Journal of Operation and Automation in Power Engineering

vol. 12, no. 4, Dec. 2024, Pages: 269-279

http://joape.uma.ac.ir

# Solution to Objectives of Supply Side Energy Management by Integrating Enhanced Demand Response Strategy

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***Abstract***— *Supply-side energy management (SSEM) aims to improve efficiency in operations and strategic planning. Both the cost of generating electricity and the amount of emissions from that generation are minimized in SSEM. It is required to formulate an optimization problem with these two competing goals in order to come up with a compromise. Resolving problems with network reliability caused by peak demand on the electricity system is another goal of SSEM. The ultimate goal of this study is to reduce energy use during peak hours while also cutting down on power losses, generation costs, and pollution from power plants. In this paper all goals of the smart grid system are satisfied and addressed optimally through the use of optimal generator scheduling and an improved demand response technique. To formulate this problem standard IEEE 30-bus system is considered as test boat. The suggested system employs the Cuckoo search method and its most recent variant, adaptive Cuckoo search, to solve a stochastic non-linear optimization problem. The adaptive Cuckoo search approach, when combined with the proposed demand side management strategy, reduces fuel costs by 7.84%, emission dispatch by 16.35%, power losses by 10.31%, and peak hour demand by 15.6%.*

***Keywords***—Demand response, Dynamic pricing, Energy management system, Peak load management.

## 1. Introduction

Load curve flattening is the reduction of power consumption at peak load hours and increasing the consumption during the low load periods. It is desired that the load curve to be as flat as possible. Because it leads various advantages [1, 2] in the operation of power plants such as reduced equipment's overloading, reduction of transmission cost and power losses, minimized consumption of fossil fuels, generation cost, and emission of greenhouse gases. Reduction of peak hour's power demand also helps to reduce the requirement of peak power plants and avoiding the purchase of high-priced energy. All these objectives of power system may be achieved by integrating supply side energy management (SSEM) programs and demand side management (DSM) programs [3]. SSEM programs take place at supply side or generation side. It enables the installed generating capacity to provide electricity at lower cost and to reduce emission of greenhouse gases (GHG) [4]. SSEM is an environmental-driven scheme of energy management. Its objectives can also be formulated and solved as optimization problems. On the other hand demand side management (DSM) is a tool for consumers to help the electrical utilities in management of electric power demand. DSM has been a subject of research for the last few years due to the demand for strategic development in generation, transmission, and distribution in the smart grid. It has been driven by the increasing demand for electricity [5]. Most DSM programs are put in place by utilities or end-user consumers. Programs of DSM can be classified as energy management, load management (load leveling, peak clipping, valley filling, load shifting), and load growth & conservation (strategic load growth, strategic conservation, flexible load shape) [6]. Form of load management can be represented by Fig. 1 [7–9].

Direct load control (DLC) and demand response (DR) are two common tools of DSM those are executed by the utility companies. Load control is the practice of intermittently cutting off power to a region by the utility company during times of high demand. The peak demand management and economic emission dispatch (CEED) problem for an IEEE 30-bus power system is solved in [6]. In this case, DSM is implemented via the DLC approach, wherein power is cut off in the least cost places in order to control the peak demand condition at generating units. In the DLC method consumers have to compromise while in the demand response there is no need to compromise. DR is a type of market-driven strategy and it can provide short term response to energy market conditions. It can change the consumer's power consumption pattern in response to the variable electricity prices i.e. dynamic pricing [8]. Table 1 represents overview of DR programs [9–11]. Major programs of demand response are as follows [12–14]:

- **Emergency demand response:** It is used to reduce the chance of brownouts or blackouts when demand threatens to be higher than supply.
- **Economic demand response:** It is employed by utilities to avoid the significantly higher costs of producing energy during peak demand times of the day.
- **Ancillary service demand response:** It is used to support the reliable and regulated transmission of electricity to loads.
- **Capacity market program:** In this program, customers commit to reduce their load with a pre-specified amount in order to postpone capacity increase.
- **Interruptible service program:** In this program consumers are given rebate for reducing their load in contingency. Consumers can also be penalized for not reducing their load.

All programs of demand response can be categorized as price-based or incentive-based programs. Price-based DR programs rely on the customer's response (change in energy consumption pattern) to the electricity price changing with time in order to reduce electricity

Received: 22 Sep. 2022
Revised: 15 Mar. 2022
Accepted: 02 May 2023
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***Research Paper***
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Table 1. Overview of demand response programs

| | Operational planning | Day-ahead scheduling | Economic dispatch | Real-time dispatch |
|---|---|---|---|---|
| **Price based DR** | Time of Use (ToU) price | Real time pricing (RTP) | Critical peak pricing (CPP) | |
| **Incentive based DR** | Ancillary services market programs (ASMP) | | Emergency demand response programs (EDRP) | Direct load control (DLC) |
| | Capacity market program (CMP) | Demand bidding | Interruptible service program (ISP) | |

