Consumer End Load Scheduling in DSM Using Multi-Objective Genetic Algorithm Approach

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***Abstract*—Demand Side Management (DSM) aims to benefit the consumer economically without taking into consideration the losses incurred during inefficient working of generating unit while supplying demand. This paper primarily focuses on generation and distribution parts of the grid. The multiple objectives that are opted for load scheduling are reduction in the electricity cost for the user and maximization of load factor benefitting the user as well as utility. Simulation results show that multi-objective approach proves advantageous in efficient and reliable operation of generating unit while supplying economically affordable electricity to the consumers. Extensive comparison between single objective and multi-objective approach is carried out, which is further justified with two-step and five-step tariff model.**

Keywords- Demand side management;Direct load control; Time based pricing; Normal distribution curve; Genetic algorithm; Incentives; Rebate; Smart grid

I. INTRODUCTION

With the increasing demand for electricity in the 21st century at a skyrocketing pace, there has been a major concern in feeding electric power in decades to come as the electric power infrastructure is rapidly running against its limitations and existing grids are struggling to keep up [1]. Furthermore, the present amount of energy generated is facing chronic under investment since it is not being efficiently transferred where it should have been through transmission and distribution, thereby deteriorating grid reliability and efficiency [2]. Smart grids have however provided aid in taking economic operations into account while supplying energy with improved reliability [3].

One of the techniques adopted in improving system stability is through Direct Load control (DLC) [4] which aims at optimizing the customer's discomfort effect along with traditional load management objectives using Monte Carlo-based dynamic programming approach [5-7]. To amend this, a concept of virtual power plant was introduced where the customers interested in controllable demands were involved in the load reduction bid and optimal control schedules were determined by the aggregator to optimize load reduction [8]. Focusing merely on the demand side, customer daily electricity usage cost was reduced by providing incentives for off-peak hour usage where the individual load profile of each consumer was shared on user network [9]. This approach however benefited consumers at the cost of inefficiently running generating units leading to reduced system reliability and operational instability.

A single objective of minimizing energy cost will not suffice both user and utility [10-11]. The system's operation is highly non-linear and complex and the classical techniques for finding the optimal solution may fail in such real-world problems [13]. Multiple approaches have been applied for optimization, linear programming [14-15] and dynamic programming [16], to obtain prime results. However these techniques are not capable of handling such non-linear, multidimensional and complex problems. Evolutionary algorithms such as GA have proved to provide apt results for such problems [17].

Researchers had earlier considered multi-objective approaches as in [18] where the objective of cost reduction and fitting to objective load curve are reckoned. Price based load response is also applied to electric power system [19] during emergency conditions but fail to acknowledge the load factor of the system which may change drastically increasing the peak consumption during low priced hours. Multiple objectives have also been reckoned [20] but no penalty or rebate constraints are there, making the system rigid for the users and utility. Different heuristic [18-20] as well as artificial intelligence techniques [11-12] have been applied on such problems.

Thus in our approach, multi-objective based genetic algorithm optimization technique is deployed to reduce customer's electricity usage cost while benefiting utility by improving its load factor at the same time. By the help of normal distribution curve the three regions are acknowledged. The consistency of hourly energy usage is further ascertained by imposing high penalty for the region 2 and 3. These parameters thus help in maintaining a flat energy consumption profile of each user thereby improving the load factor of the generating unit. Therefore, proving advantageous for both generation and consumer end The consumer's actual energy usage profile would be used in evaluating the corresponding individual load factor (LF), encouraging them to adopt load shifting strategy in order to reduce the daily electricity bill by furnishing suitable rebate. This would in return benefit the generating unit by operating the whole unit at improved load factor.

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II. SYSTEM MODEL

In this section, we provide the analytical description of the various parameters involved for the representation of residential load control.

A. Peak –to- average Ratio

Load factor is defined as ratio of average energy consumption over a period to peak energy consumption in that period.

