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Demand Response based Unit Commitment

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ABSTRACT: The predominant power system problem of energy crisis is mainly due to growing load demand and non-renewability of the traditional energies. Demand response program (DRP) is an influencing load shaping tool against continuous change in load demand due to the intermittent and the volatile nature of the renewable energy sources (RES) integrated into the modern power system. In DRP, customer behaviour is mainly influenced by the different incentive values offered and variations in price elasticity matrix elements. In this paper, the demand response based unit commitment problem (DRUCP) has been considered to investigate the customers' behaviour under different case studies of varying incentive values and price elasticity matrix elements and their associated change in load demand and total cost of the system. The simulation study is carried out using Global best Artificial Bee Colony (GABC) algorithm for a microgrid system considering solar and wind renewable sources. It is found that implementation of DRP significantly reduces the total cost of the system.

KEYWORDS: Demand Response Program (DRP), Global best Artificial Bee Colony (GABC) Algorithm, Price Elasticity Matrix (PEM), Renewable Energy Sources (RES), UnitCommitment Problem (UCP).

I.INTRODUCTION

Growing energy demand and limited generation resources require an enhanced power system with appropriate demand side management with customer based demand response program (DRP). DRP is an organized approach to reduce the load demand againsta rise in electricity price during peak hours of the day and thereby reshaping the load curve. The financial benefit is a chief motive for the customers participating in the DRP and hence, customers tend to maximize their benefit by reducing their electricity usage with the change in electricity price during the day. According to Federal Energy Regulatory Commission (FERC), demand response can be defined as the changes in electricity usage by the end user entities from their normal energy consumption patterns in response to the changes in the price of electricity or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized [1].

FERC has classified different DRPs into two main categories, namely, incentive based programs (IBP) and time based programs (TBP). The extensive IBP offers cash or discount in bill to the customers for reducing their electricity consumption during peak hours or during periods of high electricity price [2]. This IBP is broadly classified into [1]: Demand bidding/buyback (DB) program, direct load control (DLC), emergency demand response program (EDRP), interruptible load program, load as capacity resource, non-spinning reserves, regulation services and spinning reserves programs [1]. The well-known TBP motivates the customers to shift their load from peak hours to low load or off- peak hours and reshape the inconsistent load demand curve. The TBP mainly comprises: Critical peak pricing with control, peak time rebate, real-time pricing, time-of-use pricing and system peak response transmission tariff [1]. However, with demand side management, appropriate generation scheduling is a crucial optimization problem with two sub problems of power system, namely, unit commitment problem (UCP) and economic load dispatch (ELD). UCP deals with the on/off status judgment of the generating units over a scheduled period and ELD dispenses generated power among the committed units while satisfying multiple constraints to obtain minimum generation cost.

Recently, many researchers have investigated DRPs in UCP in many recent papers. One of the fundamental papers of the demand response is [3] in which generation scheduling is done with responsive loads and different incentive values are paid for curtailable loads. In [4], to investigate the economic-environmental driven measures of DRPs, the cost-economic based unit commitment model is developed to schedule the generating units and determine the optimum incentive value. The simultaneous implementation of UCP with emergency demand response program and interruptible load contracts are proposed in [5]. A critical peak pricing with load control DRP in UCP is discussed in [6]. The

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discussion of demand-side resources (DSRs) with different linear and non-linear models of responsive loads linked with supply-side resources (SSRs) to solve UCP is given in [7]. The commercial concept of DRPs with UCP is solved in [8] and day-ahead scheduling model with hourly DRP considering ramping cost of generating unit is discussed in [9]. In [10], authors have discussed customer sensitivity towards different values of incentive and penalty offered to them for several cases of price elasticity matrix elements under demand response program.

