Load Shifting Technique on 24Hour Basis for a Smart-Grid to Reduce Cost and Peak Demand Using Particle Swarm Optimization

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Abstract - *In present days, Load shifting is one of the techniques used in Demand Side Management(DSM). The increase in energy consumption in present scenario of power distribution system introduces many demand side management strategies to achieve desired changes in utility's load shape. This paper presents a demand side management strategy based on day-ahead load shifting technique, by Shifting the loads from peak hours to off peak hours. Particle swarm optimization (PSO) algorithm has been modified for the DSM problem and implemented in three area loads of smart grid i.e. residential, commercial and industrial. The Objective load curve is chosen inversely proportional to the wholesale electricity price. The performance of PSO algorithm is compared to the GA.*

The simulation results show that the proposed load shifting technique reduces overall operational cost and the peak load demand of the smart grid.

***Key Words*: Demand side management, PSO algorithm, Controllable loads, Load scheduling, Peak to average value.**

1.INTRODUCTION

For a variety of reasons, Electricity consumption is in rapid growth around the world. Large markets such as China, India and Brazil are gaining in global importance. And the more their economies grow, the greater their hunger for electricity. More people means a higher demand for electricity. Every sector is expanding and more and more electrically-powered devices are being used. To reduce carbon emissions, fossil fuels are being replaced by new technologies which also increases higher electricity consumption.

To meet this demand for electricity, more and more emphasis has been placed on improving energy efficiency for both economic and environmental reasons. However, this improvement is limited due to the existing infrastructure. Hence much attention has been shifted to the consumer side instead of altering the generation side of the power systems. Generally, the wholesale electricity system adjusts to changing demand by dispatching additional or less generation. However, during peak periods, the additional generation is usually supplied by less efficient ("peaking") sources. New technologies are introduced to handle these higher electricity demands in order to make the system sustainable, efficient and reliable. Demand side management [1]-[3] strategies generally focus on the peak load demand, increasing the efficiency and reducing cost in load scheduling. These strategies are not new – the idea has been explored since the 1970s. More recently, there are different approaches and algorithms being studied for demand side management. Energy demand management activities attempt to bring the electricity demand and supply closer to a perceived optimum, and help give electricity end users benefits for reducing their demand. With the help of recent innovations, the integrated approach to DSM is becoming increasingly common. Some focuses on reducing the generation capacity by reducing the peak load demand, some on smoothening the load profile and bringing it close to the desired load curve, and some on scheduling of the loads according to the time intervals where the power is most available and preferably the cheapest as well.

IDSM automatically sends signals to end-use systems to shed load depending on system conditions. This allows for precise tuning of demand to ensure that it match with the supply at all times, reduces capital expenditures for the utility.

In general, adjustments to demand can occur in different ways: through consumer responses to attractive price signals, such as permanent differential rates for evening and day times.

1.1 Particle Swarm Optimization

Particle swarm optimization (PSO) is a population based optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995 [4], inspired by social behavior of bird flocking or fish schooling.

In PSO algorithm, the system to be optimized is initialized with some random solutions and searches for optima by updating generations. However, unlike Genetic Algorithms (GA), PSO has no evolution operators such as crossover and mutation [5]. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching for the food in an area. If there is only one piece of food in the area being searched, all the birds do not know where the food is. But they will know how far the food is in each iteration. So the best strategy to find the food is to follow the bird which is nearest to the food.

PSO learned from above scenario and used it to solve the optimization problems. Here each single solution is a "bird" as in bird flock and call it as "particle". All of these particles have fitness values which are calculated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles as bird's scenario.

In every iteration, each particle is updated by two "best" values, the first one is the best solution (fitness) it has achieved so far and this value is called pbest. Another "best" value that is tracked by the PSO is the best value, obtained so far by any particle in the population. This best value is called gbest (global best). When a particle takes part of the population as its topological neighbors, the best value is a local best.

