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Home Energy Management System for the Residential Load Models under Dynamic Pricing Mechanism

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ABSTRACT
In this paper the scheduling of the residential load models like AC, Electric Water Heater (EWH), Cloth Dryer (CD) and Electric Vehicle (EV) considering the consumer comfort level and the preference setting. The real time pricing is considered so that peak demand shifts to the low pricing hours and saving in the electricity bill. In the electricity bill there is additional charges applied on the customer for drawing highest amount of power if it violates the demand limit level which is specified by the utility during any interval in the billing period. The comparative study of the three methods used for scheduling has been analyzed. The scheduling of home has been developed using home energy management algorithm without optimization and with consideration of load priorities. The energy management by Binary Particle Swarm Optimization (BPSO) and managing the appliances by proposed Binary Salp Swarm Algorithm (BSSA). The inference is drawn that the proposed BSSA gives the better results than the other two. The saving in the electricity bill and reduction of load factor which can be gained by the BSSA is in a noticeable range and convergence is fast as compare to BPSO.

Keywords: Home Energy Management System: Residential Load Models; Dynamic Pricing Mechanism

1. INTRODUCTION
Demand side management (DSM) program is to regulate the load demand in peak hours which is due to consumer use of electricity. There are various components involved in DSM like energy efficient end use smart devices, integration of renewable energy sources enabling load shaping and demand response (DR). To meet the peak power demand utility cuts the power or it results in blackout so reducing the peak power demand reduce the risk of power failures. Demand Response (DR) helps to handle the peak demand occurrence and avoid network congestion, as it supports the adaptability needed to change the timing of loads [1]. DSM is one of the important function in a smart grid that helps energy providers to reduce the peak load demand and reshape the load profile. The day ahead load shifting technique proposed is mathematically formulated as a minimization problem. An evolutionary

algorithm with a heuristic base that is easy to adapt to the set of rules that intended to increase the probability of solving the mentioned problem [2]. Dynamic pricing for DSM within smart grid environment. It divides the paper into two stages, in which the first stage is a composite technique developed with the aim of minimizing the operating cost of optimal power flow (OPF) within defined constraints by the use of particle swarm optimization (PSO) with heuristic algorithm. In the second stage, consumer will penalize for violating the defined limits or give incentives if they consume less than defined limits [3]. This paper shows the impact of various pricing systems such as Time of Use (ToU), Critical Peak Price (CPP), Real Time Price (RTP), and Demand Response (DR) program in the residential sector. Control Power consumption and compensate for peaks in demand, and energy cost used as a control signal. With the establishment of the smart metering framework in the future smart grid, DR will play a significant role [4]. Demand Response (DR) programmed to enhance the association among electric utility and consumer. Price significance contributed substantially. SVRGA (Support Vector Regression accompanying Genetic Algorithm) utilized to improve price prediction [5]. There are various ways of scheduling demand side resources using smart grid concept. This paper based on Mixed Integer Non Linear Programming (MINLP) for scheduling of home appliances in response to varying prices and incentives. By this proposed MINLP optimization, minimization in electricity cost is delivered without sacrificing consumer comfort[6]. Elasticity is important in the pricing method because it is a top way to exemplify a buyer's reaction towards price signal. The cluster analysis algorithm records the client's readiness to modify the load profile in accordance with the tariff forecast [7]. The Clonal Selection Algorithm (CLA) applied to the programming of the domestic DSM subject to the availability of photovoltaic production with a certain number of methodological limitations [8]. There are various components involved in DSM like energy efficient end use smart devices, integration of renewable energy sources enabling load shaping, Home Area Network to turn end use devices on/off as per requirement and a proper two way communication between utility and user all these factors reduce capital investment in power plant for meeting peak demand[9]. In this paper a binary particle swarm optimization (BPSO) is proposed. The algorithm efficiently schedule the appliances according to the users consumption pattern and the working characteristics of the appliances. The BPSO optimizes the scheduling period, which results in shifting peak period and smoothing the demand curve by the use of dynamic tariff [10]. In this paper binary particle swarm optimization (BPSO) incorporates the scheduling scheme for the interruptible loads by considering the constraints, which handles the penalty function and the different level of consumer satisfaction. It controlled by the weight factor which is introduced in the objective function [11]. Salp swarm algorithm (SSA) is a new meta-heuristic algorithms based on the behaviors of salpidae which is found in deep oceans. The paper includes a binary variant of the Salp Swarm Algorithm (SSA) called Binary Salp Swarm Algorithm (BSSA). By the use of transfer function for obtaining the global optimization the continuous SSA is converted into BSSA. The comparative study of different transfer function is done for various benchmark functions [12].

