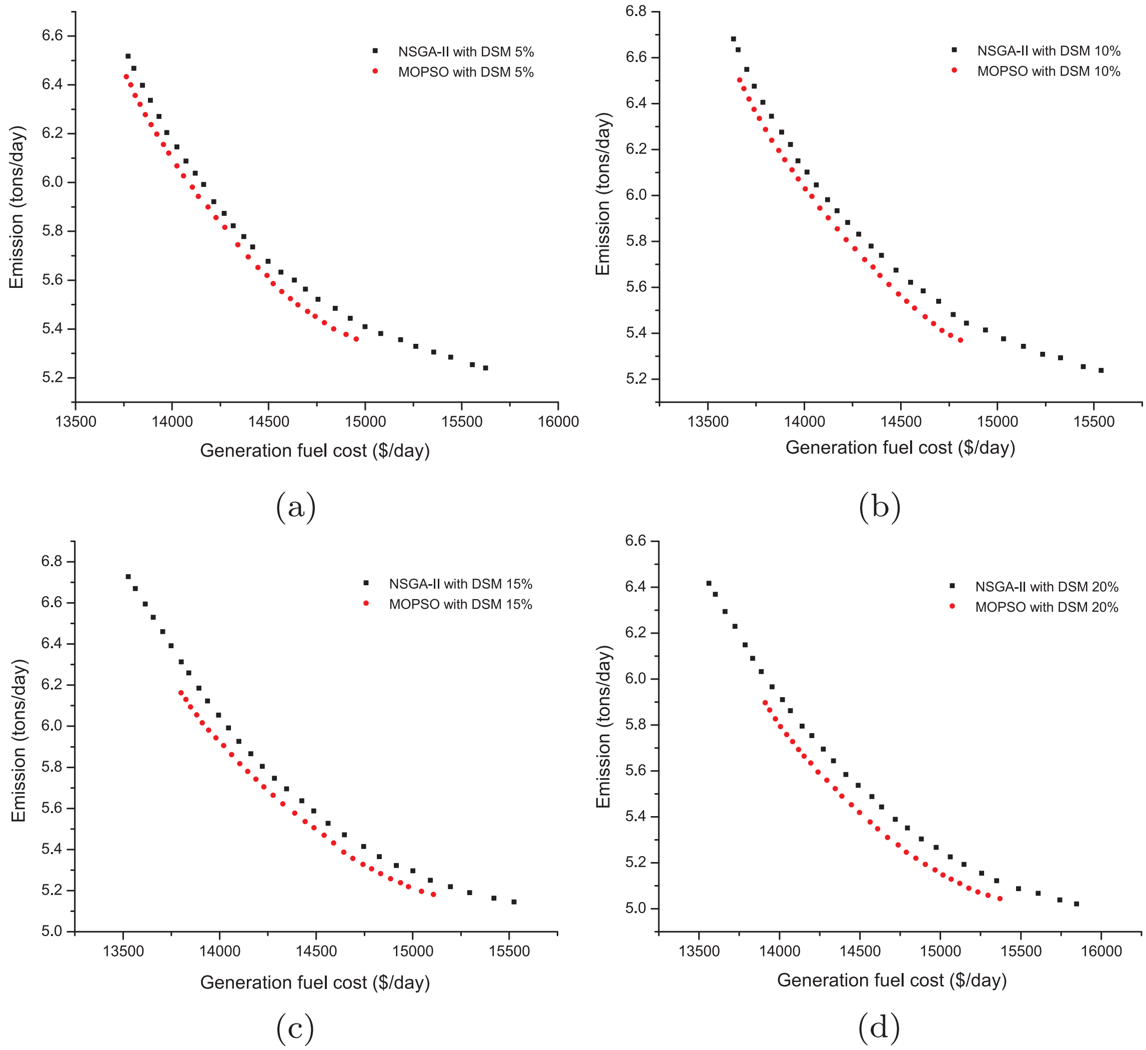

Fig. 8. Comparison of MOPSO and NSGA-II for different DSM participation levels.

Table 7
Comparison of the best compromise results of MOPSO and NSGA-II techniques.

Optimization technique	NSGA-II		MOPSO	
	Best cost ($/day)	Best emission (tons/day)	Best cost ($/day)	Best emission (tons/day)
DSM with 5%	14,371	5.878	14,341	5.745
DSM with 10%	14,345	5.781	14,312	5.720
DSM with 15%	14,283	5.747	14,229	5.705
DSM with 20%	14,272	5.695	14,167	5.656

Table 8
Hyper volume comparison of MOPSO and NSGA-II techniques.