The main objective of this study is toinvestigatethe impact of DRP on UCP and to study the customers'behaviourfor different incentive values and variation in price elasticity matrix (PEM) elements. The simulation study is carried out by employing an efficient Global best artificial bee colony (GABC) optimization algorithm. The deployment of the rest of this paper is as follows: Section 2 describes the load economic model of the DRP. Formulation of DRUCP model including solar and wind renewable sources is presented in section 3. A brief review of the GABC optimization algorithm is given in section 4. Section 5 deliberates the simulation results and comparisons of different cases considered. The conclusion is drawn in section 6.

II.DEMAND RESPONSE MODELLING STRUCTURE

In deregulated electricity market, customer participation can be accessed from the economic model of load demand which reveals the change in load demand with the change in the price of electricity and incentives offered to them during several periods of the day. This demand elasticity (E) pertaining to price is defined as [11]:

$$E = \frac{EP_o}{P_{Lo}} * \frac{\partial P_L}{\partial EP} \tag{1}$$

According to (1), price elasticity of the h^{th} time with respect to j^{th} period can be written as [11]:

$$E_{(h,j)} = \frac{EP_{o(j)}}{P_{Lo(h)}} * \frac{\partial P_{L(h)}}{\partial EP_{(j)}} \tag{2}$$

whereEP_o and EP are the electricity price before and after implementation of the DRP. Likewise, $P_{Lo}$and P_L are the load demand before and after implementing DRP. ∂EP and ∂P_L describe the change in electricity price and load demand from their initial values respectively.Customer behavior is characterized according to the load variation with respect to electricity price. There are certain stiff loads which cannot shift from one period to another period with the price variation and sensitive to single period only termed as self-elasticity. Furthermore, some flexible loads can vary from peak hours to low load periods having sensitivity to multi-period can be defined as cross elasticity. Hence, customer behavior for 24 hours can be symbolized by price elasticity matrix (PEM) which is a 24×24 matrix with self-elasticity coefficients as diagonal elements and cross elasticity coefficients as off-diagonal elements [11].

A) Single period loads

In DRP,the participating customers change their load demand according to the incentive value (A) offered to them. An incentive paid to the customer in h^{th}hour for reduction of each kWh load demand is given as [11]:

$$C_{DR(h)} = A_{(h)}[P_{Lo(h)} - P_{L(h)}] \tag{3}$$

The total benefit of the participating customer in h^{th} hour can be written as [11]:

$$T_B = B(P_{L(h)}) - P_{L(h)} * EP_{(h)} + A(\Delta P_{L(h)}) \tag{4}$$

Total maximum benefit can be attained by making $\partial T_B / \partial P_{L(h)} = 0$ which results in:

$$\frac{\partial B(P_{L(h)})}{\partial (P_{L(h)})} = EP_{(h)} + A_{(h)} \tag{5}$$

From [12], typical quadratic benefit function is written as:

$$B(P_{L(h)}) = B_{o(h)} + EP_{o(h)}[P_{L(h)} - P_{Lo(h)}]\left\{1 + \frac{P_{L(h)} - P_{Lo(h)}}{E_{(h)}P_{Lo(h)}}\right\} \tag{6}$$

After differentiating (6) with respect to $P_{L(h)}$ and substituting the result into (5), the expression obtained is:

$$EP_{(h)} + A_{(h)} = EP_{o(h)}\left\{1 + \frac{P_{L(h)} - P_{Lo(h)}}{E_{(h)}P_{Lo(h)}}\right\} \tag{7}$$

Hence, participating customer's consumption will be described as:

$$P_{L(h)} = P_{Lo(h)}\left\{1 + E_{(h,h)}\frac{EP_{(h)} - EP_{o(h)} + A_{(h)}}{EP_{o(h)}}\right\} \tag{8}$$

B) Multi-period loads

Assuming price elasticity as a constant value that is [12]:

$$\frac{\partial P_{L(h)}}{\partial EP_{(j)}} = \text{Constant for } h, \text{ where } j=1, 2\ldots\ldots 24. \tag{9}$$

By relating prices and demands linearly, multi-period load model obtained is:

$$P_{L(h)} = P_{Lo(h)}\left\{1 + \sum_{\substack{j=1 \\ j\neq h}}^{T} E_{(h,j)}\frac{EP_{(j)} - EP_{o(j)} + A_{(j)}}{EP_{o(j)}}\right\} \tag{10}$$