$w_i^h =$ load of ith device in hth time interval,
t_h = hth time interval
Average consumption of single consumer can be given by

$$Average\ Consumption = \frac{\sum_{i=1}^{i=N}\sum_{h=1}^{h=T}(w_i^h)\times t_h}{\sum_{j=1}^{j=T} t_h} \tag{1}$$

Peak energy consumption is given by

$$E_{\max} = \max\,(w_i^h \times t_h) \quad \forall\ i \in \{1\ N\}\ \text{ and } h \in \{1\ T\} \tag{2}$$

T = Total number of hours available for scheduling
N = Number of devices operating in hth hour
Load factor can be given as

$$Load\ Factor = \frac{Average\ Consumption}{E_{\max}} \tag{3}$$

B. Time Based pricing

Variable pricing encourages energy scheduling among consumers [21] who otherwise are not concerned with overall distribution system's load factor. Time based pricing is done in the present study.

In this type of pricing peak and off-peak hours are decided by utility companies and information is provided to consumers. Using this information, consumers schedule their devices so as maximize off-peak hour operation of shift able equipments. Further division of these can be done to improve pricing policies. Two type of time based pricing scenarios are used in present study. Scenario 1 and 2 are shown in table I and II.

C. DSM Techniques

Power System distribution networks are designed for peak loads. DSM ensures maximum load factor and thus maximizing total profit of utilities. Various Load management programs are listed in [22-23].

TABLE I. SCENARIO 1

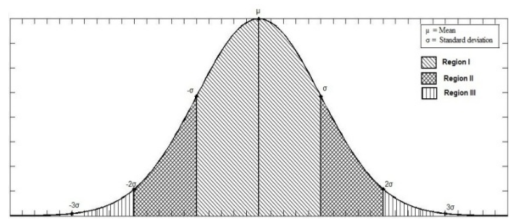
Table 1	Time	Cost (cents/KWh)
On-Peak hours	7am-11pm	7.50
Off-peak hours	11pm-7am	5.90

TABLE II. SCENARIO 2

Time	Cost (cents/KWh)
7am-9am	6.90
9m-4pm	6.20
4pm-6pm	6.50
6pm-10pm	7.50
10pm-7pm	5.90

For better insight of different techniques, load curve for a day is represented by a normal distribution curve as in *Fig. 1* Normal distribution curve helps in dividing the load into further regions which implies there deviation from the apt load consumption [12]. The penalty and rebate are imposed on the user accordingly which also acts as governing factors during optimization.

Fig. 1 . Normal Curve representation of Load profile



p_σ = Probability of load lying in region I i.e. [(μ-σ) (μ+σ)]
$p_{2\sigma}$= Probability of load lying in region II i.e. [(μ-2σ) (μ-σ)] and [(μ+σ) (μ+2σ)]
$p_{3\sigma}$ = Probability of load lying in region III i.e. [(μ-3σ) (μ-2σ)] and [(μ+3σ) (μ+2σ)]

Valley Filling: In this the loads during off peak hours are increased to achieve flatter profile. This is done by encouraging consumers to increase energy consumption.
$[\uparrow p_{3\sigma}] \Leftrightarrow$[load addition]

Load Shifting: In this the shift-able loads during peak hours are shifted to off-peak hours, resulting lower peak of valley and a flatter profile.
$[\uparrow p_{3\sigma} \cap \uparrow p_{2\sigma}] \Leftrightarrow [\downarrow p_\sigma]$

Peak Clipping: In this the load from peak hour is reduced when it cannot be shifted to other hours because of lack of installed capacity.
$[\downarrow p_\sigma] \Leftrightarrow$[load removal]

Energy Conservation: This is used when reduction in load is required all over the load curve. It is achieved by using energy efficient devices.
$[\downarrow p_\sigma \cap \downarrow p_{3\sigma} \cap \downarrow p_{2\sigma}] \Leftrightarrow$ [load removal]

Load Building: This is used when increased energy consumption is required due to surplus production. Average cost per KWh is reduced
$[\uparrow p_\sigma \cap \uparrow p_{3\sigma} \cap \uparrow p_{2\sigma}] \Leftrightarrow$ [load addition]

D. Genetic Algorithm

GA is an adaptive heuristic search algorithm inspired from natural selection and genetics. Mutation and cross-over strategies are emulated by application of various operators, while the equivalent of natural selection is the fitness function for respective chromosome. The steps of GA can be represented by pseudo code shown in *Fig. 2*.