In this research paper the development of the scheduling algorithm which reduces the peak power demand according to dynamic pricing mechanism. The principle commitments of this paper are as per the following.

- The appliances are divided into four categories: Thermostatically load which works on thermostat principle like AC and electric water heater (EWH). Uninterruptible load i.e. clothes dryer (CD) once it get started it should not get interrupt until it completed its job. Shiftable load i.e. electric vehicle (EV) it can shift any specified time without violating preference setting and it gets interrupted in between the operation of the device. The critical loads like refrigerators, kitchen appliances and entertainment devices which are neither shifted nor interrupted it operated according to the consumer requirements.
- These devices play a significant role in increasing the peak demand. So as to build up an algorithm to control the household appliances first the load models must be demonstrated which determines the power consumption of the appliances and the load priorities and consumer comfort also taken into account.

In this paper the binary salp swarm algorithm (BSSA) is proposed which minimized the cost of home energy and is compared with the binary particle swarm optimization (BPSO) and without optimized home energy management algorithm. These algorithms developed in MATLAB 2015(a).

This paper is organized as: Section II focuses on appliances modeling, Section III problem formulation, Section IV objective function, constraints and Proposed BSSA, Section V Result and Discussion Section VI Conclusion and future work.

2. DEMAND RESPONSE ENABLED LOAD MODELS

2.1. Electric Water Heater (EWH)

For each time slot i the electricity demand for water heating unit is determined as [13]

$$P_{WH,i} = P_{WH} * W_{WH,i} * \eta_{WH} * D_{WH,i} \quad (1)$$

The electric power demand additionally relies upon the demand response (DR) control signal got from an outside source for e.g. an in home controller or an utility. The DR control signal of 0 will stop the unit and DR control signal of 1 will turn on the unit.

The outlet water temperature in the tank in next time slot i is determined as [13]

$$T_{outlet,i+1} = \frac{T_{outlet,i}(V_{tank} - fr_i * \Delta t)}{V_{tank}} + \frac{T_{inlet} * fr_i * \Delta t}{V_{tank}} + \frac{1gal}{8.34lb}\left[P_{WH,i} * \frac{3412Btu}{kWh} - \frac{A_{tank} * \left(T_{outlet,i} - T_a\right)}{R_{tank}}\right] * \frac{\Delta t}{60\frac{min}{h}} * \frac{1}{V_{tank}} \quad (2)$$

The EWH status is followed as : at the point when the water temperature in the high temp water tank goes over the set point, it doesn't work. At the point when the water temperature dips under a lower bound, the heating coils start working again at its rated power until the outlet heated water temperature arrives at the upper bound [13].

2.2. Air Conditioning (AC)

In an AC unit, thermostat is utilized to keep up the temperature of the room inside the predefined extend. So as to direct the temperature, first it detects the room temperature and contrasts it with the set point and afterward cooling coils are turned on or off in like manner. An indoor regulator may turn on and off at temperatures on either side of the set point .The distinction between the upper or lower breaking point of the admissible temperature and the set point is named as the dead band or temperature deviation/differential. When the status of AC unit is om it consume electric power. The electric power of AC unit is determined as [13]

$$P_{AC,i} = P_{AC} * W_{AC,i} * D_{AC,i} \quad (3)$$

For each time slot i the room temperature is calculated as[13]

$$T_{i+1} = T_i + \Delta t.\frac{G_i}{\Delta c} + \Delta t.\frac{C_{HV,AC}}{\Delta c}.W_{AC,i} \quad (4)$$

2.3. Clothes Dryer(CD)

In the clothes dryer the power consumption comprised is from the motor part (low power range) and the heating coils which can be several kilowatts [13]

For each time slot i the power consumption of clothes dryer is calculated as [13]

$$P_{CD,i} = P_{hc} * W_{CD,i} * k + P_m * W_{CD,i} \quad (5)$$

On receiving the DR control signal the heating coils will be controlled (ON/OFF) but the motor part will not be controlled [13].

2.4. Electric Vehicle (EV)

In this paper EV is used as a load. The battery state of charge (SOC) at the previous time slot, the energy used for driving and the battery rated capacity, which is calculated as

$$SOC_0 = 1 - \frac{E_{dr}}{C_{battery}} \quad (6)$$

$$SOC_i = SOC_{i-1} + P_{EV} * \frac{\Delta t}{C_{battery}} \quad (7)$$

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For the calculation of EV power consumption the plug in time, battery SOC and rated EV power is important. The power consumption of EV is calculated as

$$P_{EV,i} = P_{EV} * W_{EV,i} * D_{EV,i} \quad (8)$$

3. PROBLEM FORMULATION

3.1. Requisites of Home Energy Management (HEM) Structure

For implementing DR strategy an Advanced Metering Infrastructure (AMI) is required, which is a two way communication at both utility level and consumer home appliances level. A demand limit signal is imposed by the utility. Home domain Home domain interface unit is the main controlling center which continuously monitored the real time energy consumption of all household loads. The DR scheme embedded in home domain interface unit control center [14]. The smart appliances are IP addressable, intelligent, more energy efficient and automatic communicate based on users convenience and preference. They receive control signal and report its status to the home domain interface unit control center.