After finding these pbest and gbest, the particle updates its velocity and positions with following equations

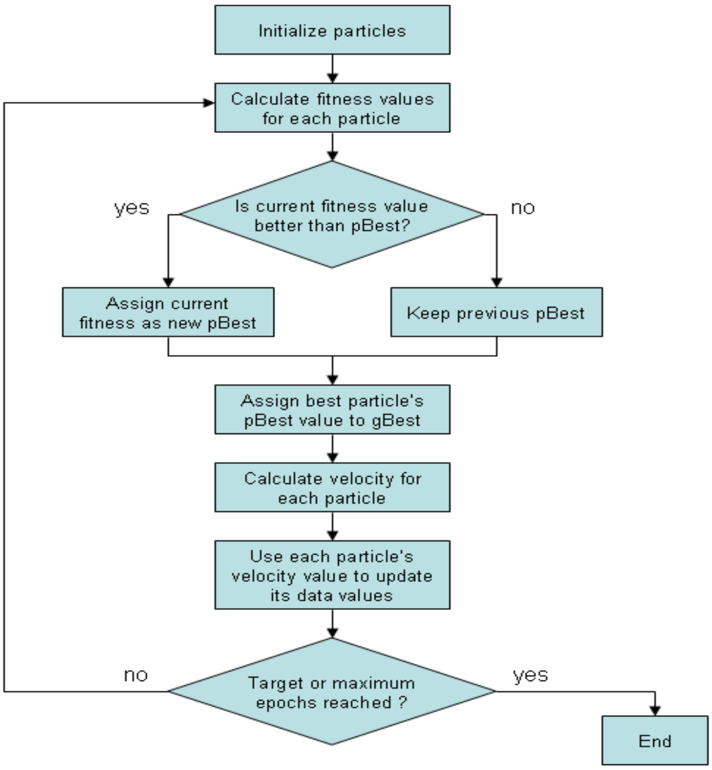
(1) v = v + c1 * rand * (pbest - prsnt) + c2 * rand * (gbest - prsnt)

(2) prsnt = prsnt + v

where prsnt represents the current particle (solution), v is the particle velocity, rand represents random number between (0,1); c1, c2 are learning factors. usually

c1 = c2 = 2.

If the sum of accelerations would cause the velocity to exceed Vmax, which is a parameter specified by the user. Then the velocity is limited to Vmax.



Flow chart of PSO algorithm

1.2 Load Shifting Technique

Load shifting is one of the techniques used in DSM. It involves moving the consumption of shift-able loads during peak hours to off-peak hours of that days [6]. It doesn't reduce net quantity of energy consumed in an electricity.

To understand the reason behind load shifting, one needs to realize that efficiency of electricity generation varies with the load demand. During peak hours, additional generation is to be supplied by less efficient generation stations available (peak load plants). This involves in increasing the operational cost, and the system may not be sustain these peak loads. As the demand in now days is in rapid growth we cannot simply alter the infrastructure of the system. To make the system reliable, efficient and sustainable, load side management attracts the researchers. Because of different load generations at any given times there are different costs associated with electricity generated. This means there exists substantial savings in generation costs if some part of load during peak hours could be moved around in time. This is where load shifting comes into play.

This shifting can happen in different ways. For example, having variable electricity price and thus encourage consumption in specific hours, remote controlling specific appliances etc.

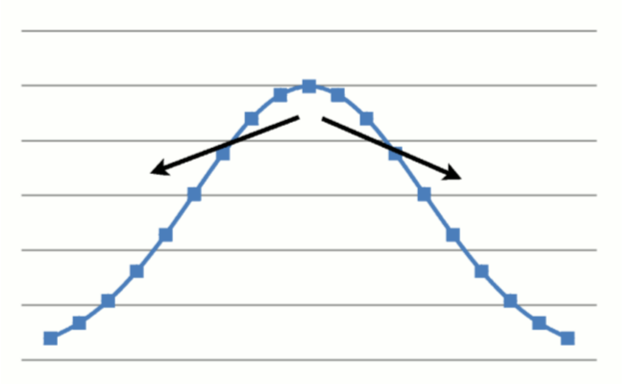


Fig 1: Load shifting

2. PROPOSED STRATEGY

a) Problem formulation

The proposed demand side management strategy schedules the connection moments of each shift-able device in the system in a way that brings the load consumption curve as close as to the objective load consumption curve. Proposed load shifting technique is mathematically formulated as follows.

Minimize: f1 $\max(load_f)$
Minimize: f2 $\sum_{h=1}^{H}(\text{load}(h) * \text{Ch})$

Where Load(h) is hourly load, Ch is the cost of electricity at hour h in ct/Kwh, H no. of hours a day. i.e. we are minimizing both peak load demand and overall cost. This can be formulated by choosing an objective load curve, and then optimizing the forecasted load curve to the objective load curve subjected to the constraints.