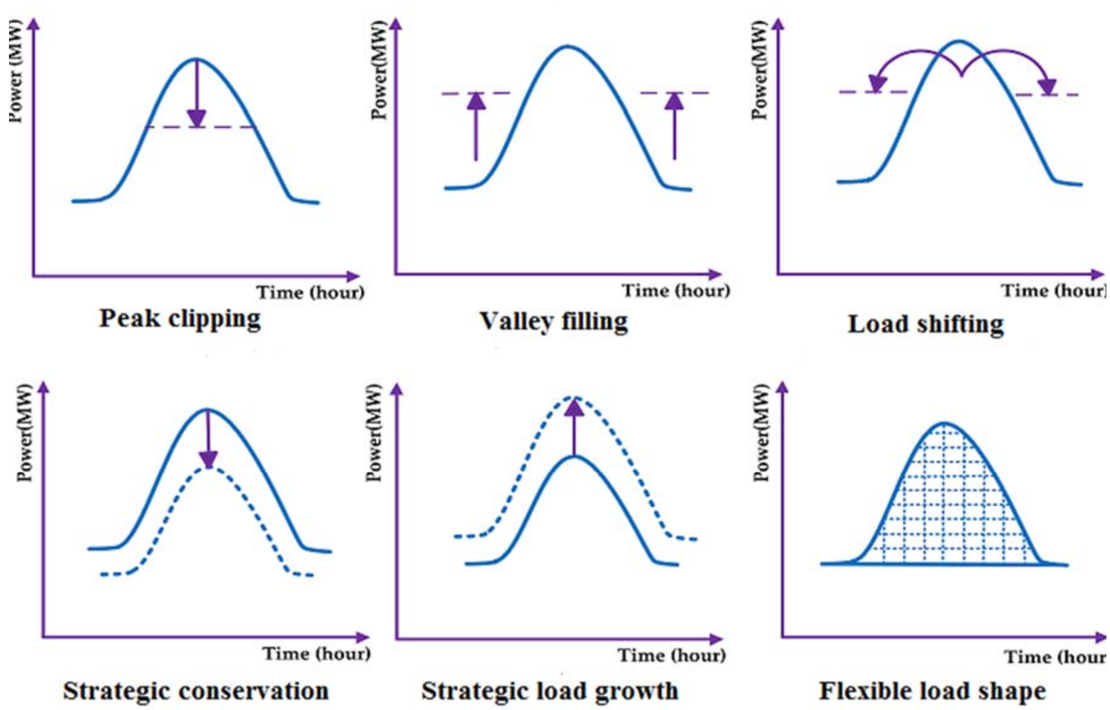


Fig. 1. Forms of load management and load growth

bill costs. On the other hand, incentive-based DR programs depend on the rebates or penalties applied to consumers for reducing or raising their power consumption [14]. In the price-based DR programs changes in electricity prices over time are transmitted to residential customers via variable electricity tariffs that fluctuate according to the wholesale electricity price [15]. Consumers may respond to this variable electricity price in different ways. One action of consumers could be taken in response to peak price by reducing their consumption only during peak hours, this result in peak clipping. Another action could be taken is shifting the use of electricity from peak hours to off-peak hours [8, 9]. The objectives for shifting the load demand can be different for different stack holders of power system network. In view of the electricity suppliers, the objective is to avoid the appearance of a high peak load demand and a long demand valley i.e. flattening of the load curve [2, 3]. This objective can be achieved by implementing load management programs. Many researches have formulated and solved various single and multi-objective problems of load management like minimization of consumer's electricity bill, reducing peak to average ratio (PAR), maximization of consumer's satisfaction, and minimization of peak hour demand [10–16].

Optimization of objectives of SSEM is as important as load management for smart grid. Objectives of SSEM can also be formulated individually or with the objectives of DSM. Like multi-objective models are proposed by [17, 18] wherein an objective function of generation cost along with emission dispatch as supply side objectives and consumer's electricity bill, user's satisfaction, incentive costs for different kinds of loads are incorporated as demand side objectives [3, 4, 6]. In these models multi-objective problems are solved by quadratic programming, multi-objective PSO (MOPSO) [19, 20], and non-dominated sorting genetic algorithm-II (NSGA-II) [21]. There are several optimization algorithms available and proposed by various researchers for the solution of different objectives of energy management viz. genetic algorithm (GA) [4, 5], harmony search algorithm (HSA) [22], wind-driven optimization (WDO), genetic harmony search algorithm (GHSA) [23], Jaya algorithm [18], whale optimization [9] Strawberry algorithm, and teaching & learning based optimization (TLBO) [24, 25] etc. Table 2 summarizes various optimization models proposed by different researchers for the solution to the objectives of DSM and SSEM.

[28] proposed solution of economic emission dispatch problem using GAMS software for a small microgrid system integrated with DR and RES. Here, peak hour demand problem for conventional generators is not considered. [29] solved the problem of peak hour demand for a modified IEEE 30-bus system integrated with RES but there is no use of any DSM program. [30] proposed a solution for cost minimization and peak demand management by reducing the power consumption using DR program with time-of-use (ToU) price.

### A. Contribution of the Research Work

Integration of DSM programs with SSEM has been resulted in benefits for the power system. But still there is a scope to enhance the DSM strategies that can help to improve the efficiency of smart grid. In this paper solution to the problem of economic emission dispatch and peak hour demand management is proposed using enhanced demand response strategy with the application of real

Table 2. Solution to objectives of DSM and SSEM using different approaches

| S. No. | Models and objectives | References | Solution method |
|---|---|---|---|
| 1 | Minimized power generation cost and carbon emission, considered consumer's behavior | [21] | Bi-level optimization using NSGA-II; Improved NSGA-II |
| 2 | Peak load minimization by mono-objective function in DSM | [25] | Quadratic programming (QP) |
| 3 | Multi-objective dynamic economic & emission dispatch | [19] | Multi-objective PSO |
| 4 | Reduction of customer's electricity bill cost | [24] | TLBO and Shuffled frog leaping (SFL) optimization |
| 5 | Minimizing peak demand, power loss & consumer's bill using variant energy sources (RES) | [26, 27] | Optimization at two stages using genetic algorithm (GA) |
| 6 | Minimization of peak load as well as customer's electricity bill cost | [22, 23] | GA, HAS, and crow search algorithm (CSA) |

time price (RTP). The key contributions of this research work are summarized as follows:

- This research work deals with integrating the objectives of SSEM and demand side management (DSM) programs.
- The performance of CS and ACS algorithms is tested in finding optimal solutions for the problem of DEED.
- Accounting for the optimal effects of enhanced DR strategy as DSM measures in peak load management
- Proposes a real-time electricity price, i.e., day-ahead real-time price (DA-RTP), to calculate the objective load curve.
- A comparative analysis of the accuracy of the objective load curve obtained through different dynamic prices, viz., ToU and DA-RTP.

The proposed strategy resulted into improved accuracy of objective load curve and optimal load curve. It further resulted into optimized fuel cost, emission of harmful gases, power loss, peak hour demand, and reduced electricity bill cost for consumers.

## 2. PROBLEM FORMULATION

### B. Dynamic Economic Emission Dispatch (DEED)

DEED aims to minimize fuel cost and volume of greenhouse gases by optimal scheduling of committed generators to mitigate certain load demand in a specified interval. Objectives of DEED problem can be formulated mathematically and given by nonlinear equations (1) and (2) [31].

$$f_{(t)}^{cost} = \sum_{i=1}^{NG} \Big( a_i Pg_{i,t}^2 + b_i Pg_{i,t} + c_i + \left| d_i * \sin\left\{ e_i * \left( Pg_i^{\min} - Pg_{i,t} \right) \right\} \right| \Big) \tag{1}$$

$$f_{(t)}^{emission} = \sum_{i=1}^{NG} \left( p_i Pg_{i,t}^2 + q_i Pg_{i,t} + r_i + s_i \exp(t_i Pg_{i,t}) \right) \tag{2}$$

Here, $f_{(t)}^{cost}$ and $f_{(t)}^{emission}$ represent total cost of power generation and emission dispatch at interval t by all the generating units.

### C. Peak Hour Demand Management

In order to reduce the energy consumption in peak hours, minimized the objective function of difference between objective load and optimal load given in (3) [4].

$$\textbf{Minimize } f_1 = \sum_{t=1}^{T} x^t(d) - Obj^t(d) \tag{3}$$

Here, $T$ is total number of time slots in a day i.e. 24. $x^t(d)$, and $Obj^t(d)$ denotes the optimal power consumed and objective load in time slot t respectively on day d$\in N$. $x^t(d)$, and $Obj^t(d)$ can be given by (4) and (5) respectively [9].

$$x^t(d) = \sum_{\ell=1}^{\pounds} x_\ell^t(d) \tag{4}$$

$$Obj^t(d) = \frac{1/p^t(d)}{\sum_{t=1}^{T} p^t(d)} \sum_{t=1}^{T} y^t(d) \tag{5}$$

In the (4), $x_\ell^t$ represents the energy consumption schedule for a load $\ell \in \pounds$ at time slot $t$ of a day d$\in N$. Here, $\pounds$ denotes the full set of available loads (deferrable and non-deferrable). In the (5) $y^t(d)$ is the forecasted demand at interval $t$. Here, it is considered that end-user is served by a utility which employs dynamic pricing of electricity which is known to the customer in advance for the day. The price at time slot t on the day d is denoted by $p^t(d)$.

A smart home energy controller connected at consumer's premises is responsible for the optimal scheduling of deferrable appliances based on the objective load curve considering consumer's preferences and their comfort. The proposed algorithm determines the objective power demand and optimal power consumption for each interval on behalf of dynamic price for that interval and consumer's pattern of using appliances so that the difference between optimal and objective demand is minimized. As the objective demand represented in (5) is inversely proportional to the price, so that it helps to obtain an objective demand curve with high power demand in low price hours and low demand in high price hours [4, 9]. In literature time-of-use price is used as the dynamic price in [5] but it can't represent the actual condition of power demand in system whereas the real time price can represent the actual condition of power demand and available generating capacity more accurately.