3.2. Demand Response (DR) Scheme

Demand response scheme started when the total power consumption ($P_{h,i}$) of home exceeds the demand limit (DL_i) level. In this paper, appliances are categorized into two parts: non critical power intensive loads and critical loads. Non critical power intensive loads like AC, Water Heater (WH), clothes dryer (CD), and EV are the controllable loads. The critical loads such as light, refrigerator, and other plug loads. DR enabled load models of AC, Water Heater, Cloth Dryer, EV are developed according to [13] considering load priority and convenience preferences of consumer. The assigned priority of the load decides the order of the appliance type during demand response program. Assuming the priority of the load and comfort preference for our target home is shown in Table 3.

Table 3 Preset Appliance Priorities

APPLIANCE TYPE	APPLIANCE PRIORITY
EV	4
CD	3
AC	2
WH	1

The assigned priority of the load decides the order of the appliance type during demand response program. Lower priority loads will be moved to later time spans, where as far as demand limits are high. As indicated by that the EV load is the first to be curtail then Cloth Dryer (CD), AC, and Water Heater (WH). Assuming the priority of the load for our target home are shown in Table 3.

The control function for the house is given by the Eq.9. [14]

$$P_{l,i} + Pc_{,i} \leq DL_i \quad (9)$$

Where

$P_{l,I}$ is the power consumption of all non-critical loads in time step i in KW.

$$P_{l,i} = \sum_{j=1}^{N} P_{lj,i} \, (L_j = \text{Controllable loads}) \quad (10)$$

$Pc_{,i}$ is the power consumption of all critical loads in time slot i, in KW.

$$P_{c,i} = \sum_{j=1}^{K} P_{Ck,i} \, (C_k = \text{Critical loads}) \quad (11)$$

DL_i is the demand limit imposed by the utility in time slot i in KW.

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When the demand limit is above than the total load or there is an end of demand response (DR) program all the non-critical power intensive loads will operate in normal way. This called as load scheduling and peak shifting.

4. PROPOSED OBJECTIVE FUNCTION AND ITS CONSTRAINTS

The objective function is minimizing the energy consumption cost with the considerations of the constraints and consumer's comfort. The minimization of the objective function is according to the Eq. 12.

$$\text{Objective function} = \min(f) \tag{12}$$

$$f = \text{Total cost (T)} + \text{Penalty function (P)} \tag{13}$$

$$\text{Total cost (T)} = \sum_{t=1}^{T} \Pr(t)\ [E_{AC}(t)+E_{EV}(t)+E_{WH}(t)+E_{CD}(t)+E_{Cr}(t)] \tag{14}$$

$$\text{Penalty function (P)} = \sum_{t=1}^{T} \Pr(t)\ [\text{Total cost (t)} - DL(t)] \tag{15}$$

Objective function is the total cost of 1440min (24hr) and penalty function is also added. Penalty function is defined for the total power consumption at each min. Power consumption is checked with demand limit (DL). DL vary with time and it imposed by the utility. If it exceeds the DL penalty is added in the form of cost in the objective function.

Constraints

The room temperature of the AC T_{AC} (t) and the outlet water temperature of the WH T_{WH} (t) is restricted in between minimum and maximum values. SOC of an EV battery varies from initial charge to the maximum charge. The accumulated time of the drying operation (min) is less than the required time /duration of the drying operation (min) of the CD. The different constraints for minimization of fitness function has been categories and shown in Table 4 according to the consumers comfort setting.

$$T_{AC}^{min}(t) < T_{AC}(t) < T_{AC}^{max}(t) \tag{16}$$

$$T_{WH}^{min}(t) < T_{WH}(t) < T_{WH}^{max}(t) \tag{17}$$

$$SOC_{EV}^{min}(t) < SOC_{EV}(t) < SOC_{EV}^{max}(t) \tag{18}$$

$$T_{Accumulated} < T_{required} \tag{19}$$

Table 4 Consumer Comfort Setting

Type	Residential appliances	Characteristics & requirement
1st category	Critical loads	24 hours power consumption profile
2nd category	Washing Machine(WM)	Work Time[7-10AM,7-10PM] 75min without interruption on
3rd category	Water Heater (WH)	4times on in a day Work Time[7-7:10, 8:00-8:10, 20-20:15, 21-21:15]
	Air Conditioner(AC)	Room temperature is kept between fixed interval over a duration of 24hrs
4th category	Electric vehicle(EV)	Charging in 4 hrs in anytime between 6PM- 6AM