Minimize: f_h $[|RLM_h|-|\Delta Load_h|]$

Where RLM is the reduced load margin, $\Delta Load_h$ is calculated load that is to be1 either connected or disconnected at each hour h.

RLM_h= Forecast(h)-Objective(h)

If RLM is >0 , load is to be disconnected. i.e.

$\Delta Load_h$ =Disconnect(h)

If RLM is <0 , load is to be connected. i.e. $\Delta Load_h$ =Connect(h) In this paper, our main objective is reducing the cost, this can be achieved by choosing the load curve inversely proportional to wholesale cost of electricity at each time step.

Objective(h)=(Pavg/Pmax) *($\sum_{h=1}^{H} \text{forecast}(h)$)/Ph

Mathematical expressions:

$$\text{Disconnect}(h) = \left(\sum_{k=1}^{D} \text{Xkh} * \text{P1k}\right) + \left(\sum_{j=1}^{l-1} \sum_{k=1}^{D} Xk(h+j) * P(1+j)k\right)$$

The above equation calculates the total power consumption by the X number of devices at hth hour in the first part. If the device is having more than one operating hours then with the same quantity of devices, power consumption is calculated at successive hours, i.e. h+1, h+2… (h+l-1) in the second part of the equation. Here Xkh and Xk(h+l) is the quantity of devices of type k assumed to be operating at hour h and h+l, P1k is the power consumption of device k in the first hour of operation and Pk(1+j) is the power consumption of the same device at subsequent hours.

$$\text{Connect}(h) = \left(\sum_{k=1}^{D} \text{Xkh} * \text{P1k}\right) + \left(\sum_{j=1}^{l-1} \sum_{k=1}^{D} Xk(h+j) * P(1+j)k\right)$$

Connect(h) is similar to the expression of disconnect(h). This minimization problem is subjected to following constraints

1) The number of devices shifted away from a time step cannot be more than the number of devices available for control at the time step.
2) The no of devices that are to be shifted is always positive at any time instant.

$$Xkh>0 \quad \text{for all } k,h$$

b) Controllable Loads:

Firstly, DSM controller fetches the user inputs for the pre-scheduled loads. For each load, the user will input the starting time (i.e. the earliest time the load can run), the deadline (i.e. the latest time by when the load must finish running), the load duration and the ideal time for the load to run. Furthermore, the loads are classified into following three classes.

Class 1 – Uncontrollable Loads: These are fixed loads, those have highest priority and must be run at ideal times specified by the users No load shifting will be performed for class 1 loads. ex: Tv, Fan etc.

Class 2 – Controllable but Uninterruptable Loads: These are the loads which can perform their work at any instant of time but operation should not interrupted after starting. By considering starting time (Ti), max time (Fi), working duration (Li) , min time (Si) and power demand (Pi), the proposed algorithm will find the optimal slot within minimum and maximum time which incurs the lowest cost. Example for class 2: Washing machine, Dryer etc.

Class 3 – Controllable and Interruptible Loads:
In this case, the schedule of the loads will still in between the starting time (Ti) and the Maxtime (Fi). However, the user can interrupt the operation of load to work in 2 or more different slots, results in giving a large number of possible solutions.

To solve this nature of problem, binary particle swarm optimization(BPSO) algorithm is introduced here. In BPSO proposed, a particle or a solution is represented by a row of vector with n variables, which in this case will be the number of hours in a day. Thus, for each load, as solution is represented by the equation S= [s_1, s_2 ,s_3 .....,s_{23} ,s_{24}]
Where, each variable s_i can be either '0', if the load is not connected or '1', if the load is connected. The fitness function in this algorithm is defined to serve the objective of the demand side management approach – to save cost. Hence for each load i with a schedule, S, the fitness function can be formulated as below.

$$\text{Cost}= \sum_{i=1}^{H} S(t)\, i * Pi * r(t))$$

Where, S(t)i is the status of load i at time slot t, Pi is the power demanded by load i, r(t) is the electricity rate at time slot h.

Here the three areas in a smart grid are considered with different types of controllable devices:

1) Residential Area: There are total 2604 controllable devices comprising 14 different devices as mentioned in[7].
2) Commercial Area: There are total 808 controllable devices of 8 different types with their consumption, starting time and operating duration as mentioned in[7].
3) Industrial Area: There are total 109 controllable devices of 6 different types available as mentioned in[7].