### D. Equality Constraints:

- Power balance equation is given by (6) as an equality constraint [21].

$$\sum_{i=1}^{NG} (Pg_{i,t}) = \sum_{j=1}^{NB} (Pd_{j,t}) + Pl_t \tag{6}$$

Here, $Pg_{i,t}$ is power output by generating unit $i$, $Pd_{j,t}$ is power demand at bus $j$, and $Pl_t$ is total power loss at time slot $t$. NG and NB also denote number of conventional power generators and total number of buses present in power system respectively.

- Scheduling of the appliances also has some equality and inequality constraints. Such as energy consumption schedule of appliances for the time slots other than their operational time is zero [6].

$$x_\ell^t(d) = 0 \qquad t \notin T_\ell \tag{7}$$

- Energy scheduled should also meet with energy requirement of the day $d \in N$, denoted by $(DR_\ell)$ [10].

$$\sum_{t=1}^{24} x_\ell^t(d) = DR_\ell \qquad \ell \in \pounds \tag{8}$$

### E. Inequality Constraints:

- Min.-Max limits of power generation given by (9) and ramp rate limits of $i^{th}$ unit given by (10) and (11) are also considered as inequality constraint [30].

$$Pg_i^{\min} < Pg_i < Pg_i^{\max} \tag{9}$$
$$Pg_i^t - Pg_i^{(t-1)} \le UR_i \quad t = 2, \ldots, T \tag{10}$$
$$Pg_i^{(t-1)} - Pg_i^t \le DR_i \quad t = 2, \ldots, T \tag{11}$$

Here, $Pg_i^t$ and $Pg_i^{(t-1)}$ are the power outputs of $i^{th}$ unit at the t$^{th}$ time interval and $(t-1)^{th}$ interval respectively. UR and DR are the up and down ramp-rate limits of the ith unit in MW/hour.

- The load which belongs to power deferrable category can operate within a certain minimum and maximum power limit.

$$x_\ell^{\min} \le x_\ell^t(d) \le x_\ell^{\max} \qquad t \in T_\ell \tag{12}$$

- Other type of loads that operate at fixed power level ($P_\ell$), only ON-OFF control is allowed [18].

$$x_\ell^t(d) \in \{0, P_\ell\} \qquad t \in T_\ell \tag{13}$$

## 3. SOLUTION TECHNIQUES

Objective functions of DEED problem are highly non-linear and non-differential too. This requires highly robust algorithms to avoid getting stuck at local optimum solutions. In this paper cuckoo search (CS) algorithm is used to optimize the objective functions and its results are compared with adaptive cuckoo search algorithm. Optimal scheduling of appliances is obtained by binary particle swarm optimization (BPSO).

### F. Cuckoo search algorithm

Cuckoo search (CS) is one of the popular meta-heuristic type stochastic algorithms. This algorithm is inspired by obligate brood parasitism of cuckoo species. In this algorithm most optimal solution of the optimization problem is found on the basis of breeding behavior of cuckoos. The brooding behavior of cuckoo birds is represented in Fig. 2.

### G. Adaptive cuckoo search (ACS) algorithm

Performance of CS method is improved in ACS method by adding new equations for adaptive adjustments of inertia weight $(w)$; step size $(\alpha)$; and skewness parameter $(\lambda)$ [33].

$$w = 1 - e^{-\frac{1}{t}} \tag{14}$$
$$\alpha_i(t) = 0.5 + 1.5(\frac{1}{\sqrt{t}}) \left| \frac{f_{best}^t - f_i^t}{f_{best}^t - f_{worst}^t + \varepsilon} \right| \tag{15}$$
$$\lambda_i(t) = 0.5 + 0.1 \left| \frac{f_{best}^t - f_i^t}{f_{best} - f_{worst} + \varepsilon} \right|^t \tag{16}$$

$f_{best}$ and $f_{worst}$ are global best and global worst fitness values of function$f$respectively; $t$ is the iteration count. Fig. 3 shows the Pseudo code of CS algorithm [32, 33].

### H. Binary PSO algorithm

Discrete or binary PSO (BPSO) was proposed in 1995 by Kennedy and Eberhart. This version of PSO algorithm adopts the swarming approach to solve optimization problems where the decision variables have discrete values. Fig. 3 shows the Pseudo code of BPSO [34].

In the BPSO, a decision variable $(x_i)$ is either 0 or 1 and the corresponding $(\nu_i)$ is used to determine the state of $(x_i)$ using a sigmoid function $(S(\nu_i))$ given by (17).

$$S(\nu_i) = \frac{1}{1 + \exp(-\nu_i)} \tag{17}$$

$(S(\nu_i))$ is mapped to a real value generated randomly between 0 and 1. The value of $(x_i)$ is determined by (18).

$$x_i = \begin{cases} 1, & \text{if} \quad (S(\nu_i)) > \rho \\ 0, & \text{if} \quad (S(\nu_i)) \le \rho \end{cases} \tag{18}$$

Here, $\rho$ is the random number generated by uniform distribution between 0 to 1 using $rand()$. The procedure of BPSO is given in Fig. 4 [34, 35].

Table 3. Min-Max power limits of IEEE 30-bus system

| Gen. unit | $P_g^{min}$ (MW) | $P_g^{max}$ (MW) | DR (MW/h) | UR (MW/h) |
|---|---|---|---|---|
| 1 | 50 | 120 | 80 | 60 |
| 2 | 20 | 80 | 28 | 15 |
| 3 | 15 | 50 | 20 | 10 |
| 4 | 12 | 30 | 10 | 5 |
| 5 | 10 | 25 | 10 | 5 |
| 6 | 10 | 25 | 10 | 5 |

Table 4. Hourly power demand in IEEE 30 bus system before applying DSM

| Time slot | Load (MW) | Time slot | Loade (MW) | Time slot | Load (MW) | Time slot | Load (MW) |
|---|---|---|---|---|---|---|---|
| T1 | 62.32 | T7 | 208.09 | T13 | 219.95 | T19 | 210.25 |
| T2 | 68.28 | T8 | 260.01 | T14 | 221.48 | T20 | 218.32 |
| T3 | 70.16 | T9 | 262.25 | T15 | 219.83 | T21 | 261.41 |
| T4 | 50.84 | T10 | 261.95 | T16 | 185.06 | T22 | 195.86 |
| T5 | 74.43 | T11 | 309.6 | T17 | 120.97 | T23 | 153.69 |
| T6 | 126.64 | T12 | 298.84 | T18 | 240.93 | T24 | 69.54 |

## 4. TEST SYSTEM

Problem of DEED with and without implementing DSM is tested on standard IEEE 30-bus system with six generating units. Table 3 gives the power output limits and ramp rate limits for all the generating units in IEEE 30-bus system. Standard values of fuel cost coefficients, emission coefficients, and line loss coefficients for IEEE 30-bus system are considered as given in [21]. Both the objective functions are converted into a composite function (CF) with the help of price penalty factors [19] and optimized by CS and ACS techniques using MATLAB-2013. Here, Gauss-Seidel method is used for power flow solutions. Table 4 gives the information of hourly power demand (MW) by all the consumers in IEEE 30-bus system [10]. Table 5 gives the information of power consumption in 24 hours by the different residential consumers present in IEEE 30 bus system. It also gives the information of their deferrable and non-deferrable appliances. Here, total number of consumers including all the categories is assumed as 15000.