Table 4 shows the convenience preferences of the consumer. The consumer set the comfort setting of different appliances like critical loads switch on in any time without any delay. WM turns on for 75min between 7AM to 10AM and 7PM-10PM. Once it get

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started in any mentioned time span WM completed its job without any intervention. Consumer turns on WH 4 times a day at above mentioned time in Table4. AC kept the specified room temperature over a duration of 24hrs. EV takes 4hrs to completely charge its battery and it can schedule in anytime between 6PM to 6AM.

4.1. Salp Swarm Optimization (SSA)

SSA is a recently swarm intelligence algorithm developed in 2017 by Mirjalili at. El. SSA is a population based method. SSA behaves like mimic of salp swarms in oceans. It is kind of salpidae that have a transparent barrel shaped body and similar tissues like jellyfishes structure. They are living in deep oceans and moving by water forces to find their food which organized as swarms called salp chains. It is categorized into two parts: one is leader salp and others are followers [12].

4.1.1. Main steps of Salp algorithm

The algorithmic steps are:-

Parameter initialization

The algorithm starts by initializing the parameters such as population size, no of iterations N and maximum no of iterations max_{itr}.

Initial Population

We generate the initial population x_i , i = {1,.....,n} randomly in the range [u,l] where u , l are upper and lower boundaries respectively.

Individual evaluation

Each individual (sol) in the population are evaluated by calculating its value using the objective function and the overall best solution is assigned to F.

Exploration and exploitation

c_1 plays an influential role in SSA. It maintain exploration and exploitation. The estimation of c_1 is appeared as:

$$c_1 = 2e^{-(\frac{4l}{L})^2} \quad (20)$$

Where, l is the present iteration and L is the max no of iterations.c2 and c3 are randomly generate in the interval [0,1]

Upgrade the leader and follower position of the solution

The leader position updated according to Eq. (21) and the follower are updated respectively as shown in Eq. (23)

$$x_j^1 = \begin{Bmatrix} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right)c_2 \;\geq\; 0 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right)c_2 \;<\; 0 \end{Bmatrix} \quad (21)$$

Where x_j^1 position of the 1st leader salp in the jth dim. F_j is the food source, ub and lb are upper and lower bound respectively, c_1 c_2 c_3 are the random numbers.

$$x_j^i = \frac{1}{2}at^2 + v_o t \quad (22)$$

Where i ≥2, x_j^i is the location of i^{th} follower in j^{th} dimension,, t is the time , v_o is the initial speed and a = v_{final}/ v_o. if iteration is equal to 1 and v_o=0 this can be expressed as

$$x_j^i = \frac{1}{2}(\, x_j^i + x_j^{i-1}) \quad (23)$$

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Boundaries violations and termination criteria

If any solution violates the range of search space during the update process, it returns back in the range of the problem. The no of iterations is increased gradually until is reaches to the max no of iterations. Then the algorithm terminates the search process and produce the overall best solution found so far [12].

4.1.2. Case 1: Mathematical Problem

This problem has been used as a benchmark constrained optimization problem. The problem can be stated as follows [12]:

Function	Dim	Range	Shift Position	fmin
$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	20	[-10,10]	[-3,-3,…….,-3]	0

Objective function

Minimize : $f_{obj} = @F_2$ (24)

Subject to:

lb = -10 , ub = 10 , dim= 10 (25)

x= -100:3:100, y=x

Search Agents no N = 30; % Number of search agents

Function name f_{obj} = 'F1'; % Name of the test function

Maximum iteration = 1000;

For this problem, the best score and the best_ position for N= 30 obtained by SSA are given as follows:

Best score	Best position
5.8154e-06	1.0e-05 * 0.0414 -0.0230 -0.1198 -0.0951 0.1022 -0.1025 0.0127 0.0530 0.0314 -0.0004

The mathematical problem successfully finds the global minimum.

