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Intelligent Residential Energy Management in Smart Grid

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Abstract

Objectives: Providing efficient energy management for smart home through appropriate scheduling of household appliances is addressed in this paper, with two objectives namely, electricity peak demand minimization and electricity cost minimization. **Methods/Statistical Analysis:** The residential load scheduling problem requires the prior knowledge about the residential electricity demand and electricity price information, for scheduling the appliances. Two different algorithms namely, Discrete Non-dominated Multi-objective Particle Swarm Optimization (DNMPSO) algorithm and Manhattan distance based Non-dominated Multi-objective Genetic Algorithm (MNMGA) are proposed to solve the problem in this paper. **Findings:** Both the algorithms were simulated in order to evaluate their performance. The Peak-To-Average Ratio value is used as the measure to assessing the peak load in electricity demand. Based on the results, it is observed that the DNMPSO algorithm obtains significant cost reduction with the acceptable Peak-To-Average Ratio value than the MNMGA algorithm. In addition to that, the DNMPSO algorithm provides better diversity than the MNMGA algorithm. **Application/Improvements:** The proposed algorithm can be used to enhance the energy management for residential load in smart grid. Further, the cost efficiency can be improved by incorporating renewable energy resource.

Keywords: Residential Energy Management, Scheduling, Smart Grid

1. Introduction

Electricity has become an in-built and essential component in our day-to-day life. There are many survey reports which evident the rapid growth of electricity demand for the recent years. In general, most of the people are being unaware about their electricity consumption in their daily usage. The dynamic nature of the consumers has added peaks in the aggregated electricity demand and further causes frequent fluctuations in the total electricity load submitted to the power companies. From the point of utilities, they need to spend more investment to satisfy the electricity peak demand. It can also lead to frequent cascading mechanical failures occurring in the older and centralized electricity grid system. Since, the early centralized electricity network was not able to find a successful solution for this problem, there is a need to move towards Smart grid. Smart grid utilizes electricity in bi-directional approach between the user and grid. Smart Grid[1–3] has replaced the conventional power grid using features such as sensors, smart meters, invertors, distribution box, online portal, communication techniques and other control mechanisms to manage power grid resources effectively for providing better reliability, efficiency and sustainability. Since, the smart grid incorporates a huge number of elements, it suffers from integrity and reliability issues. The reliability of the Smart grid can be enhanced by handling the energy management successfully. Attaining a perfect balance between the electricity demand and supply is one such an inevitable reliability challenge for the smart grid. The Demand Side Management (DSM) is an important concept for solving this issue. The main goal of DSM is to support users to consume power according to the power generation pattern as far as possible. Thus, the reliability of Smart grid can be enhanced through the efficient energy management at residential consumers. So far, many works are attempted to schedule appliances

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with task deadlines as soft constraints. But, this work has focused on the scheduling of shiftable appliances in smart home with the task deadlines as hard constraints and made of use of the two multi-objective evolutionary algorithms. Both of the algorithms had manipulated the solutions in the decision variable space, rather than the objective space of the problem. In this context, this paper concentrates on the residential energy management problem in smart grid.

2. Related Works

The Residential Energy Management problem concentrates on either the costumer side or the utility side. Only few works had focused on both the conflicting objectives from the consumer and utility provider point of view. The related works reviewed the residential energy management problem with various objectives under different constraints and scenario as follows.