Table 5. Power consumption and appliance information of consumers

| Category of consumer | Range (kWh/month) | Power consumption (kWh) | Total appliances | Deferrable appliances |
|---|---|---|---|---|
| 1 | < 600 | 18.62 | 8 | 3 |
| 2 | 601 – 750 | 21.82 | 9 | 3 |
| 3 | 751 – 1000 | 31.58 | 14 | 6 |
| 4 | 1001 – 1250 | 38.08 | 14 | 6 |
| 5 | 1251 – 1500 | 43.75 | 12 | 7 |
| 6 | 1501 – 2000 | 57.75 | 14 | 9 |
| 7 | 2001 – 2500 | 79.75 | 15 | 10 |


Fig. 2. Brooding behavior of Cuckoo birds

```
Begin
objective function f(X),  X=(x1, x2,......., xD)T
generate initial population Yi of n host nest (i=1,2,......,n)
evaluate the fitness and find best nest (P_best)
        while (t < max iterations)
        t=t+1
        generate new solutions randomly from (P_best)
        evaluate fitness of new solutions
        choose randomly a nest among n nests (say, j)
if (Fi < Fj),   i = j
        replace j by new solution
end if
        A fraction of worst nests (Pa) are abandoned
        new solution are built
        evaluate the fitness
        keep the better solutions
        rank the solutions and find global best (G_best)
        end while
post process results and visualization
End
```

Fig. 3. Pseudo code for CS algorithm

**begin**

*Objective function* $f(x)$, $x=(x_1,x_2,.....x_d)^T$

*Random initialization of solution vector* $x_i$ *, and velocity vector* $v_i$

*Transform the solution vector* $x_i$ *into binary position using sigmoid function,* $S(v_i)$

*Evaluate objective function* $f(x)$ *for solution vector* $x_i$

*Find local optimum* $P_{best}^t$ *and global optimum* $G_{best}^t$ *as per PSO*

**while** *(t < Maximum Iteration)*

*Calculate velocity of particles by PSO using the equation*

$$v_i^{t+1}=wv_i^t+c_1R_1(P_{best}^t-x_i^t)+c_2R_2(G_{best}^t-x_i^t)$$

*Position update of* $x_i$ *by adding updated velocity* $(v_i^{t+1})$

*Evaluate objective function again for updated solution vector*

*Update the values of* $P_{best}^t$ *as well as* $G_{best}^t$

**end while**

*Post process results and visualization*

Fig. 4. Pseudo code for BPSO

## 5. SIMULATION RESULTS AND ANALYSIS

### I. Formation of objective load and reduction of peak hour demand in IEEE 30-bus system:

To manage the power demand in peak hours, difference between the objective and optimal load curve is reduced with the help of optimization function given by (3). Objective load can be obtained by (5) using dynamic pricing scheme. In literature ToU is used to find the objective load curve. But ToU price is designed prior a period of time and remains fixed during this time period whereas DA-RTP is decided prior a day based on forecasted demand and generation. So that DA-RTP can represent the condition of power demand and supply in power system more accurately in comparison of ToU price. In this research work it is proposed to find the objective load with the help of DA-RTP in place of ToU price. In the Table 6 ToU price, DA-RTP, and hourly power demand for 24 time slots is given. In the ToU price structure peak demand hours are from time slots T12 to T17. Here, it can be observed that in the hourly demand peak hours are from T8 to T12 which can be more accurately represented by DA-RTP.

Table 7 gives the objective power demand observed by (2) using ToU price and DA-RTP as the dynamic pricing schemes. Fig. 5 represents the comparison of mean absolute error (MAE) and mean absolute percentage error (MAPE) between actual hourly demand of power and objective load obtained with ToU price and DA-RTP. From this figure it can be observed that objective power demand obtained with the help of ToU resulted into **66.63 MW** MAE and **38.16 %** MAPE. In comparison of this objective power demand obtained with DA-RTP resulted into **51.61 MW** MAE and **28.89%** MAPE. By this comparative analysis it can be said that objective load curve calculated with the help of DA-RTP is more accurate.

In order to reduce the energy consumption in peak hours, objective function given by (3) is minimized using BPSO algorithm and optimal load for 24 hours is obtained. The smart home energy controller connected at consumer's premises receive the information of electricity price sent by the utility and artificial intelligence based algorithm (BPSO) finds the optimal scheduling of deferrable appliances based on the objective load curve and consumer's preferences of using appliances. The BPSO algorithm determines the hourly optimal power consumption in order to minimize the difference between optimal and objective demand with satisfying the equality and inequality constraints. This version of the PSO algorithm uses discrete valued (0 or 1) decision variables that helps to find the on/off state of deferrable appliances. Table 8 gives the optimal power demand for 24 hours obtained for all

Table 6. Variation of hourly pricing and power demand

| Time slot | ToU price (Cents/kWh) | DA-RTP (Cents/kWh) | Hourly power demand (MW) | Time slot Time slot | ToU price (Cents/kWh) | DA-RTP (Cents/kWh) | Hourly power demand (MW) |
|---|---|---|---|---|---|---|---|
| T1 | 6.50 | 6.50 | 62.32 | T13 | 13.40 | 11.30 | 219.95 |
| T2 | 6.50 | 6.40 | 68.28 | T14 | 13.40 | 10.20 | 221.48 |
| T3 | 6.50 | 6.40 | 70.16 | T15 | 13.40 | 6.60 | 219.83 |
| T4 | 6.50 | 6.40 | 50.84 | T16 | 13.40 | 6.60 | 185.06 |
| T5 | 6.50 | 6.40 | 74.43 | T17 | 13.40 | 7.90 | 120.97 |
| T6 | 6.50 | 6.50 | 126.64 | T18 | 9.40 | 7.90 | 240.93 |
| T7 | 6.50 | 6.60 | 208.09 | T19 | 9.40 | 7.90 | 210.25 |
| T8 | 9.40 | 9.80 | 260.01 | T20 | 6.50 | 8.10 | 218.32 |
| T9 | 9.40 | 9.80 | 262.25 | T21 | 6.50 | 8.10 | 261.41 |
| T10 | 9.40 | 10.50 | 261.95 | T22 | 6.50 | 6.50 | 195.86 |
| T11 | 9.40 | 10.40 | 309.6 | T23 | 6.50 | 6.50 | 153.69 |
| T12 | 13.40 | 11.30 | 298.84 | T24 | 6.50 | 6.50 | 69.54 |
| | Off-peak hours | | Peak hours | | | Mid-peak hours | |