Salp Swarm Algorithm Convergence Curve

The primary qualitative outcome in Fig.1 shows the search history of search agents in SSA through the span of iterations. Search history figure generally shows the position of all agents during optimization. It observes the sampled regions of the search space by an algorithm and the probable search patterns in the entire swarm. Examining search history it is clear that the SSA algorithm tests the utmost favorable area of search space. Examining the convergence curve in Fig.1 it is clear that the fitness of the estimation of the global optimum got in every iteration is improved by the SSA algorithm over the span of iterations. The convergence curve is very smooth and steady which shows SSA profits by high exploitation and convergence. It initially investigates the search space afterwards exploits it. The accuracy of SSA improves by legitimate equalization of exploration/ local optima avoidance and exploitation/ convergence [12].

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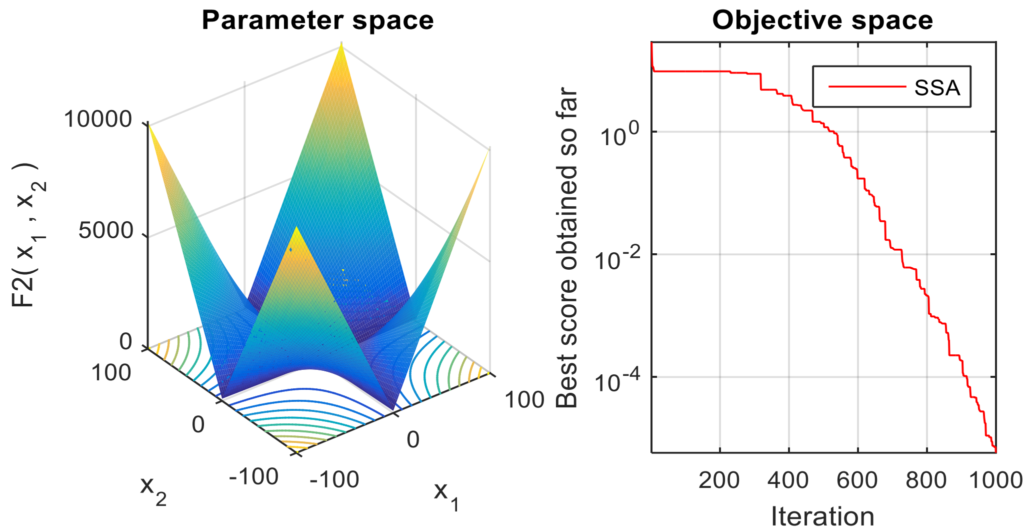

Fig.1 Simulation Result of the SSA Convergence Curve

Table 5 Results of the algorithm on the test function

F	SSA		PSO		BA	
	average	St deviation	average	St deviation	average	St deviation
F2	0.2272	1.0000	0.2858	0.0867	1.0000	0.4826

From the Table 5 it is clear that the SSA gives a comparatively better result than other algorithm in average and standard deviation [12].

5. SIMULATION RESULTS AND DISCUSSIONS

Parameters and their values used to determine the load profiles and the consumer convenience are as follows in Table 6. These are used to calculate the values of the developed load models.

Table 6 Parameters and their values

Parameters		**Parameters value**		
Electric Vehicle(EV)				
Parameter	Battery size	Energy available	All electric range	Charge power
Nissan Leaf [14]	24 KWh	19.2KWh	100mi (LA4 mode)	3.3KW
Clothes Dryer(CD)				
P_{hc}		3.7KW [15]		
P_m		0.3KW [15]		
M		5		
Electric Water Heater(EWH)				
$T_{WH,s}$		118 °F [16]		
ΔT_{WH}		10 °F		
T_{inlet}		68 °F (Assumed to be same as ground temperature)[17]		
η_{WH}		0.85		
f_{ri}		A typical hot water usage profile assumed for three people in the house.		

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A_{tank}	14ft²
V_{tank}	80 gallons[18]
R_{tank}	16 °F. ft² .h/Btu [18]
Δt	1 minute
$P_{WH,i}$	4KW
Space Cooling / Heating	
ΔT	4 °F
$T_{out,i}$	93 °F
T_s	68 °F
P_{AC}	2.352KW
$C_{HV,AC}$	According to ASHRAE handbook[19]
R_{wall}, $R_{ceiling}$, R_{window}	16 °F. ft² .h/Btu
$A_{ceiling}$	2664ft²
A_{wall}	1564ft²
A_{window}	228ft²

The start time of the charging of EV is 6pm and 1 min interval is used. While the initial state of charge of the battery is considered as 40%. The battery is fully charged in 4hrs. The operation of the CD completed in 90 minutes. Once it get started it should not interrupt in between its working. The EWH turns on 4 times in a day. The room temperature is kept between fixed interval over a duration of 24hrs for AC. The outdoor temperature T_o°C for 24 hours is used from previous study [20]. Real time prices in US [22] are selected for the case study.