TABLE I: Forecasted load demands and wholesale prices

Time (hr.)	**Wholesale Price (cents/kWh)**	**Hourly Forecasted Load(kWh)**		
		Residential	*Commercial*	*Industrial*
1	12.00	540.9	661.5	1170.5
2	9.19	593.8	892.4	1560.1
3	12.27	593.6	1181.0	1274.9
4	20.69	594.1	1293.0	1372.3
5	26.82	558.8	1257.4	680.1
6	27.35	545.6	1257.4	898.6
7	13.81	535.4	1139.8	898.6
8	17.31	529.6	1318.6	842.4
9	16.42	513.8	1338.4	1145
10	9.83	866.4	1301.7	706.7
11	8.63	1085.6	1446.0	917.0
12	8.87	1196.6	1246.1	809.7
13	8.35	1228.3	1298.7	863.6
14	16.44	1117.3	1096.7	964.9
15	16.19	911.2	923.5	970.1
16	8.87	545.4	577.2	1022.7
17	8.65	395.3	404.0	974.0
18	8.11	331.9	375.2	876.6
19	8.25	364.7	375.2	827.9
20	8.10	348.8	404.0	730.5
21	8.14	269.6	432.9	730.5
22	8.13	269.6	432.9	779.2
23	8.34	412.3	432.9	1120.1
24	9.35	539.1	663.8	1509.7

3. SIMULATION STUDIES AND RESULTS

a) Residential Area

Simulation using PSO algorithm is performed on a residential area load mentioned in [7]. Both the peak load demand, Peak to average(PAR) value and cost are reduced, and results are better compared to GA[8]. Peak load, PAR are reduced by 23.25% shown in Fig2 while cost is reduced by 7.22%.

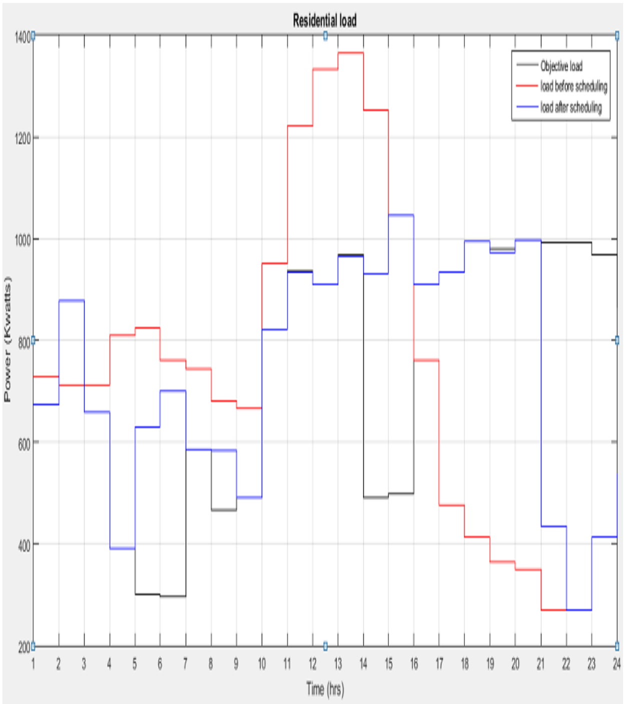


Fig 2: DSM results for Residential area load

TABLE II: CALCULATED DATA FOR RESIDENTIAL AREA LOAD

Parameters	Without DSM	With DSM		% reduction	
		GA[8]	PSO	GA[8]	PSO
Peak load(Kw)	1363.6	1114.4	1046.5	18.3	23.25
Cost	2302.90	2188.3	2136.43	4.97	7.22
PAR ratio	1.85	1.51	1.42	18.3	23.24

b) Commercial Area

Simulation using PSO algorithm is performed on a Commercial area load mentioned in [7]. Both the peak load demand, Peak to average(PAR) value and cost are reduced, and results are better compared to GA[8]. Peak load, PAR are reduced by 17.61% shown in Fig3 while cost is reduced by 8.71%.