Table 7. Objective load obtained with ToU price and DA-RTP in IEEE 30-bus system

| Time slot | Objective load (MW) | | Time slot | Objective load (MW) | | Time slot | Objective load (MW) | |
|---|---|---|---|---|---|---|---|---|
| | ToU | DA-RTP | | ToU | DA-RTP | | ToU | DA-RTP |
| T1 | 132.25 | 148.65 | T9 | 191.25 | 224.12 | T17 | 272.62 | 180.65 |
| T2 | 132.25 | 146.36 | T10 | 191.25 | 240.12 | T18 | 191.25 | 180.65 |
| T3 | 132.25 | 146.36 | T11 | 191.25 | 237.84 | T19 | 191.25 | 180.65 |
| T4 | 132.25 | 146.36 | T12 | 272.62 | 258.41 | T20 | 132.25 | 185.24 |
| T5 | 132.25 | 146.36 | T13 | 272.62 | 258.41 | T21 | 132.25 | 185.24 |
| T6 | 132.25 | 148.65 | T14 | 272.62 | 233.26 | T22 | 132.25 | 148.65 |
| T7 | 132.25 | 150.93 | T15 | 272.62 | 150.93 | T23 | 132.25 | 148.65 |
| T8 | 191.25 | 224.12 | T16 | 272.62 | 150.93 | T24 | 132.25 | 148.65 |

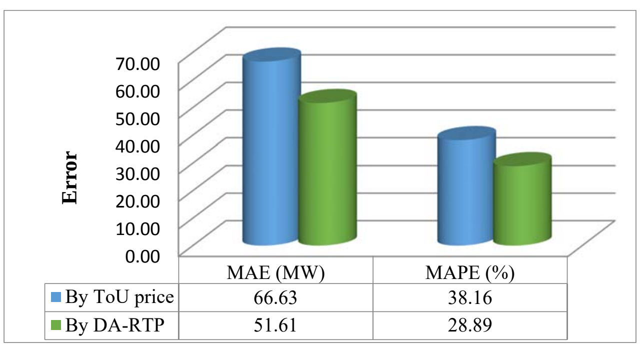


Fig. 5. Comparison of MAE and MAPE in objective load curves by ToU price and DA-RTP

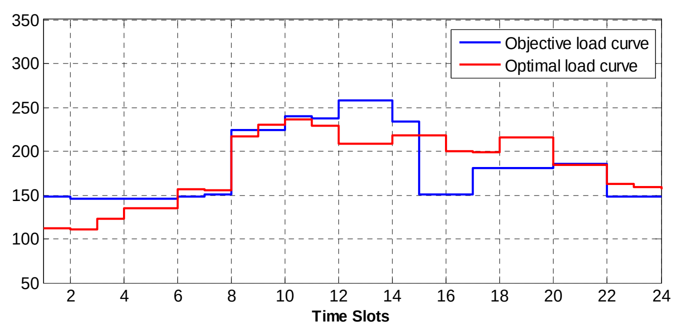


Fig. 6. Comparison of optimal and objective load curves in IEEE 30-bus system

the consumers after applying demand response. Fig. 6 represents the comparison of optimal power demand and objective load with DA-RTP. As a result reduced **MAE** between objective and optimal load curve is **21.28 MW** and **MAPE** is **12.24 %.** Fig. 7 represents the comparison of peak hour's demand before and after application of DSM in IEEE 30-bus system. It is observed that by the application of DR and optimal scheduling, peak hour's demand can be **reduced** from 1834.08 MW to 1547.16 MW.

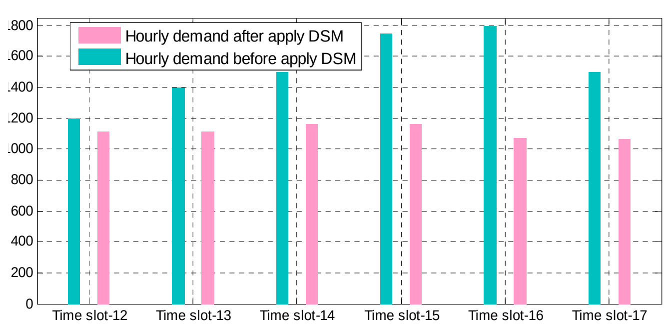


Fig. 7. Comparison of peak hour's demand before and after application of DR

### J. Fuel cost and emission dispatch before optimal scheduling of generators in IEEE 30-bus system:

Hourly fuel cost ($/h) and emission dispatch (Kg/h) before optimization for the power generation required for 24 hours are calculated using (1) and (2) and given in Table 9. Power generation scheduling of all the six generators for the power demand given in Table 4 is also given in Table 9. Here, total power demand

Table 8. Optimal hourly power demand after applying DSM

| Time slot | Optimal load (MW) | Time slot | Optimal load (MW) | Time slot | Optimal load (MW) |
|---|---|---|---|---|---|
| T1 | 111.87 | T9 | 230.71 | T17 | 198.78 |
| T2 | 110.82 | T10 | 235.78 | T18 | 215.67 |
| T3 | 123.08 | T11 | 228.69 | T19 | 215.65 |
| T4 | 134.95 | T12 | 208.12 | T20 | 184.58 |
| T5 | 135.02 | T13 | 208.14 | T21 | 184.70 |
| T6 | 157.21 | T14 | 218.28 | T22 | 162.50 |
| T7 | 155.23 | T15 | 217.80 | T23 | 158.65 |
| T8 | 217.44 | T16 | 200.30 | T24 | 156.31 |

and power loss for 24 hours are 4370.7 MW and 154.80 MW respectively. As per the power balance condition given in (6), required power generation is 4525.50 MW (load+loss) but the actual generation is 4830.93 MW. Because of power generation scheduled is higher than the power required at low load periods due to the inequality constraint given by (9).

### K. Optimal solution of DEED in IEEE 30-bus system without use of DR:

Table 10 shows the optimal scheduling of all the six generators by ACS algorithm as the solution of DEED problem for the hourly power demand given in Table 4. Fuel cost and gases emission are minimized using objective functions given in (1) and (2) using CS and ACS. The optimal scheduling of generators using CS minimized fuel cost as well as gases emission by 4284.60 \$ and 1568.05 Kg. as compared to the results before optimal scheduling. In comparison of this ACS algorithm reduced the fuel cost as well as gases emission by 5106.96 \$ and 2254.74 Kg. respectively. Optimal setting of control variables also resulted into reduced total power generation and power loss. As shown in Table 10 total power demand and power losses for 24 hours are 4370.7 MW and 149.83 MW respectively. As per the power balance condition required power generation is 4520.53 MW but the actual generation is 4821.12 MW. Because of the minimum power generation limits of generating units, there is generation of extra power of 305.43 MW before optimal scheduling and 300.59 MW after optimal scheduling during low load periods. This extra power generation also results into higher power generation cost and emission of harmful gases.

There are two solutions to this problem. One is at the macro level where different states/utilities can share load so that the load curve is consistent in power system. This solution is more complex & time consuming due to various economic and political hurdles. Another solution is at the micro level where the application of DSM programs can modify the load curve by the help of dynamic pricing schemes. This not only minimizes the imbalance between load demands during different times but also helps in peak shaving. This approach helps both the customers to lower down there monthly billing cost and also reduce operational cost for utilities.

### L. Optimal solution of DEED in IEEE 30-bus system with use of DR:

This optimal power demand is distributed among committed generating units. Hourly scheduling of generating units is also obtained in order to minimize the fuel cost and emission dispatch. Power generation scheduling of all six generators obtained by CS and ACS algorithms for the optimal power demand. Optimal scheduling by ACS algorithm and resulted power loss, fuel cost and emission dispatch is given in Table 11. From the optimal results given in Table 11, it can be observed that total power demand and power loss for 24 hours are 4370.7 MW and 138.66 MW. Here, required power generation is 4509.36 MW (load+line losses) on the other hand total power generation is 4519.36 MW. In comparison of this optimal scheduling by CS algorithm resulted into 152.89 MW and 142.52 MW line losses before and after applying DR respectively. Similarly actual power generation by CS before and after applying DR is 4825.64 MW and 4535.84 MW as comparative results given in Table 12. The optimal scheduling of generators after application of DR minimized fuel cost as well as gases emission by 7615.51 \$ and 3058.46 Kg. using CS algorithm. In comparison of this ACS algorithm further reduced the fuel cost as well as gases emission by 8366.75 \$ and 3400.45 Kg.