A Matlab program for the proposed EMS algorithm have been developed by considering the operation of non-critical power intensive load model. In this simulation tool, 24 hour period is taken in to consideration and the reference starting time is taken as 6 a.m.

The operation of non-critical loads and the total household power demand with the control strategy of the EMS based on demand limits and priorities of the loads are observed and the obtained results are presented.

Before Demand Response

- The total household load in which the critical and non-critical loads are include without EMS the maximum power demand of the household is 14.652 kW and it occurs during 7.00 p.m. – 7.14 p.m.
- The total energy consumption of the selected day which is obtained is 87.0395 kWh.
- Typical average electricity energy consumption of the household in this case is 3.6266 kWh and the load factor is 24.75%.

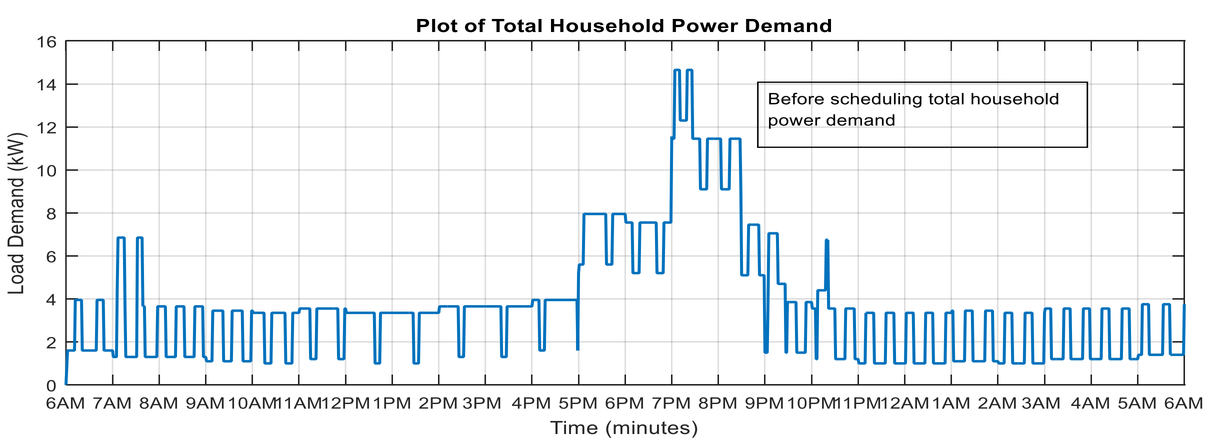

Fig.2 The Total household power demand before scheduling

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After Demand Response

The scheduling of the home appliances with and without optimization methods. The total household power demand with the home energy management algorithm considering load priorities, consumer comfort and demand limit level and without optimization is shown in Fig.2, and with optimization scheduling of the total household with HEMS algorithm in Fig.3. The peak load of the household has been reduced from 14.6520 kW to 8.6 kW. The total household power demand with BSSA is shown in Fig.4. The peak load of the household has been reduced from 14.6520 kW to 8.30 kW by BSSA which is more reduction as compare to other methods.