C) Load economic model

The combination of (8) and (10) results in load economic model as follows [11]:

$$P_{L(h)} = P_{Lo(h)}\left\{1 + E_{(h,h)}\frac{EP_{(h)} - EP_{o(h)} + A_{(h)}}{EP_{o(h)}} + \sum_{\substack{j=1 \\ j\neq h}}^{T} E_{(h,j)}\frac{EP_{(j)} - EP_{o(j)} + A_{(j)}}{EP_{o(j)}}\right\} \tag{11}$$

Assuming an equal value of electricity price before and after implementation of DRP (i.e. $E_{Po} = E_P$) and βas possible customer participation (in %) in the DRP, equation (11) can be written as:

$$P_{L(h)} = (1-\beta)P_{Lo(h)} + \beta P_{Lo(h)}\left\{1 + \sum_{j=1}^{T} E_{(h,j)}\frac{A_{(j)}}{EP_{o(j)}}\right\} \tag{12}$$

III.PROBLEM FORMULATION

The classic UCP performs optimal scheduling of generating units after appropriate on/off decision of generating units to attain minimum generation cost while handling load demand, power balance, spinning reserve, generation limits and minimum up/down constraints over a scheduled period of 24 hours. Furthermore, initial status (*IS*) of each generating unit must consider before commencement of scheduling. The objective function of DRUCPmodel characterized as:

$$\min TC = \sum_{i=1}^{N}\sum_{h=1}^{T} FC_{i(h)}u_{(i)h} + SUC_{i(h)}\left\{u_{(i)h}(1-u_{(i)(h-1)})\right\} + C_{DR(h)} \tag{13}$$

where $FC_{i(h)}$ and $SUC_{i(h)}$ are referred to as the fuel cost and start-up cost of i^{th} thermal unit at hour *h* respectively. *TC* describes the total cost of the system and $C_{DR(h)}$ expressesthe amount of incentive to be paid to the customers for their participation in the DRP at hour *h*.Furthermore, *N* and *T* represent the total number of generating units and scheduled time period respectively. The thermal unit index and hour index are symbolized as*i* and *h* respectively and *u* indicates the on /off status of the thermal units (*1*= on and *0* = off). The fuel cost of generating unit in quadratic polynomial function of power generated is classically expressed as:

$$FC_{i(h)} = a_i + b_i P_{gi(h)} + c_i P_{gi(h)}^2 \tag{14}$$

wherea_i, b_i and c_i are the fuel cost coefficients of each thermal unit *i*and $P_{gi(h)}$ refers as power generated from unit *i* at hour *h*. The start-up cost is categorized as hot start-up cost (*h_cost*) and cold start-up cost (*c_cost*) depending on the temperature of a thermal unit and can be given as:

$$SUC_{i(h)} = \begin{cases} h\_\cos t_{i(h)} & if \quad MD_{i(h)} \le T_i^{off} \le MD_{i(h)} + CSH_i \\ c\_\cos t_{i(h)} & if \quad T_i^{off} > MD_{i(h)} + CSH_i \end{cases} \tag{15}$$

where*MD*, T_i^{off} and *CSH* are denoted as minimum down time, minimum off time and cold start hour respectively. The execution of the above DRUCP model must satisfy several constraints listed below:

Power balance constraint: The accumulation wind power (P_W), solar power (P_S) along with the generated power from the thermal units must satisfy the load demand as [13]:

$$P_{gi(h)} + P_{W(h)} + P_{S(h)} = P_{L(h)} \tag{16}$$

The generated output power from the wind turbine model is calculated as [14]:

$$P_{W(h)} = \begin{cases} q \times v_{(h)}{}^3 - z \times P_R & v_{ci} < v_{(h)} < v_r \\ P_R & v_r < v_{(h)} < v_{co} \\ 0 & otherwise \end{cases} \tag{17}$$

where $q = P_R / (v_r{}^3 - v_{ci}{}^3)$ and $z = v_{ci}{}^3 / (v_r{}^3 - v_{ci}{}^3)$. Also, v_c, v_{co} ,$v_r$and P_R are referred to as cut-in, cut-out, rated speed and rated power output of wind turbine respectively.