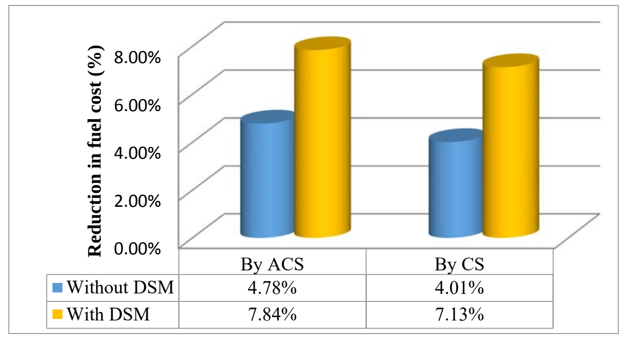


Fig. 8. Saving in fuel cost by optimal scheduling of generators with and without DR

Comparison of performance evaluation of CS and ACS in minimization of generation cost and emission dispatch with and without applying DSM is given by Fig. 8 and Fig. 9 respectively. From these graphical representations it can be observed that optimal scheduling of generating units in IEEE 30-bus system minimized the generation cost and emission dispatch **4.78%** and **10.84%** respectively by ACS algorithm and 4.01% and 7.54% by CS algorithm. In comparison of this application of enhanced DSM strategy (demand response with real time price) resulted into further minimization of power generation cost and emission dispatch by **7.84%** and **16.35%** with optimal scheduling of generating units by ACS algorithm and 7.13% and 14.71% by CS. From the Table 12 it can also be observed that by the application of DR consumers are also benefited in term of reduced electricity bill cost by **3985.27 \$** per day. Table 13 gives comparison of results obtained for similar objectives of SSEM by different optimization algorithms with or without integrating DSM measures with optimal results given ACS algorithm with integrating proposed DSM program. From the Table 13 it can be noticed percent reduction in fuel cost and emission dispatch is more in [4] and [25] using GA as optimization algorithm. Here, in [4] objective function are minimized using DR as DSM measures. In this paper renewable energy sources (RES) are also integrated in the system like PV systems, and wind turbines (WT). RES are economic and emission free. In the research papers [6] and [25] optimal direct load control (DLC) has been applied as the DSM measure. It results into reduced peak demand, fuel cost as

Table 9. Fuel cost and emission dispatch for hourly power consumption before optimization (case study-1)

| Time slot | Load (MW) | Pg1 (MW) | Pg2 (MW) | Pg3 (MW) | Pg4 (MW) | Pg5 (MW) | Pg6 (MW) | Loss (MW) | Total gen (MW) | Fuel Cost ($/h) | Emission dispatch (Kg/h) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 62.32 | 50.00 | 20.00 | 15.00 | 12.00 | 10.00 | 10.00 | 2.202 | 117.00 | 3471.80 | 417.74 |
| 2 | 68.28 | 50.00 | 20.00 | 15.00 | 12.00 | 10.00 | 10.00 | 2.413 | 117.00 | 3471.80 | 417.74 |
| 3 | 70.16 | 50.00 | 20.00 | 15.00 | 12.00 | 10.00 | 10.00 | 2.479 | 117.00 | 3471.80 | 417.74 |
| 4 | 50.84 | 50.00 | 20.00 | 15.00 | 12.00 | 10.00 | 10.00 | 2.153 | 117.00 | 3471.80 | 417.74 |
| 5 | 74.43 | 50.00 | 20.00 | 15.00 | 12.00 | 10.00 | 10.00 | 2.630 | 117.00 | 3471.80 | 417.74 |
| 6 | 126.64 | 54.32 | 19.43 | 16.70 | 16.07 | 11.94 | 13.05 | 4.475 | 131.52 | 3670.72 | 450.89 |
| 7 | 208.09 | 81.08 | 65.91 | 24.28 | 15.70 | 12.77 | 15.51 | 7.353 | 215.25 | 4629.12 | 884.20 |
| 8 | 260.01 | 118.83 | 60.46 | 40.46 | 21.00 | 14.10 | 14.59 | 9.188 | 269.44 | 5160.17 | 1365.53 |
| 9 | 262.25 | 117.83 | 70.61 | 35.23 | 20.48 | 15.10 | 12.59 | 9.267 | 271.51 | 5139.90 | 1404.00 |
| 10 | 261.95 | 115.83 | 65.46 | 37.46 | 22.40 | 16.10 | 14.26 | 9.256 | 271.84 | 5186.54 | 1348.06 |
| 11 | 309.6 | 119.59 | 78.14 | 48.84 | 26.89 | 24.64 | 23.75 | 10.940 | 321.85 | 5640.89 | 1571.73 |
| 12 | 298.84 | 119.54 | 60.88 | 54.36 | 27.81 | 24.32 | 23.59 | 10.560 | 310.50 | 5611.78 | 1467.09 |
| 13 | 219.95 | 85.64 | 60.92 | 38.54 | 18.14 | 10.44 | 14.66 | 7.772 | 228.34 | 4817.97 | 931.69 |
| 14 | 221.48 | 106.9 | 51.66 | 30.33 | 12.45 | 18.29 | 10.61 | 7.826 | 230.24 | 4828.35 | 1110.68 |
| 15 | 219.83 | 82.64 | 62.92 | 38.54 | 18.14 | 12.44 | 13.66 | 7.768 | 228.34 | 4814.71 | 913.60 |
| 16 | 185.06 | 72.37 | 27.67 | 34.09 | 25.23 | 18.33 | 14.55 | 6.539 | 192.24 | 4475.36 | 655.77 |
| 17 | 120.97 | 54.9 | 18.46 | 15.84 | 13.02 | 12.85 | 11.68 | 4.275 | 126.75 | 3628.06 | 449.84 |
| 18 | 240.93 | 105.38 | 77.4 | 24.31 | 18.31 | 12.07 | 13.3 | 8.513 | 250.77 | 4902.93 | 1254.57 |
| 19 | 210.25 | 88.62 | 40.89 | 36.67 | 19.55 | 17.88 | 14.44 | 7.429 | 218.05 | 4775.81 | 860.77 |
| 20 | 218.32 | 82.64 | 62.92 | 36.54 | 18.14 | 10.44 | 16.66 | 7.714 | 227.34 | 4793.55 | 909.67 |
| 21 | 261.41 | 113.83 | 67.46 | 40.46 | 21.89 | 14.1 | 14.09 | 9.237 | 271.83 | 5186.38 | 1339.82 |
| 22 | 195.86 | 80.04 | 35.02 | 37.17 | 22.85 | 12.51 | 14.75 | 6.921 | 202.34 | 4589.09 | 749.90 |
| 23 | 153.69 | 73.49 | 25.91 | 22.15 | 15.45 | 13.31 | 10.48 | 5.431 | 160.79 | 4085.12 | 618.48 |
| 24 | 69.54 | 50.00 | 20.00 | 15.00 | 12.00 | 10.00 | 10.00 | 2.457 | 117.00 | 3471.80 | 417.74 |
| **Total** | **4370.7** | | | | | | | **154.80** | **4830.93** | **106767.23** | **20792.72** |