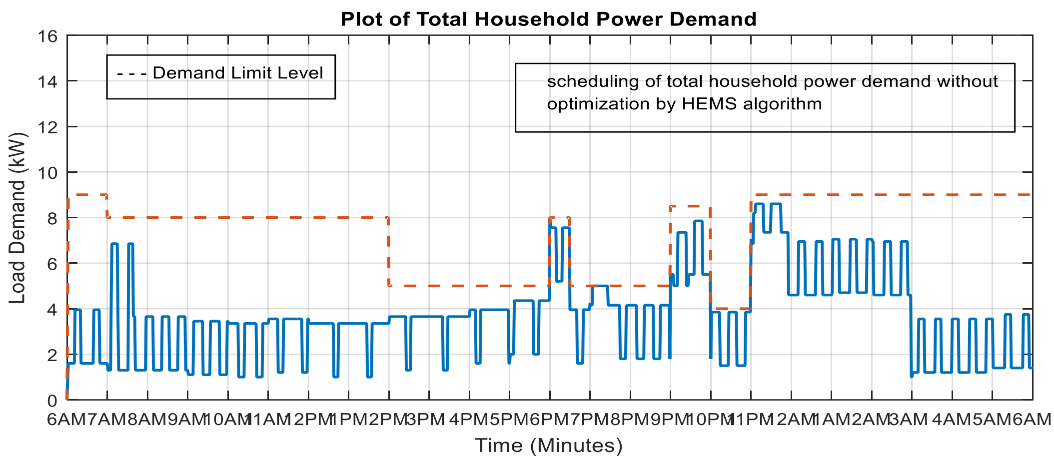

Fig.3 Total Household Power Demand after scheduling by HEMS algorithm

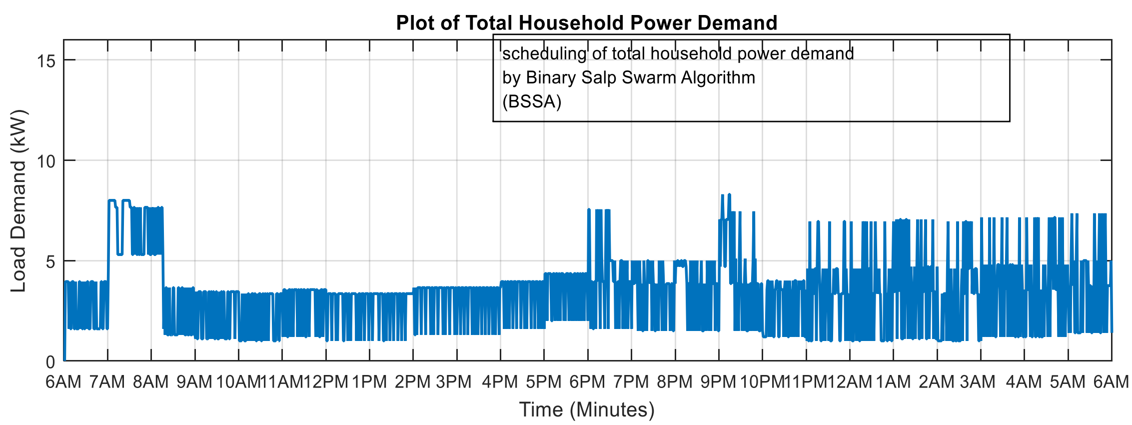

Fig.4 Scheduling of Total Household Power Demand by BSSA

Comparison of BPSO and BSSA for Scheduling of Residential Controlled Loads Electricity Cost Minimization

Binary Salp Swarm Optimization (BSSA) showed better convergence characteristics than the Binary Particle Swarm Optimization (BPSO). While the BSSA in Fig.5 starts converging at about the 20th iteration, the BPSO in Fig.5 starts to converge at about the 40th iteration. Both the optimization gives a best result of convergence but the binary salp swarm algorithm outperforms the BPSO and the scheduling algorithm without optimization due to modified sigmoidal function. The deviation due to difference of values in two optimization algorithm is 0.388%. Thus, it is clear that the daily energy cost has been reduced by 33% by use of BSSA. The proposed salp swarm algorithms outperforms in a better way as compare to the other two methods and due to that consumer saves on the electricity bill.

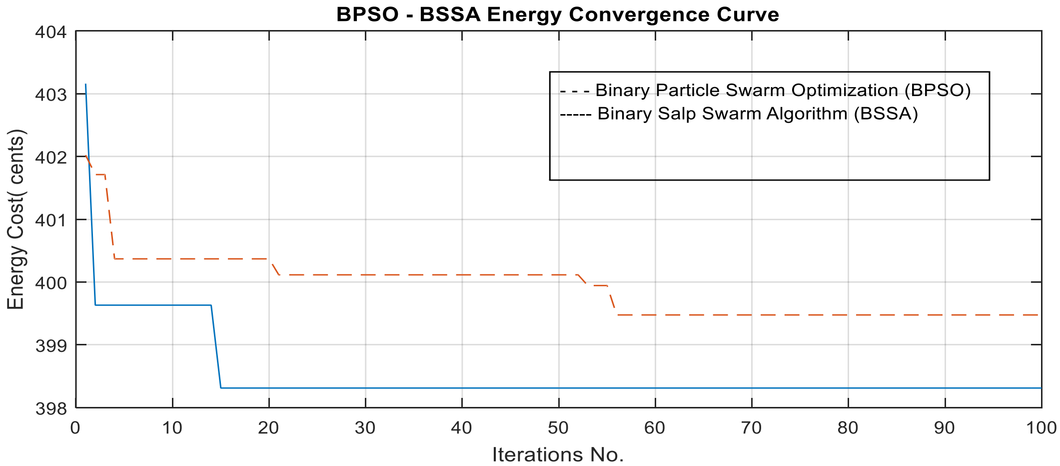

Fig.5 The Energy Cost Convergence Curve

Table 7 Comparative Results of the Scheduling Algorithms

Methods	Energy Cost(cents)	Maximum Demand(KW)	% Saving
Scheduling without EMS	451.965	14.652	
Scheduling with EMS	407.0324	8.60	34.48%
Scheduling with Optimization	398.311	8.30	33%

The home energy management (HEM) algorithms with and without optimization efficiently shift the operational time of the appliances to the off peak hours and gained saving in electricity cost. Table 7 shows that the proposed BSSA algorithm outperforms in reducing the daily energy consumption cost.