The power output of photovoltaic module depends on area (χ) and efficiency of pv model (η) and solar radiation (*G*) is calculated as [15]:

$$P_{S(h)} = \chi \times \eta \times G_{(h)} \tag{18}$$

Generation limit constraint: Power output of each generating unit must be within its minimum ($P_g{}^{min}$) and maximum ($P_g{}^{max}$) limits as:

$$P_{gi}{}^{\min} \le P_{gi} \le P_{gi}{}^{\max} \tag{19}$$

Spinning reserve constraint: Usually, a certain amount of spinning reserve (SR) has to be maintained for system reliability as:

$$\sum_{i=1}^{N} P_{gi}{}^{\max} u_{i(h)} \ge P_{Lnew(h)} + SR_{(h)} \tag{20}$$

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***Minimum up/down constraint*:** Each thermal unit must remain on/off for the particular time duration before any transition occurs.

$$T_i^{on} \geq MU_i \quad T_i^{off} \geq MD_i \tag{21}$$

where T_i^{on} and MU are the minimum on time and minimum up time respectively.

IV.OVERVIEW OF GABC ALGORITHM

Karaboga has developed the basic concept of artificial bee colony algorithm which emphases the food finding habits of honeybees. The artificial bees are mainly distributed into three groups, namely, employed bees, onlookers and scouts [16]. These bees fly in multidimensional search space to pursue their food source. Employed bees use their own experience to find the food source while scout bees hunt their food source arbitrarily. The onlooker bees pick good food source from those founded by the employed bees and they further search food source nearby the selected food source. Each food source signifies the possible solution of the optimization problem and quality of the food source is judged by the nectar amount of the food source. In ABC,the initial population P of N_p possible solution is generated randomly. Each P_i $(i= 1, 2,\ldots\ldots N_p)$ is a D dimensional vector where D is the number of optimized parameters. In employed bee phase, the new random food source is generated as follows:

$$v_{ij} = P_{ij} + \varphi_{ij}(P_{ij} - P_{kj}) \tag{22}$$

where P_{ij} and v_{ij} indicate the previous and new food source respectively and φ_{ij} denotes a random number between 0 to 1, j € $\{1,2\ldots D\}$ and P_k indicates an alternative solution chosen randomly from the population. In GABC, global best (gbest) solution is used to improve the search mechanism and the equation (22) is modified as [17]:

$$v_{ij} = P_{ij} + \varphi_{ij}(P_{ij} - P_{kj}) + \Psi_{ij}(y_j - P_{ij}) \tag{23}$$

The added term in (23) is *gbest* term, y_j is the j^{th} element of the global best solution and Ψ_{ij} is a random number in [0, C] where C is a nonnegative constant. In onlooker phase, each onlooker bee chooses a food source according to the probability value $p_i = fit_i / \Sigma_n fit_n$ where *fit* describes the fitness of a solution. Thereafter, onlooker bees further searches for better solution (food source) in the neighbourhood of the selected one according to (23). If the solution has not improved after certain trials, then scout bees generate new food source and repeat the hunting process.