The parameters chosen for genetic algorithm are: population size: 20, crossover probability: 0.8, mutationprobability:0.15, maximum number of generations :100, size of each chromosome :16.

III. PROBLEM FORMULATION

The problem methodology used is described in this section and is used to bring out significances of scheduled energy consumption. Single objective optimization with objective of cost minimization is done. Multi-objective optimization done for cost minimization and Peak-to-average minimization.

A. Unscheduled Energy Consumption

When smart meter scheduling is not used all the devices which can be shifted (i.e. shift able devices) to off peak hours will normally be used during morning or evening peak hours This results in lower load factor of single consumer as well as of distribution networks as whole.

B. Scheduled Consumption

When smart meter scheduling is not used all the devices which can be shifted (i.e. shift able devices) to off-peak hours will normally be used during morning or evening peak hours This results in lower load factor of single consumer as well as of distribution networks as whole.

1) Single-objective optimization for cost minimization: The total energy consumption in time interval th given by Eq. (4).Using the above values the total consumption cost will be:

$$Consumption\ \cos t = \left[\sum_{i=1}^{i=N} \sum_{h=1}^{h=T} (w_i^h) \times \mathrm{t}_h \times c_h \right] \tag{4}$$

Where,
C_h = cost per unit power in h^{th} hour

Penalty or rebate in a particular hour is awarded according to position of load in normal distribution curve. Rebate is given for loads lying in region I, with variable value depending on its closeness to mean value.

$$Total\ rebate = \left[\sum_{h=1}^{h=T} \left| avg - \sum_{i=1}^{i=N} w_i^h \right| \times k_0 \right] \tag{5}$$

where
k_0 = rebate factor
T = number of hours with load in Region I
N = number of devices operating in h^{th} hour
avg = average load over the day

Penalty is given loads in Region II and III with variable value depending on its deviation from average load.

$$\text{Penalty} = \left[\sum_{h=1}^{h=T_1} \left| avg - \sum_{i=1}^{i=N} w_i^h \right| \times k_1 \right] + \left[\sum_{h=1}^{h=T_2} \left| avg - \sum_{i=1}^{i=N} w_i^h \right| \times k_2 \right] \tag{6}$$

Fig. 2. Flowchart of GA

<u>Genetic Algorithm</u>
Objective function f(x), x = $\{x_1, ..., x_n)^T$
Encode the solution into chromosomes (binary strings)
Define fitness F (e.g., F $\propto$ f(x) for minimization)
Generate the initial population
Initial probabilities of crossover (p_c) and mutation (p_m)
while (t <Max number of generations)
Generate new solution by crossover and mutation
if p_c>rand, Crossover; **end if**
if p_m>rand, Mutate; **end if**
Accept the new solutions if their fitness decrease
Select the current best for new generation (elitism)
end while
Decode the results and visualization

$k_1$and k_2 = penalty factors for Region II and III
T_1andT_2 = number of hours with loads in Region I and II
Adding rebate and penalty in consumption

$$Total\ Cost = \left[\sum_{i=1}^{i=N} \sum_{h=1}^{h=T} (w_i^h) \times \mathrm{t}_h \times c_h \right] + \text{Penalty} - \text{Rebate} \tag{7}$$

The value of the constants k_0, k_1 and k_2 is being decided by the utility provider. The rebate will be decided by the provider for the region 2 and region 3 such that the factors doesn't offend the consumers but also drives them to schedule their load requirements accordingly. The effects of penalty and rebate factors are clearly evident in *Fig. 3* and *Fig. 4*, provided for comparative analysis. Cost minimization is beneficial from point of view of consumer while load factor improvement is beneficial for utility.