6. CONCLUSION

In the power system network DSM acts a significant part in shifting the consumption pattern to non-peak period. With the growth towards the smart grid system specially in the DISCOM there is an immediate need for load models, that can aid in the analysis of change in electrical energy consumption with respect to consumer reactions and demand limits given by several utility. The proposed algorithm for optimum home appliances scheduling can manage the non-critical loads without affecting and violating the consumers comfort preferences. EMS can switch the appliances from high demand hours to low demand hours by considering the real time pricing. The scheduling algorithm results in electricity bill savings and improve the load factor and mitigate the maximum demand from peak hours. Hence the stability of the grid can be improved and the risk of failures in the distribution network can be reduced without compromising the customer comfort.

The different abbreviations have been used in this paper which is given in Table 1 and Table 2 of nomenclature.

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Nomenclature

Table 1

T_{inlet} is inlet water temperature (°F)

T_a is the ambient temperature (°F)

fr_i hot water flow rate in time slot i (gpm)

A_{tank} surface area of the tank (ft^2)

V_{tank} volume of the tank (ft^3)

R_{tank} heat resistance of the tank (°F.ft^2.h/Btu)

Δt is the duration of the time slot i (hours)

$P_{WH,i}$ referes to power consumption of the water heater (kW) in time slot i

P_{WH} is the rated power of the water heater (kW)

$W_{WH,i}$ refers to status of the water heater in time slot i

η_{WH} is the efficiency factor

$W_{AC,i}$ is the status of AC unit in time slot,i

T_i room temperature in time slot i(°F)

$T_{AC,s}$ thermostat set point of AC unit (°F)

ΔT_{AC} refers to allowable temperature deviation / dead band of the AC unit (°F)

$P_{AC,i}$ power consumption of the AC(kW) in time slot i

P_{AC} Rated power of the AC(kW)

Δt length of the time slot i(hours)

G_i heat gain rate of the house during time slot i, positive value results in an increase in room temperature and negative value results in a decrease in room temperature(Btu/h)

$C_{HV,AC}$ cooling / heating capacity , positive for heating and negative for cooling(Btu/h)

Δc energy needed to change the temperature of the air in the room by 1°F(Btu/°F)

A_{wall} is the area of the wall (ft^2)

R_{wall} heat resistance of the wall (°F.ft^2.h/Btu)

$A_{ceiling}$ area of the ceiling (ft^2)

$R_{ceiling}$ heat resistance of the ceiling (°F.ft^2.h/Btu)

A_{window} area of the window(ft^2)

R_{window} heat resistance of the window(°F.ft^2.h/Btu)

$P_{CD,i}$ is power consumption of the clothes dryer(KW) in time slot i

P_{hc} denoted rated power of the heating coils of the clothes dryer(KW)

$W_{CD,i}$ refers to status of the clothes dryer in time slot i

k drying level with several possibilities as (k= 1/M, 2/M ,…..,M/M)

P_m power consumption of the motor part of the clothes dryer(KW)

Table 2

M total no of drying levels

$P_{EV,i}$ is power consumption of the electric vehicle(kW) in time slot i

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P_{EV} Rated power of the electric vehicle (kW)
$W_{EV,i}$ highlights the status of the electric vehicle in time slot i
SOC_0 initial charge state of the battery
SOC_i charge state of the battery in time slot i
SOC_{i-1} charge state of the battery in time slot i-1
E_{dr} energy used in driving (KWh)
$C_{battery}$ Rated capacity of the battery (KWh)
P_{EV} charge power of the electric vehicle (KW)
Δt length of the time slot i (minutes)
$D_{WH,i}$ Control signal received by the water heater from EMS in time slot i
$D_{AC,i}$ control signal received by the AC from EMS in time slot i
$D_{CD,i}$ is the control signal received by the clothes dryer from EMS in time slot i
$D_{EV,i}$ control signal received by the electric vehicle from EMS in time slot i
$E_{AC}(t)$ energy consumption of the AC in time slot t
$E_{EV}(t)$ energy consumption of the Electric Vehicle(EV) in time slot t
$E_{WH}(t)$ energy consumption of the Water Heater(WH) in time slot t
$E_{CD}(t)$ energy consumption of the Cloth Dryer(CD) in time slot t
$E_{CR}(t)$ energy consumption of the Critical Load(Cr) in time slot t
Pr(t) real time price in time slot t
DL(t) demand limit in time slot t

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Conflict of Interest
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Data and materials availability
All data associated with this study are present in the paper.

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