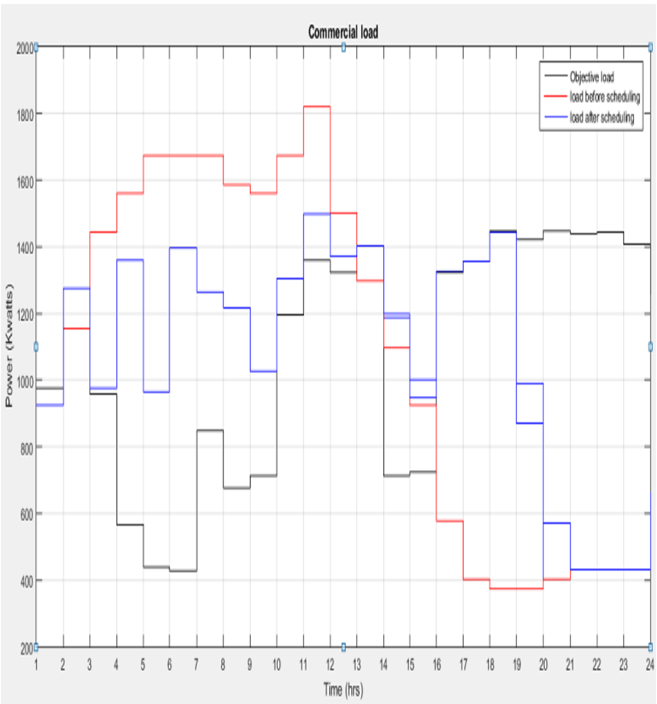


Fig 3: DSM results for Commercial area load

TABLE III: CALCULATED DATA FOR COMMERCIAL AREA LOAD

Parameter	Without DSM	With DSM		% reduction	
		GA[8]	PSO	GA[8]	PSO
Peak load(Kw)	1818.2	1485.2	1497.9	18.3	17.61
Cost	3626.66	3424.3	3310.7	5.8	8.71
PAR ratio	1.7	1.39	1.4	18.23	17.61

c) Industrial Area

Simulation using PSO algorithm is performed on a Industrial area load mentioned in [7]. Both the peak load demand, Peak to average(PAR) value and cost are reduced, and results are better compared to GA[8]. Peak load, PAR are reduced by 8.24% shown in Fig4 while cost is reduced by 18.13%.

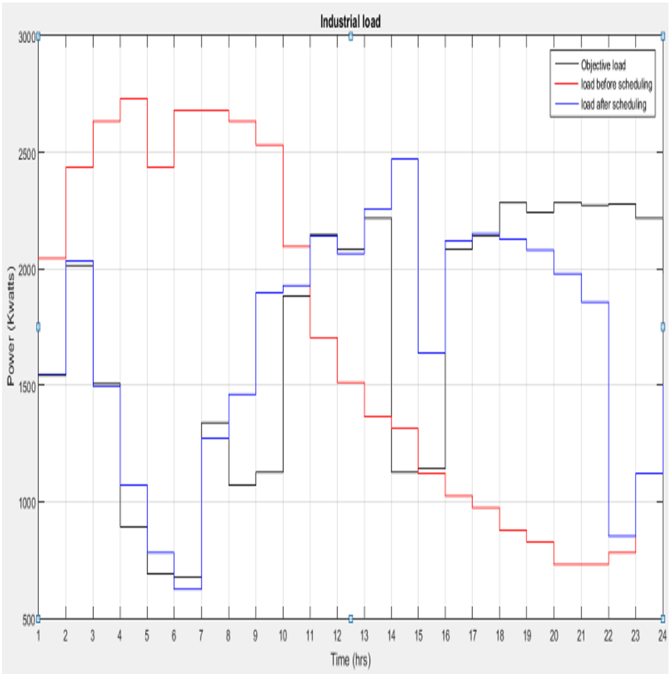


Fig 4: DSM results for Industrial area load

TABLE IV: CALCULATED DATA FOR INDUSTRIAL AREA LOAD

Parameter	Without DSM	With DSM		% reduction	
		GA[8]	PSO	GA[8]	PSO
Peak load(Kw)	2727.3	2343.6	2502.4	14.2	8.24
Cost	5712.1	5141.6	4675.9	10.0	18.13
PAR ratio	1.617	1.38	1.483	14.65	8.28

4. CONCLUSION

Load shifting technique proposed in this paper reduces the peak load demand , so that the entire power system is sustainable. It also reduces the overall operational cost by improving the load factor. PSO gives better results compared to GA and simulation has been carried out on a smart grid consists of residential, commercial and industrial loads.

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