Load Factor maximization:
Load factor maximization objective can be written as in Eq. (8) from Eq. (1) and Eq. (2).

$$\max imize \left(\frac{\sum_{i=1}^{i=N} \sum_{h=1}^{h=T} (w_i^h) \times \mathrm{t}_h}{\left(\max\ (\mathrm{w}_i^h \times \mathrm{t}_h) \right) \left(\sum_{j=1}^{j=T} t_h \right)} \right) \tag{8}$$

So the multi-objective function for optimized distribution network can be defined from Eq.(9) and Eq.(10) as

$$\min f_1 = \left[\sum_{i=1}^{i=N}\sum_{h=1}^{h=T}(w_i^h)\times t_h \times c_h\right] + \text{Penalty} - \text{Rebate} \tag{9}$$

$$\max f_2 = \left(\frac{\sum_{i=1}^{i=N}\sum_{h=1}^{h=T}(w_i^h)\times t_h}{\left(\max\,(w_i^h\times t_h)\right)\left(\sum_{j=1}^{j=T} t_h\right)}\right) \tag{10}$$

IV. SIMULATION RESULTS

In this section, we present the simulation results evaluated using the proposed algorithm, thereby assessing the performance at the same time. In our model, we have considered single consumer for the purpose of scheduling their energy consumption. For study purpose, the consumer household is considered to have 25 electric appliances with almost equal number of devices with shift able and non-shift able operation. Multi objective GA approach ascertains to provide better load scheduling by consolidating the hourly loads close to mean value, consequently reducing the standard deviation. This leads to improved load factor of consumer appliance enhancing device efficiency.

A. Unscheduled Energy Consumption

This type of scenario involves working of household electrical appliances at predetermined time intervals. The functional hours of each appliance is determined as per the consumer interest and feasibility and is in dependent of the daily load change of the area. Load profile for unscheduled consumption is shown in *Fig .3*.

B. Scheduled Energy Consumtion

Energy Consumption profile obtained for two-step cost function is shown in *Fig. 4*. Five-step energy consumption profile is similarly shown in *Fig.5*.Energy cost pattern obtained for two-step and five-step cost function using single-objective and multiobjectiveapproach for each hour of the day is demonstrated in *Fig.6* and *Fig. 7* respectively.

Fig. 3. Load profile for unscheduled consumption

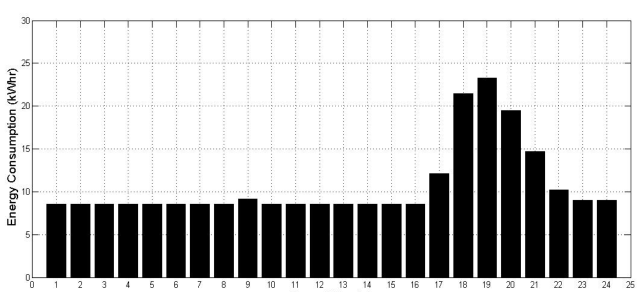


Fig. 4.Comparison of single-objective & multi-objective two-step pricing with unscheduled consumption

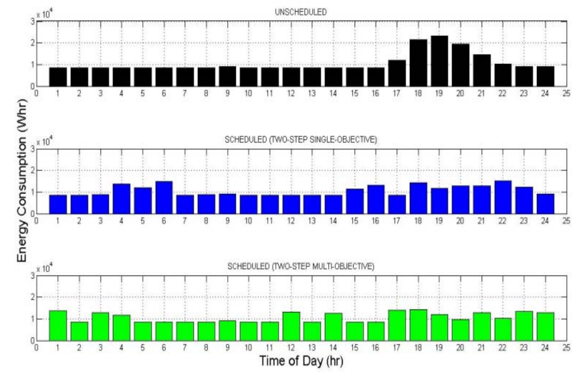


Fig . 5. Comparison of single-objective & multi-objective five-step pricing with unscheduled consumption