Participation	Hyper volume indicator (I_H)	
Level	NSGA-II	MOPSO
DSM with 5%	0.8358	0.9006
DSM with 10%	0.8350	0.9143
DSM with 15%	0.8468	0.9026
DSM with 20%	0.8516	0.899

5.2.1. Case 1: dynamic economic dispatch with DSM

In this case, the single objective dynamic economic dispatch problem with DSM was considered to study the impact of DSM in the fuel cost alone. In order to study it in detail, four different participation levels were considered in the DSM program. Both the dynamic economic dispatch and DSM problems were minimized using PSO algorithm. Table 3 shows the simulation results of dynamic economic dispatch problem with and without DSM. Fig. 5 shows the convergence characteristics of DED problem with and without DSM. From the results, it is clear that the DSM technique helps the generating companies reduce their fuel cost. Simulation results show that the generation fuel cost value was minimized more at higher participation levels of DSM. For example, DSM with a participation level of 20% there is a reduction of 0.7% in the total day fuel cost against without DSM. The generation companies can save $94 every day in their fuel cost due to the implementation of DSM.

5.2.2. Case 2: dynamic emission dispatch with DSM

In this case, the single objective dynamic emission dispatch problem with DSM was considered. The simulation results of dynamic emission dispatch with and without DSM are shown in Table 4. Fig. 6 shows the convergence characteristics of dynamic emission dispatch problem with and without DSM. According to the results, it is clear that there is a considerable reduction in emission level with DSM implementation. For example, DSM with a participation level of 20% there is a reduction of 0.061 ton per day in the emission level against without DSM.

5.2.3. Case 3: dynamic economic and emission dispatch with DSM

In this case, the multi-objective dynamic economic and emission problem with DSM was considered. The objectives of DEED problem were simultaneously minimized using MOPSO. Table 5 shows simulation results of MODEED problem with the implementation of different DSM participation levels. Fig. 7 shows the different Pareto sets of MODEED optimization problem with various DSM participation levels. The best compromise values of fuel cost and emission were found using the fuzzy membership approach. From the results, it is clear that the proposed model is able to give the better solutions than the single objective case for the same participation levels in DSM. For example, the generating companies can get per day fuel cost savings of $63, $92, $175 and $237 respectively for the participation levels of 5%, 10%, 15% and 20% of the total residential load demand. At the same time the generating companies can also reduce their per day total emission levels. The reduction in emission levels are 0.029 ton, 0.054 ton, 0.069 ton and 0.118 ton respectively for the above participation levels. The generation values of the units for 24 h power schedules of the proposed model at 20% of DSM participation level with and without DSM cases are given in Table 6.

For a comparison purpose, the objectives of MODEED problem were also simultaneously minimized using NSGA-II. The results of the MOPSO algorithm have also been compared with the NSGA-II technique for the same participation levels. The Pareto-optimal sets of both MOPSO and NSGA-II are shown in Fig. 8. The best compromise resutls of MOPSO and NSGA-II are given in Table 7. The performance quality of multi objective Pareto fronts are compared by using different performance indicators [37]. Hyper volume indicator (I_H) [38] is one of the performance measures for multi objective problems which measures the dominated objective space hyper volume by a given Pareto front. In order to compare the Pareto fronts of MOPSO and NSGA-II, the average I_H values for different DSM participation levels were compared and given in Table 8. It is clear that the MOPSO method is not only able to give a better Pareto-optimal set than NSGA-II but a better compromise solution too.

6. Conclusion

This paper proposes a combined model of MODEED problem with DSM to exploit the benefits of DSM on the utility and generation sides. In the DSM process, a day ahead based load shifting technique was employed for handling the residential loads and the utility energy bill minimization function was considered as the objective. According to the consumers' daily lifestyle all necessary constraints were included for satisfying their comfort level.

The objectives of dynamic economic and emission dispatch problem were minimized individually and simultaneously for a six thermal generating units system. Four different residential participation levels were considered for the proper investigation of DSM impacts on the generation side. The non dominated sorting based MOPSO algorithm was used for minimizing the MODEED problem. The simulation results were also compared with NSGA-II technique. From the overall result analysis, it is clear that proposed model is able to bring the benefits to both utility and generation sides. It is also observed that the benefits are high at 20% participation level. The authors are planning to extend the proposed combined model to a micro grid environment with various distributed generation and energy storage systems.

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