V. RESULT AND DISCUSSION

This study investigates the impact of DRP on generation scheduling and total cost of the system for different incentive values and price elasticity matrix elements. The microgrid system containing 12 thermal units with 3 wind turbines and a single solar system is considered for simulation analysis. The microgrid system parameters, load demand and market price data extracted from [18] are listed in Table.1, Table.2 and Table.3 respectively. Load demand curve is distributed in three major periods of the day, namely, low load period (1.00 hrs – 5 hrs), off-peak period (6 hrs – 9 hrs and 17 hrs – 24.00 hrs) and peak period (10 hrs – 16 hrs). Plots of solar radiation and wind speed of a normal sunny day for 24 hours are revealed in Fig. 1 and Fig. 2 respectively.The essential price elasticity matrix for implementation of DRP is given in Table.4 and it is obtained from [4] with some modification. The spinning reserve assumed is 10% for system reliability and 40% customer participation is considered in this study. For simplicity, value of electricity price has been presumed to be identical before and after implementation of the DRP. The optimum result is obtained after 20 simulated trials of GABC algorithm considering population = 50 and the number of iterations = 200 for different cases listed in Table.5. For GABC, employed bees, onlooker bees and scout bee are considered as 50, 100 and 1 respectively. The hourly wind speed and solar irradiation data of the particular day required for simulation are acquired from NREL's data center [19].

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Table 1 Microgrid system data

Unit	P_g^{max} (kW)	P_g^{min} (kW)	*a* (cts/h)	*b* (cts/kWh)	*c* (cts/kWh2)	*MU* (h)	*MD* (h)	*h_cost* (cts)	*c_cost* (cts)	*CSH* (h)	*IS* (h)
1	410	100	65	15.20	0.00052	5	5	550	1100	3	5
2	410	100	60	15.30	0.00061	5	5	500	1000	3	5
3	270	50	45	16.60	0.00210	3	3	450	900	2	3
4	270	50	41	16.50	0.00211	3	3	460	920	2	3
5	140	25	40	18.50	0.00420	2	2	800	1600	1	2
6	140	25	38	18.76	0.00530	2	2	750	1500	1	-2
7	90	20	38	26.70	0.00080	2	2	360	720	1	-2
8	90	20	35	26.90	0.00120	2	2	350	700	1	-2
9	65	15	30	29.71	0.00090	1	1	280	560	0	-1
10	65	15	24	29.92	0.00130	1	1	285	570	0	-1
11	45	10	18	26.20	0.00240	1	1	200	400	0	-1
12	45	10	15	26.79	0.00310	1	1	205	410	0	-1

Table 2 Solar and wind parameters

PV system (1×360kWp)		Wind Plant (3×140kWp)	
χ	1659×870 mm	P_R=140 kW	v_{ci}=3 m/sec
η	15 %	v_r=12 m/sec	v_{co}=25 m/sec

Table 3 Hourly load demand and market price

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Demand (kW)	1000	1030	1050	1070	1090	1150	1300	1400	1640	1700	1870	1870
EP(cts)	29.8	29.9	30.0	30.1	30.2	30.3	30.4	30.5	30.6	30.7	30.8	30.9
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Demand (kW)	1850	1800	1720	1700	1650	1630	1550	1450	1350	1200	1150	1050
EP(cts)	30.9	30.8	30.7	30.6	30.5	30.4	30.3	30.2	30.1	30.0	29.9	29.8