The demand response program was implemented[4] to improve customer satisfaction and try to maintain total load under specific threshold values. Further, it uses the predefined priorities for the controllable appliances. The price-based home energy management for scheduling the operation of household appliances was focused[5]. The priority among the home appliances for scheduling was introduced through the use of value of lost load. The binary particle swarm optimization was proposed[6] for scheduling complex interruptible load with the objective for hourly load curtailment. Architecture for home energy management system and also a framework for load scheduling in smart home with the help of genetic algorithm were presented[7] for scheduling the household appliances. An appliance commitment algorithm was utilized[8] to minimize end user cost and maximize comfort based on electricity consumption forecast. The proposed algorithm schedules household loads which is thermostatically controlled. The €-approximate evolutionary algorithm was developed[9] and applied to solve the multi objective energy optimization problem with the objective to reduce the total energy generation cost and to maximizes the utility function. A multi objective genetic algorithm is proposed[10] for demand side management which had the objectives to minimize both the electricity cost and to minimize the deviation of actual demand curve from target demand curve. The particle swarm optimization algorithm was used to handle unit commitment along with uncertainties of renewable energy resources and plug-in gridable vehicles[11]. Efficient management of energy consumption within multiple smart homes in microgrid was concentrated[12]. The distributed demand response framework for scheduling appliances of multiple users is proposed[13]. The work had concentrated to reduce electricity cost for the consumers using a greedy iterative approach where each consumer was aware about the electricity price information which in turn depends upon the aggregated load of other consumers. A distributed demand-side power management system is proposed to reduce total energy demand, peak-to-average ratio and electricity cost of individual users using game theory concept in smart grid environment[14]. An adaptive scheduling approach was introduced[15] to lower the generation cost and the peak demand. The work concentrated on the energy consumption scheduling in a local area network with uncertainty in the demand neighbor microgrid. An energy management system with a fuzzy logic controller was proposed to minimize the operating cost and emission level of microgrid[16]. The hybrid method of two evolutionary algorithms combined with dynamic programming was proposed to solve the security constrained unit commitment problem[17]. A sample microgrid along with smart energy planning was designed and discussed with the objective to improve energy utilization of the microgrid[18].

The rest of the paper is organized as follows. In section 3, the problem description is given in detail. In Section 4, the Non-dominated Manhattan distance based Multi-objective Genetic algorithm and Discrete Multi-objective Particle swarm optimization algorithm are experimented for solving the problem. The numerical simulations are presented in Section 5. Finally, the paper is concluded in Section 6.With this in mind, this paper has focused on solving the residential load scheduling problem.

3. Problem Description

This section deals with the residential load scheduling problem along with the objectives and constraints in detail.

3.1 Residential Load Model

The objective of this paper is to generate a schedule which reduces both the electricity cost and Peak-To-Average ratio for a smart home. The residential appliances in a smart home can be categorized into different types. In this paper, the appliances are grouped into three types namely, base load, *shiftable load* and *non-shiftable load*. The base load refers to the appliances that to be operated continuously throughout the day. The non-shiftable loads are the appliances which must be turned ON immediately when it is needed and it cannot change its working time period. The shiftable loads are the appliances that can complete its task within the preferred time interval. Further, the shiftable load can be divided into two type's namely *interruptible* and *non-interruptible load*. The interruptible load refers the appliances which can be given discrete time intervals to complete its working cycle. The non-interruptible loads are the appliances which are turned ON exactly once to complete its job. In this paper, the shiftable load is only concentrated for the reason that they only induce the possibility of shifting the user electricity demand.

The set of shiftable appliances in the smart home considered in this paper is denoted as *A* and the number of items in *A* is *N*.The power consumption values of all appliances are stored in the matrix *P* where row stands for each appliance and each column stands for each slot. In general, an electrical appliance can be operated in different number of operating modes and the amount of its power consumption can also vary in each mode. But, in this work for ease of implementation, it is assumed that all the appliances are operated in only one mode and so that each appliance consume constant amount of power. The work can also be easily extended to situation, where various number of operating modes for each appliance is allowed.

The term 'scheduling time window' denotes the time period for which appliances are to be scheduled to work and it is denoted as *T*. While scheduling, the entire scheduling horizon is splitted into number of pieces called 'Time slots'. The total number of time slots in the entire scheduling horizon is denoted as *t*. The length of time taken as a time slot is denoted *tlen* and size of scheduling horizon is determined either by the user or utility. In this study it taken as 15 minutes.