Table 10. Fuel cost and emission dispatch by optimal scheduling of generators (without DR) by ACS algorithm (case study-2)

| Time slot | Load (MW) | Pg1 (MW) | Pg2 (MW) | Pg3 (MW) | Pg4 (MW) | Pg5 (MW) | Pg6 (MW) | Loss (MW) | Total gen (MW) | Fuel cost ($/h) | Emission dispatch (Kg/h) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 62.32 | 50.03 | 20.07 | 15.12 | 12.08 | 10.10 | 10.02 | 2.202 | 117.42 | 3177.36 | 417.23 |
| 2 | 68.28 | 50.10 | 20.04 | 15.06 | 12.10 | 10.15 | 10.01 | 2.413 | 117.46 | 3178.13 | 417.57 |
| 3 | 70.16 | 50.11 | 20.08 | 15.05 | 12.11 | 10.06 | 10.19 | 2.479 | 117.60 | 3179.30 | 418.75 |
| 4 | 50.84 | 50.15 | 20.14 | 15.10 | 12.09 | 10.20 | 10.12 | 2.153 | 117.80 | 3182.36 | 417.15 |
| 5 | 74.43 | 50.11 | 20.10 | 15.21 | 12.10 | 10.15 | 10.06 | 2.630 | 117.73 | 3181.56 | 416.89 |
| 6 | 126.64 | 51.23 | 24.52 | 17.65 | 13.72 | 11.85 | 12.12 | 4.475 | 131.09 | 3350.82 | 421.68 |
| 7 | 208.09 | 90.69 | 52.96 | 20.12 | 17.85 | 16.36 | 17.15 | 6.235 | 215.13 | 4513.90 | 671.04 |
| 8 | 260.01 | 118.74 | 74.10 | 33.64 | 17.24 | 12.42 | 13.25 | 9.188 | 269.39 | 5107.54 | 1173.95 |
| 9 | 262.25 | 118.96 | 68.17 | 24.03 | 23.45 | 14.84 | 22.20 | 9.267 | 271.63 | 5120.92 | 1228.69 |
| 10 | 261.95 | 117.90 | 67.24 | 22.30 | 29.24 | 20.35 | 14.31 | 9.256 | 271.33 | 5105.92 | 1208.66 |
| 11 | 309.6 | 119.93 | 75.53 | 45.94 | 29.40 | 24.99 | 24.65 | 10.126 | 320.44 | 5348.16 | 1436.00 |
| 12 | 298.84 | 120.00 | 79.88 | 45.13 | 21.58 | 24.67 | 17.97 | 9.560 | 309.22 | 5290.07 | 1389.26 |
| 13 | 219.95 | 80.82 | 64.49 | 25.11 | 29.40 | 16.16 | 11.61 | 7.772 | 227.59 | 4803.18 | 845.16 |
| 14 | 221.48 | 117.56 | 42.40 | 21.21 | 22.57 | 10.02 | 15.55 | 7.826 | 229.31 | 4733.59 | 861.41 |
| 15 | 219.83 | 80.82 | 64.49 | 25.11 | 29.40 | 16.16 | 11.61 | 7.768 | 227.59 | 4653.18 | 816.66 |
| 16 | 185.06 | 62.60 | 34.00 | 53.00 | 15.70 | 12.22 | 14.22 | 6.539 | 191.75 | 3859.37 | 630.16 |
| 17 | 120.97 | 53.48 | 24.76 | 15.00 | 12.00 | 10.00 | 10.00 | 4.275 | 125.25 | 3283.97 | 430.57 |
| 18 | 240.93 | 118.76 | 56.09 | 22.07 | 22.16 | 16.28 | 13.08 | 7.561 | 248.44 | 4930.39 | 1160.58 |
| 19 | 210.25 | 51.49 | 72.74 | 35.14 | 18.80 | 15.89 | 22.56 | 6.349 | 216.62 | 4528.40 | 673.65 |
| 20 | 218.32 | 67.41 | 65.79 | 32.15 | 21.77 | 24.65 | 14.88 | 7.714 | 226.65 | 4679.91 | 809.49 |
| 21 | 261.41 | 119.96 | 68.73 | 30.13 | 25.46 | 13.42 | 12.95 | 9.237 | 270.65 | 5116.53 | 1232.44 |
| 22 | 195.86 | 71.10 | 40.45 | 37.79 | 25.27 | 11.14 | 17.13 | 6.921 | 202.88 | 4572.34 | 575.90 |
| 23 | 153.69 | 56.71 | 24.84 | 30.28 | 14.30 | 10.58 | 23.44 | 5.431 | 160.16 | 3609.81 | 466.94 |
| 24 | 69.54 | 50.30 | 20.15 | 15.30 | 12.03 | 10.14 | 10.08 | 2.457 | 118.00 | 3153.54 | 418.16 |
| **Total** | **4370.7** | | | | | | | **149.83** | **4821.12** | **101660.27** | **18537.98** |

Table 11. Fuel cost and emission dispatch by optimal scheduling of generators (with use of DR) by ACS algorithm (case study-3)