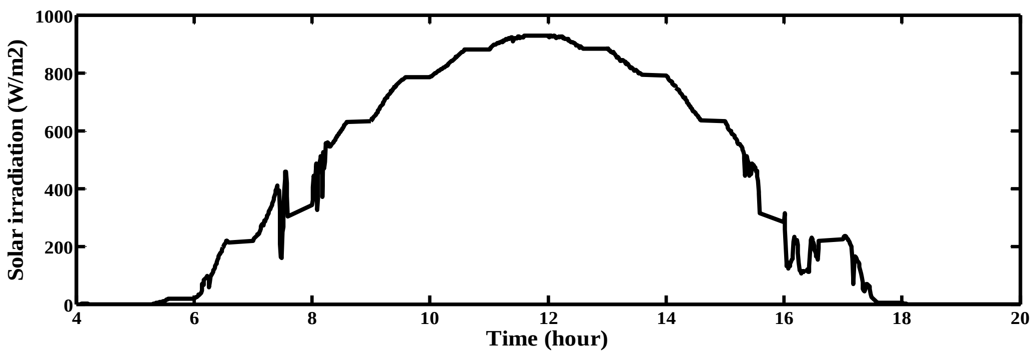

Fig. 1 Solar radiation of a normal sunny day

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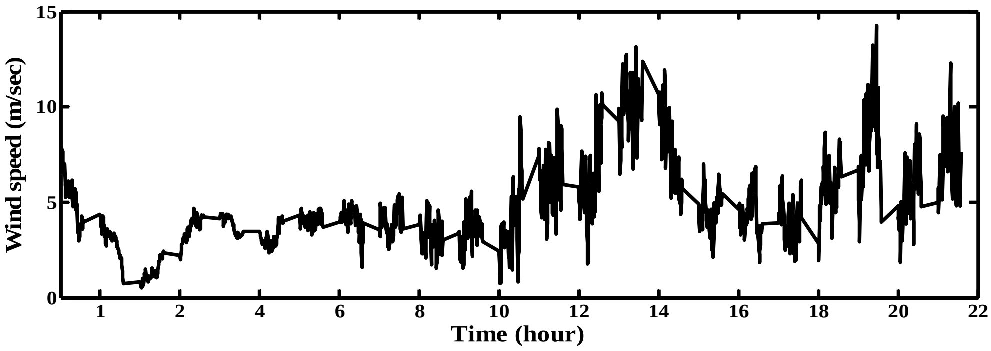

Fig. 2 Wind speed of a normal day

Table 4 Price elasticity matrix

	Low	Off-peak	Peak	Off-peak
Low	-0.04	0.05	0.04	0.05
Off-peak	0.05	-0.16	0.02	0.04
Peak	0.04	0.02	-0.16	0.02
Off-peak	0.05	0.04	0.02	-0.16

Table 5 Different cases

cases	Incentive offered	Price elasticity matrix
1	-	-
2	4	As Table.4
3	8	As Table.4
4	2	As Table.4
5	4	As double the value of Table.4
6	4	As half the value of Table.4

Case 1: UCP is solved considering the effect of RES without implementing DRP in this case. This case is assumed as the base case for the rest of the study. The generation scheduling with total generation cost using GABC is presented in Table.6. From Table.6, it can be seen that the generating units U1 to U4 share major portion of the load demand and the other units U5 to U12 are committed to satisfy the power balance and spinning reserve constraints. Integration of wind and solar RES with thermal units reduces the load demand, whichresults in a total cost of516643.2 cents. Plot of load demand without and with RES is shown in Fig.3 which yields that the availability of renewable energy significantly reduces the overall load demand and hence, the total cost of the system