The matrix *S* contains the schedule for the entire shiftable appliances. This matrix is a binary matrix where each column is meant for each appliance and each row represents the schedule for each time slot. Each element $s_{(ij)}$ in the matrix *S* can have values as either 0 or1 which represents the ON or OFF of the appliance *j* at time slot *i* respectively. This is enforced through the eq.1.

$$s_{ij} = \begin{cases} 0 & \text{if appliance } j \text{ is OFF in time slot } i \\ 1 & \text{if appliance } j \text{ is ON in time slot } i \end{cases} \text{ where } i = (1,2,\ldots,t), j = (1,2,\ldots n) \qquad (1)$$

The number of time slots needed by each appliance must be either equal to or greater than the required time period to finish its task. The required number of time slots for each appliance is given through the matrix *TSLOT* which enforced through the eq.2. Each element in the matrix *TSLOT* is represented by $tslot_{(j)}$.

$$tslot_j = \sum_{i=1}^{t} s_{ij} \; \forall j = (1,2,\ldots n) \qquad (2)$$

Each shiftable appliance may need different time interval to complete its task which is known as deadline. If there is no deadline for an appliance, then the entire scheduling horizon is taken as the deadline. These deadlines are usually given by the user. The matrix *DL* stores the deadline of each appliance $dl_{(ij)}$, where *j* denotes the index of the appliance. If *i=1* then, $dl_{(ij)}$ denotes the starting time of the deadline and if *i=2* then, $dl_{(ij)}$ denotes the finishing time of the deadline. The deadline is treated as a constraint which is ensured in the eq.3.

$$s_{ij} = \begin{cases} 1 & \text{if } dl_{1j} \le i \ge dl_{2j} \\ 0 & \text{otherwise} \end{cases} \text{ where} \forall j = (1,2,\ldots n) \qquad (3)$$

The matrix *SL* is a column vector that contains total load of shiftable appliances for each time slot *t* which can be computed by matrix multiplication of *S* and *P*.

3.2 Electricity Cost Model

Among the various energy cost model available, this paper makes use of the Inclining Block Rate (IBR) model. In this paper, it is assumed that the price of electricity changes over every hour which is given by the matrix *TR*. This can be expressed as follows,

$$TR = tr_i \text{ where } i = 1,2,\ldots,t \qquad (4)$$

$$\mathbf{tr_i = [(p]_h(l_h))iff\ 1 \le i \le m}$$

$tr_i=(p_h\ (l_h))$ *iff* $l \le i \le m$ *where* $l=(((h\text{-}1\ )*60/tlen)+1)$, $m=((h*60)/tlen))$, $\forall\ h=(1,2,\ldots T)$ (5)

$$p_h(l_h) = \begin{cases} a_h & \text{if } 0 < l_h \le c \\ b_h & \text{if } l_h > c \end{cases} \text{ where c is a threshold } \forall h = (1,2,\ldots T) \qquad (6)$$

The term p^h stands for price of electricity at hour *h* and tr_i stands for price of electricity at time slot *i*.

3.2 Optimization Problem

With the given electricity price and residential demand information, the objective of this paper is to generate a binary schedule matrix for scheduling the shiftable appliances. Thus, the residential load scheduling problem can be stated as follows.

$$Minimize\ Cost = SL \times TR \quad (7)$$

$$Minimize\ PAR = \frac{Max\{TR\}}{\sum_{i=1}^{t} TR_i} \quad (8)$$

subject to, Eq.1,2,3,4,5 and 6.

4. Methodology

This section describes in detail about the two different multi-objective meta heuristic algorithms for solving the residential load scheduling problem.

4.1 Constrained Multiobjective Optimization Problem

In the real world, most of the optimization problems involve multiple objectives rather than single objective. When the problem to be solved as a multi-objective one, then the solution for the problem is also a collection of solution points which shows the best trade-off among the various objectives of the problem[19,20]. This solution set is termed as 'Pareto Optimal Set'. By using the population based meta heuristic algorithms, the pareto optimal set for the problem can be easily found in a single run and hence they attracted by the research community for problem solving. Generally, there are two different strategies for solving the multi-objective optimization problem. The first method uses a weight sum approach for scalarzing multiple objectives and make it as a single objective problem before solving the problem. But, the solutions found by this method are very sensitive with respect to the weight vector. The second method did not require any prior knowledge about the problem and it tries to find all the best possible trade-off solutions. This paper handles the residential load scheduling problem as a multi-objective problem and tried to find the pareto solution set.