| Time slot | Load (MW) | Pg1 (MW) | Pg2 (MW) | Pg3 (MW) | Pg4 (MW) | Pg5 (MW) | Pg6 (MW) | Loss (MW) | Total gen (MW) | Fuel cost ($/h) | Emission dispatch (Kg/h) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| T1 | 111.87 | 50.11 | 20.05 | 15.01 | 12.13 | 10.06 | 10.10 | 2.202 | 117.00 | 3171.80 | 417.74 |
| T2 | 110.82 | 50.08 | 20.14 | 15.20 | 12.16 | 10.07 | 10.05 | 2.413 | 117.00 | 3171.80 | 417.74 |
| T3 | 123.08 | 53.09 | 21.02 | 16.20 | 12.70 | 12.19 | 11.91 | 3.978 | 127.11 | 3217.62 | 442.24 |
| T4 | 134.95 | 57.06 | 21.62 | 17.37 | 15.38 | 15.62 | 12.22 | 4.361 | 139.26 | 3417.36 | 475.40 |
| T5 | 135.02 | 53.86 | 25.14 | 22.60 | 15.69 | 11.41 | 10.68 | 4.364 | 139.37 | 3419.98 | 464.45 |
| T6 | 157.21 | 72.61 | 18.45 | 19.83 | 19.88 | 13.55 | 18.11 | 5.081 | 162.44 | 3613.78 | 604.03 |
| T7 | 155.23 | 58.82 | 22.62 | 27.09 | 16.66 | 19.85 | 15.93 | 5.017 | 160.97 | 3558.59 | 513.56 |
| T8 | 217.44 | 68.76 | 46.49 | 44.60 | 21.60 | 22.25 | 20.98 | 7.027 | 224.67 | 4683.06 | 734.37 |
| T9 | 230.71 | 115.11 | 40.68 | 25.45 | 19.85 | 18.70 | 18.82 | 7.456 | 238.61 | 4803.35 | 1178.39 |
| T10 | 235.78 | 118.88 | 55.50 | 22.63 | 12.03 | 16.44 | 18.15 | 7.620 | 243.63 | 4861.28 | 1292.54 |
| T11 | 228.69 | 93.19 | 71.92 | 19.82 | 12.35 | 21.11 | 18.06 | 7.391 | 236.45 | 4827.09 | 1062.14 |
| T12 | 208.12 | 100.70 | 27.83 | 26.94 | 19.34 | 19.86 | 20.25 | 6.726 | 214.92 | 4537.51 | 946.06 |
| T13 | 208.14 | 63.79 | 72.07 | 17.89 | 26.01 | 11.01 | 24.10 | 6.727 | 214.87 | 4525.67 | 789.81 |
| T14 | 218.28 | 111.86 | 28.95 | 20.93 | 28.89 | 17.88 | 16.81 | 7.054 | 225.32 | 4752.66 | 1093.69 |
| T15 | 217.80 | 100.80 | 30.97 | 29.67 | 29.38 | 18.95 | 15.27 | 7.039 | 225.04 | 4728.20 | 967.79 |
| T16 | 200.30 | 78.27 | 61.46 | 15.88 | 13.29 | 14.72 | 23.18 | 6.473 | 207.21 | 4434.71 | 830.20 |
| T17 | 198.78 | 64.42 | 42.75 | 32.56 | 28.83 | 14.15 | 22.67 | 6.424 | 205.38 | 4477.65 | 649.47 |
| T18 | 215.67 | 61.26 | 62.42 | 32.50 | 26.91 | 24.65 | 14.87 | 6.970 | 223.01 | 4718.05 | 732.37 |
| T19 | 215.65 | 70.84 | 52.07 | 37.88 | 30.14 | 16.88 | 14.84 | 6.969 | 222.69 | 4725.18 | 755.93 |
| T20 | 184.58 | 66.32 | 45.58 | 32.51 | 15.67 | 10.56 | 19.94 | 5.965 | 190.61 | 3895.73 | 654.46 |
| T21 | 184.70 | 80.55 | 21.36 | 22.22 | 21.63 | 22.53 | 22.37 | 5.969 | 190.86 | 3907.54 | 706.19 |
| T22 | 162.50 | 64.35 | 38.66 | 18.67 | 14.34 | 17.27 | 14.45 | 5.252 | 167.80 | 3741.80 | 581.70 |
| T23 | 158.65 | 55.86 | 26.34 | 22.60 | 26.67 | 16.41 | 15.90 | 5.127 | 163.79 | 3628.62 | 501.05 |
| T24 | 156.31 | 69.61 | 20.45 | 19.83 | 19.44 | 13.85 | 18.16 | 5.052 | 161.35 | 3581.45 | 580.95 |
| **Total** | **4370.70** | | | | | | | **138.66** | **4519.36** | **98400.478** | **17392.27** |

Table 12. Comparison of optimal results by generator's scheduling in IEEE 30-bus system with & without use of DR

| S. No | Parameter | Before optimization | Optimal solution by ACS algorithm | | Optimal solution by CS algorithm | |
|---|---|---|---|---|---|---|
| | | | Without DR | With DR | Without DR | With DR |
| 1 | Load (MW) | 4370.70 | 4370.70 | 4370.70 | 4370.70 | 4370.70 |
| 2 | Line loss (MW) | 154.80 | 149.83 | 138.66 | 152.89 | 142.52 |
| 3 | Load + Loss (MW) | 4525.50 | 4520.53 | 4509.36 | 4523.59 | 4513.22 |
| 4 | Total gen. (MW) | 4830.93 | 4821.12 | 4519.36 | 4825.64 | 4535.84 |
| 5 | Fuel cost ($/h) | 106767.23 | 101660.27 | 98400.48 | 102482.63 | 99151.72 |
| 6 | Emission dispatch (Kg/h) | 20792.72 | 18537.98 | 17392.27 | 19224.67 | 17734.26 |
| 7 | Peak hour demand (MW) | 1834.08 | 1834.08 | 1547.16 | 1834.08 | 1547.16 |
| 8 | Saving in fuel cost ($) | | 5106.96 | 8366.75 | 4284.60 | 7615.51 |
| 9 | Reduction in emission dispatch (Kg) | | 2254.74 | 3400.45 | 1568.05 | 3058.46 |
| 10 | Cost saving by consumers in 24 hours after applying DR | | | | 3985.27 $ | |

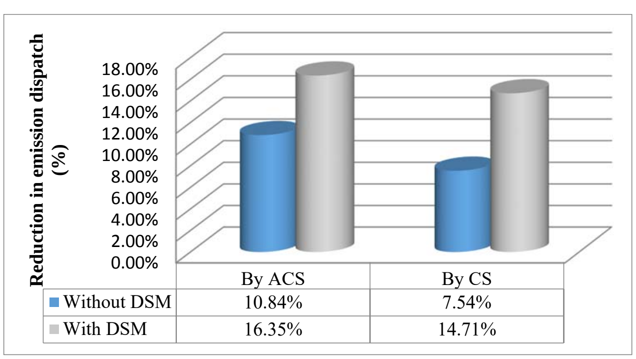


Fig. 9. Reduction in emission dispatch by optimal scheduling of generators with and without DR

well as emission dispatch. But in the DLC method optimal load is shaded, that leads to consumer's compromise. In comparison of this there is no power cut in the DR program and its application with DA-RTP using ACS algorithm demonstrated its effectiveness in the optimization of objectives of SSEM.

## 6. CONCLUSION

This research work focused on integrating supply side energy management system with demand response programs. In this paper two conflicting objectives of dynamic economic-emission dispatch problem are considered for the study and formulated an optimization problem with the help of price penalty factors. A compromised solution for both the objectives is also obtained by cuckoo search and adaptive cuckoo search algorithm. In this paper peak hour's demand and overloading condition of generating units is also resolved by integrating enhanced DR program using DA-RTP. The proposed approach is implemented on IEEE 30-bus

Table 13. Comparison of results by different optimization techniques for similar objectives with/without DSM measures (for IEEE 30-bus system)

| S. No. | Method | % Min. of power loss | % Min. of fuel cost | % Min. of emission dispatch | % Min. of peak hour demand |
|---|---|---|---|---|---|
| 1 | Multi-objective PSO (MOPSO) [19] | 3.54 % | 3.12 % | 4.53 % | — |
| 2 | Bi-level optimization using NSGA-II with DSM using time of use tariff [21] | – | 7.25 % | 8.12 % | – |
| 3 | GA with (EE+ DR+ RES) [4] | – | 10.6 % | 11.51 % | 9.6% |
| 4 | GA with optimal load control [25] | – | 9.41 % | 10.64 % | |
| 5 | CSA with optimal load control [6] | – | 5.63 % | 11.12 % | 10.61 % |
| 6 | ACS without DSM | 3.21 % | 4.78 % | 10.84 % | – |
| 7 | **ACS with DSM (Proposed scheme)** | **10.31 %** | **7.84 %** | **16.35 %** | **15.64 %** |

system. Implementation of dynamic pricing on consumers also benefitted them in terms of reduced electricity bill. This research work is divided into three case studies and their comparative result analysis is also given. The proposed solution of DEED problem and peak hour demand management resulted into reduced power generation cost and harmful gases, reduced peak hour demand, reduced power losses, and beneficial for both customers as well as utility. The following are suggestions for future research direction in this area:

1) Implementation of DR programs for different types of load viz. residential, industrial, and commercial.
2) Implementation of DSM programs integrated with different functionalities of smart grid to make the system more efficient.

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