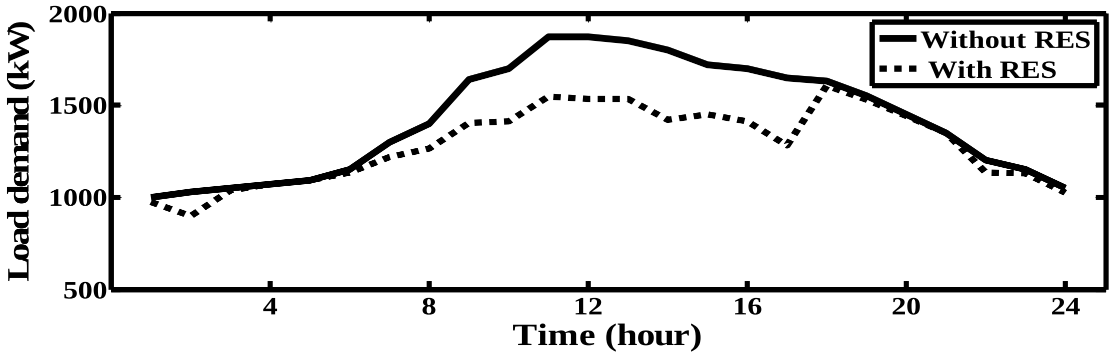

Fig.3 Load demand with and without RES

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Case 2, 3, 4: These cases are solved to investigate the customers' behavior for varying incentive values. The incentive values considered are 4 cents (as base), 8 cents (double of base) and 2 cents (as half of base) for case 2, case 3 and case 4 respectively. For case 2, the generation cost obtained is 506975.2 cents which result in 1.43 % reduction in the total cost as compared to the case 1. In case 3, load demand is reduced and in case 4, load demand is raised compared to case 3 which indicates that customers' concern is highly inclined towards the offered incentive value. The total amount of incentive paid to the customers are 2274.6 cents, 9098.0 cents and 568.62 cents in cases 2, 3 and 4respectively, which indicate that the customers tend to participate more actively in the DRP as incentive value increases. As the customer benefit rises, net utility profit and % reduction in cost decays and vice a versa. The load demand plots of these three cases are shown in Fig.4.

Table 6 Optimul generation scheduling

Unit/ Hour	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	TC
1	410.0	410.0	0.0	152.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15418.4
2	410.0	410.0	0.0	79.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	14186.5
3	410.0	410.0	0.0	101.0	115.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	17572.5
4	410.0	410.0	0.0	162.3	87.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	17289.6
5	410.0	410.0	154.2	115.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	17904.6
6	410.0	410.0	227.3	85.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	18209.7
7	410.0	410.0	210.5	187.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	19654.9
8	410.0	410.0	169.1	249.2	25.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	21321.5
9	410.0	410.0	256.9	145.5	120.6	60.4	0.0	0.0	0.0	0.0	0.0	0.0	24776.5
10	410.0	410.0	202.5	270.0	77.7	42.7	0.0	0.0	0.0	0.0	0.0	0.0	23313.4
11	410.0	410.0	238.3	262.7	54.4	123.0	21.1	0.0	0.0	0.0	26.1	0.0	27373.4
12	410.0	410.0	206.7	268.2	112.9	87.0	38.2	0.0	0.0	0.0	0.0	0.0	25956.5
13	410.0	410.0	223.4	270.0	138.3	31.4	30.2	0.0	0.0	0.0	19.7	0.0	26219.2
14	410.0	410.0	270.0	267.4	25.0	37.9	0.0	0.0	0.0	0.0	0.0	0.0	23365.8
15	410.0	410.0	269.0	210.4	127.0	25.0	0.0	0.0	0.0	0.0	0.0	0.0	24056.5
16	410.0	410.0	174.6	270.0	89.9	55.8	0.0	0.0	0.0	0.0	0.0	0.0	23314.2
17	410.0	410.0	88.1	270.0	102.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	20982.0
18	410.0	410.0	268.7	270.0	140.0	0.0	20.0	20.0	0.0	0.0	39.1	28.7	30047.3
19	410.0	410.0	270.0	270.0	57.9	37.3	56.2	20.6	0.0	0.0	0.0	0.0	26904.2
20	410.0	410.0	254.4	218.2	72.4	76.8	0.0	0.0	0.0	0.0	0.0	0.0	23878.5
21	410.0	410.0	269.3	137.4	123.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	22220.4
22	410.0	410.0	129.0	184.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	18190.5
23	410.0	410.0	181.3	127.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	18126.9
24	410.0	410.0	97.4	108.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	16360.1
TC= 516643.2 cents													

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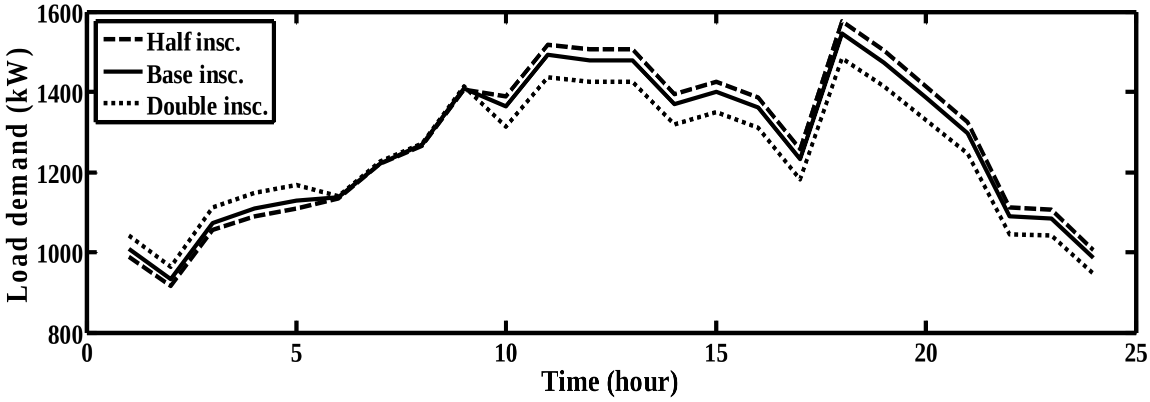