4.2 Working Principle of Genetic Algorithm

Genetic algorithm is a population based meta-heuristic algorithm which was developed by the inspiration of human biological evolution and natural selection. The genetic algorithm comprises mainly of three operators namely, selection, crossover and mutation. The pseudo code of the simple genetic algorithm is shown as in Figure 1.

Pseudo Code Of The Simple Genetic Algorithm

Step :1Initialize the set of chromosomes randomly in the solution space
Step :2Loop until the termination condition reached
Step :3 Evaluate the fitness function for each chromosome in the population
Step :4Apply the Selection, Crossover and mutation operators
Step :5Update the population
Step :6End Loop

Figure 1. Pseudo of simple genetic algorithm.

4.3 The MNMGA Algorithm

A simple genetic algorithm can be extended for solving the multi-objective problem with the modification in the fitness assignment step and selection operator. The idea behind the MNMGA Algorithm is to manipulate the solutions in the decision variable space, rather than on the objective vector space. In order to assign the fitness to the solutions in the same pareto front, the MNMGA algorithm uses the Manhattan Distance as a metric. The Manhattan distance between the chromosomes provide the insight about the diversity of solutions in search space and hence helps to improve the exploration process of the algorithm. Each chromosome to the residential load scheduling problem corresponds to a binary matrix which represents the ON/OFF state of each appliance in each timeslot. The MNMGA algorithm is depicted in detail in the Figure 2.

4.4 Overview of Particle Swarm Optimization

Particle Swarm Optimization (PSO) technique is one among the swarm intelligence techniques for solving the optimization problems in various fields. It is well suited for solving continuous and non-convex optimization problems. Its working procedure is based on the group behavior of birds and/or animals. As in other heuristic techniques, PSO algorithm also has to deal with premature convergence problem.

Each candidate solution for the optimization problem is treated as a particle for the algorithm. The search space

Flowchart Of MNMGA Algorithm

Step:1 Create Random Initial population with size N
Step:2 Evaluate fitness for current population of size N
Set i=1
Get the i^{th} pareto front from the current population
Assign the same rank for all solutions in the i^{th} pareto front
Remove the i^{th} pareto front
Increment i by one
If last pareto front is reached, then go to step3
Else go to step2(b)
Step:3 Apply Stochastic universal sampling solution scheme
Create Mating pool of size MP
Set P=0, L=0
(P – Size of current mating pool, L- Size of current pareto front)
If MP=L then
Output the mating pool and go to next step4
Else
Get the ithpareto front
If MP>L+P then
Calculate the Manhattan distance for each solution in the current pareto front
Put the chromosome with the highest Manhattan distance from the current pareto i
Update P=P+1
If P< MP then go to step e(i)
Else go to step 4
Else
Put the entire pareto font into mating pool and increment i
Update P=P+L and go to step 3(f)
Step:4 Apply crossover and restricted rotation based mutation operators
Step:5 Replace current population with new population
Step:6If current_iteration>Max_Iteration then
output new population and go to step 8
Else go to step2
Step:8 End

Figure 2. Flowchart of MNMGA algorithm.

can be thought of as an n-dimensional space where each dimension represents the particular objective of the problem. By traversing through the solution space, the set of particles try to reach the optimum region in the solution space. The navigation of particles is guided by the movement of other particles in the swarm and also its own history of movements. As the recombination operators in genetic algorithm, the movement of a particle is acquired by updating the velocity and position of a particle. The communication between the particles enables the information sharing among them. Each particle is assumed to have some memory to store information regarding the movement of particles in their neighborhood.