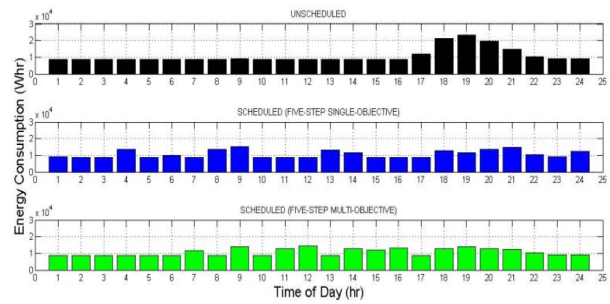


Fig. 6. Energy cost curve for two-step cost function

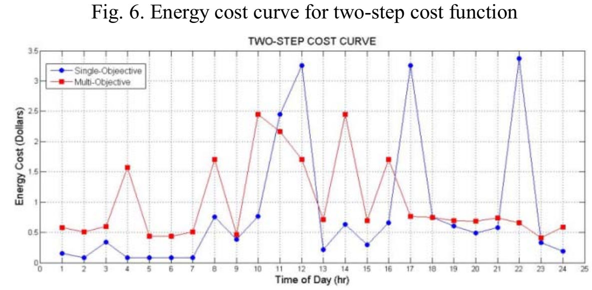
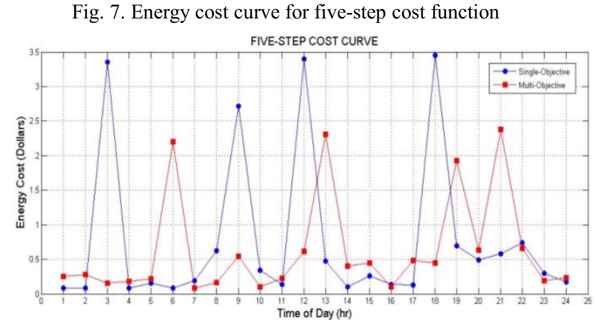


Fig. 7. Energy cost curve for five-step cost function



Convergence graph for two-step and five-step cost function shown in *Fig. 8* & *Fig. 9* respectively, shows thebest value of fitness function for each iteration run for single-objective cost function.

Fig. 8. Fitness curve for two-step cost function

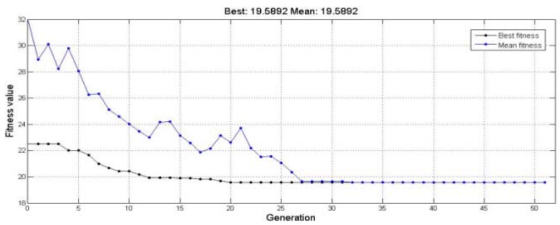
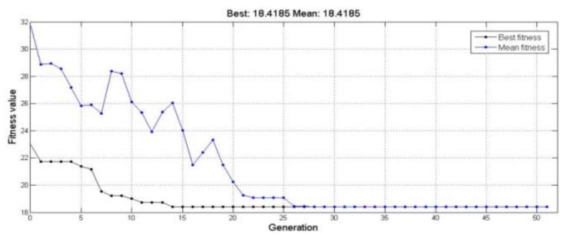


Fig. 9.Fitness curve for five-step cost function



Similarly, Pareto Front obtained for multi-objective optimization of two-step and five-step cost function is shown in *Fig. 10* and *Fig. 11*.They demonstrate the dependencies and variation of energy cost with the peak-to-average ratio, for different combinations.