Fig. 4 Load demand variation for different incentive values

Case 5, 6: These cases are considered to comprehend the effect of varying price elasticity matrix (PEM) elements with base incentive. In case 5, PEM elements are doubled and in case 6 PEM elements are divided by 2 which result in duplication of case 3 and case 4 respectively. These two cases reveal the fact that PEM is a measure of customer participation in the DRP. The higher PEM elements specify more customer flexibility towards load shifting with higher benefit while lower PEM elements indicates that the customers become stiff and less sensitive to load shifting causing minimum benefit.The summarized results table for all cases is given in Table.6.The comparison of different costs for different cases is given in Fig. 5 which shows that minimum generation cost and utility costs are achieved in case 3 and case 5 due to higher incentive value and price elasticity matrix elements with a maximum incentive offered to the customers.

Table 6 Cost comparison of different cases

Cases	Generation cost (cts)	Incentive paid (cts)	Utility cost (cts)	Net utility Profit (cts)	% reduction in cost
1	516643.2	-	516643.2	-	-
2	506975.2	2274.6	509249.8	7393.4	1.43
3	496129.4	9098.0	505227.4	11415.8	2.21
4	509885.9	568.6	510454.6	6188.6	1.19
5	496129.4	9098.0	505227.4	11415.8	2.21
6	509885.9	568.6	510454.6	6188.6	1.19

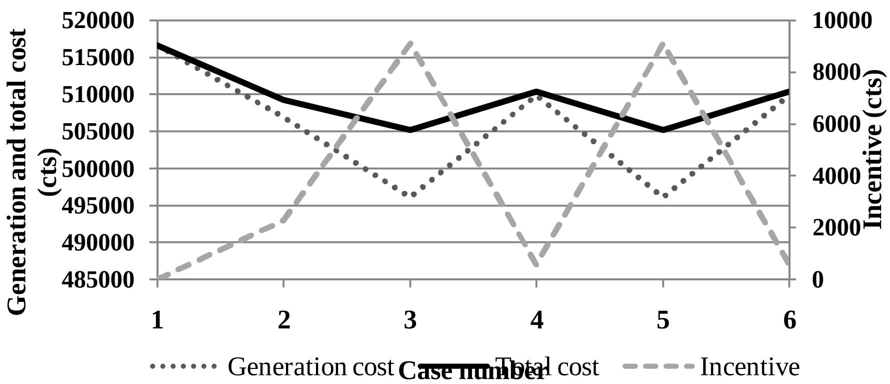

Fig .5Comparisons of different costs for different cases

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VI.CONCLUSION

Demand response program enhances the inconsistent load profile and offers a financial benefit to the participating customers. The proposed demand response based unit commitment model (DRUCP) with wind and solar renewable sources evaluates the customer behavior and total generation cost for several test cases. This study confirms that the incorporation of DRP reduces the generation cost. Customer flexibility towards load shifting from one period to other is totally influenced by the incentive value which means higher incentive value motivates the customers to shift their load from peak hours to off-peak hours resulting in higher customer benefit. However, higher customer benefits in turn increase total generation cost and decays net utility profit. This study also shows that the price elasticity matrix elements are the measure of customer flexibility to load shifting which enlarges the customer benefit for higher value of PEM elements and vice a versa. Hence, it can be seen that DRP proves beneficial to both, the customers and the utility.

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