4.5 The WDNMPSO Algorithm

In the DNMPSO algorithm, each particle represents a schedule for the residential load scheduling problem. Since the scheduling problem is a discrete optimization problem, the DNMPSO algorithm is well suited for solving it. In the DNMPSO algorithm, there is a separate external local pareto set is maintained for each particle and a global pareto set is maintained for each the entire swarm. Using the DNMPSO algorithm, the velocity for a particle at the t^{th}time can be given by the following eq. 10.

$$v_i^{(t+1)} = w.v_i^t + c_1.rand().\left(xlbest_{ij}^t - x_i^t\right) + c_1.rand().\left(xpbest_{ij}^t - x_i^t\right) \quad (10)$$

Here, *wt* denotes the inertia factor which defines the amount of velocity taken from the previous velocity. The variables c_1,c_2 refers to the socio and cognitive factors which usually takes the value as 2. The velocity vector is restricted to have values between the range [V_{min}, V_{max}]. Figure 3 shows the framework of DNMPSO algorithm.

Framework of DNMPSOalgorithm

Step :1Place the initial set of particles randomly in the solution space
Step :2Loop until the no of iterations isreached
Step :3Findthe local best pareto setfor each particle i in the swarm
Step :4Find the global best pareto setfor each the entire swarm
Step :5Update the position and velocity vector for each particle i as given in eq.(10)
Step :6End Loop

Figure 3. Framework of DNMPSO algorithm.

5. Results and Discussion

In this section, the simulation results are presented and the performance of both the MNMGA algorithm and DNMPSO are evaluated and compared. A smart home with 20 appliances is taken for the experimental study. The simulations are carried with the following algorithm parameters.

- No of Appliances = 20
- Population or Swarm size = 50
- Number of Iterations =100
- Crossover Probability = 0.7
- Mutation Probability = 0.01
- C1=c2=2
- *W*=0.6

The simulation was carried out several times for each of the two algorithms. Out of the several run, the result of the best execution trial is taken in account for analyzing the algorithms' performance.

The appliance information and the electricity price information are analyzed from various related works[18, 21–23]. Figure 4 shows the sample electricity price information taken this paper for execution.

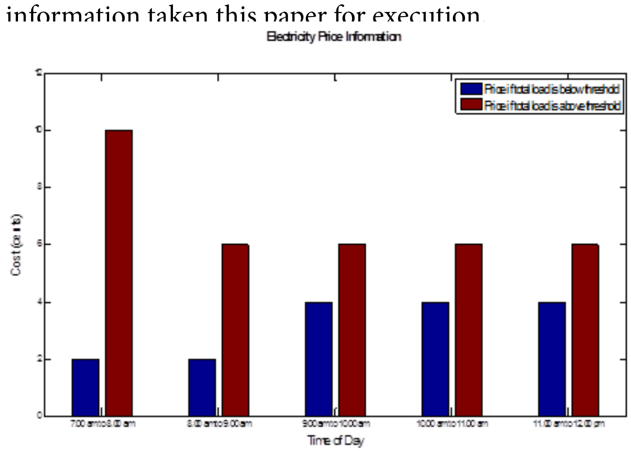

Figure 4. Electricity cost model.

Figure 5 shows the scheduled shiftable electricity load sample of a smart home.

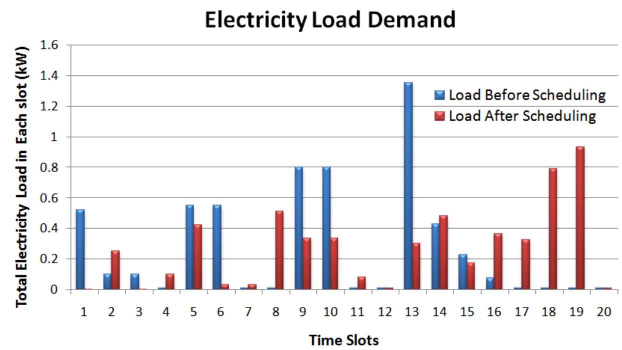

Figure 5. Electricity load scheduling.

From the figures (Figures 6 and 7), it is clear that the DNMPSO algorithm provide faster convergence for the minimization of both two objectives of the problem.