Fig. 10.Pareto front for two-step cost function

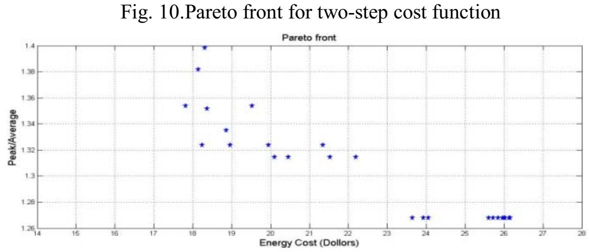


Fig. 11.Pareto front for five-step cost function

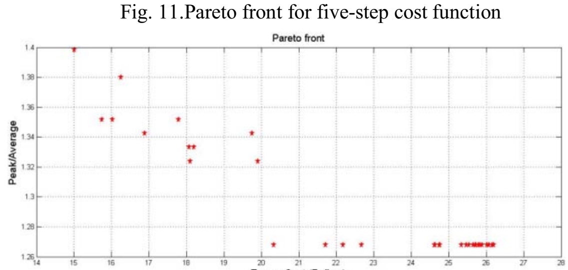


TABLE III (a).TWO-STEP PRICING COST FUNCTION SINGLE-OBJECTIVE GA APPROACH

Feature	Unscheduled	scheduled	Percent Change
Cost	32.09	19.59	38.95
PAR	2.174	1.417	34.82
Std Dev	4.306e+3	2.342e+3	45.61

TABLE III(b).MULTI-OBJECTIVE GA APPROACH

Feature	Unscheduled	scheduled	Percent Change
Cost	32.09	18.14	43.47
PAR	2.174	1.357	37.58
Std Dev	4.306e+3	2.1416e+3	50.24

TABLE III(c). FIVE-STEP COST FUNCTION PRICINGSINGLE OBJECTIVE GA APPROACH

Feature	Unscheduled	scheduled	Percent Change
Cost	32.09	18.42	42.59
PAR	2.174	1.408	35.23
Std Dev	4.306e+3	2.269e+3	47.31

TABLE III(d).MULTI-OBJECTIVE GA APPROACH

Feature	Unscheduled	scheduled	Percent Change
Cost	32.09	16.89	47.37
PAR	2.174	1.342	38.27
Std Dev	4.306e+3	2.135e+3	50.41

The percentage saving achieved for various scenarios have been demonstrated in the table. As a purpose ofconcern, the percentage saving in the energy cost using single-objective and multi-objective two-step costfunction, as shown in *Fig. 6* is 38.95% and 43.47% respectively. *Fig. 4*shows the effectiveness ofscheduling electric appliances by reduction in PAR, which renders 34.82% and 37.58% saving onimplementation of both the approaches respectively. [Table III(a) & (b)].

Similarly reduction in PAR and energy cost is achieved using five-step cost function by fattening of energyload profile using optimization based on multi-objective approach, as shown in *Fig. 6&7* respectively.The percentage saving in energy cost is 42.59% and 47.37% and the reduction in peak obtained is 35.23%and 38.27% using single-objective and multi-objective approach, respectively,[TableIII (c) & (d)] from the unscheduled load profile.

Simulation results confirm that the increase in number of steps in cost function (from two-step to five step) improves the plant load factor as well as the energy cost consumption significantly and simultaneously, thus verifying the effectiveness of application of multi-objective approach on the system. Thus the time based pricing model along with the multi-objective approach, being monitored by the normal distribution curve method, renders better results than the conventional method of considering from the consumer's end and only concentrating on a single objective of reducing the electrical cost of the energy for the consumer. The scheduling of electrical load thus prevents the imposition of cost penalty by retaining them in non-penalty zone i.e. Region I.

V. Conclusion

In this paper, we present an optimal and incentive based energy consumption scheduling technique to reduce energy (consumption and generation) cost and improve the overall load factor at the consumer as well the utility end, thus promising economical operation at both the end. A multi-objective genetic algorithm optimization technique has proven to be more economically viable over single-objective technique, in generating revenue by efficient plant operation whilst benefitting consumers by providing them rebate for intelligent load scheduling. In this work, we assumed single user with single utility trying to minimize their energy expenses. To obtain a better estimate of the likely behaviour of the users considering various users with different objectives and different levels of price-responsiveness is an interesting topic for future work.

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