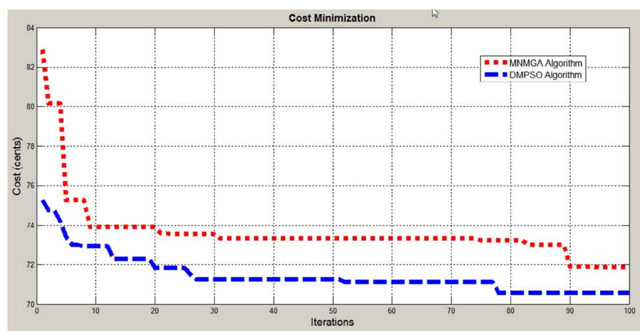

Figure 6. Fitness evaluation history for cost minimization objective.

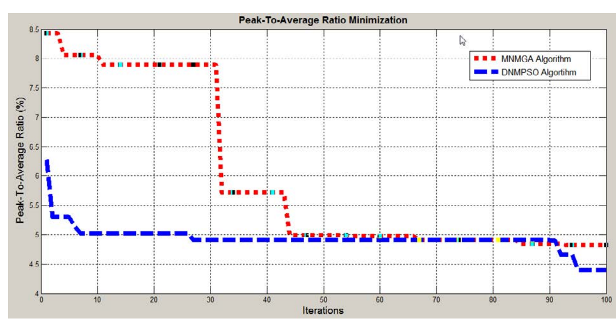

Figure 7. Fitness evaluation history for PAR minimization objective.

Figure 8 shows the final pareto front obtain by both the algorithms. It clearly shows that the MNMGA algorithm provide better exploration and diversity over DNMPSO algorithm. The exploration can be investigated in terms of the number of solutions in the pareto set. The diversity among the solutions can be measured through the distance between adjacent points in the pareto front.

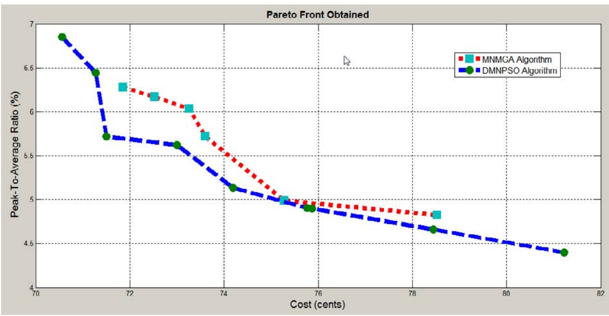

Figure 8. Framework of DNMPSO algorithm.

6. Conclusion and Future Work

In this paper, the residential load scheduling problem is formulated as a constrained multi-objective optimization problem. To solve the problem, two heuristic techniques are developed namely MNMGA algorithm and DNMPSO algorithm. Numerical simulations for both algorithms have been conducted in order to evaluate their performance. Both the algorithms produce a set of Pareto-optimal solutions. The two developed algorithms have generated solutions within the feasible region of the search space.From the results, it can be demonstrated that the DNMPSO algorithm provides better exploration than the MNMGA algorithm. However, there have been always the tradeoff between the electricity cost minimization and PAR value reduction. The work presented in this paper can be extended to schedule the residential load with the help of various renewable energy resources and storage.

7. References

1. Farhangi H. The path of the smart grid. IEEE Power and Energy Magazine. 2010; 8(1):18–28.
2. Clastres C. Smart grids: Another step towards competition. Energy Security and Climate Change Objectives. Energy Policy.2011; 39(9):5399–408.
3. Koutsopoulos I, Tassiulas L. Challenges in demand load control for the smart grid. IEEE Network. 2011; 25(5):16–21.
4. Pipattanasomporn M, Kuzlu M, Rahman S.An algorithm for intelligent home energy management and demand response analysis. IEEE Transaction Smart Grid. 2012; 3(4):2166–73.
5. Rastegar M, Fotuhi-Firuzabad M,ZareipourH. Home energy management incorporating operational priority of appliances. Electrical Power and Energy Systems. 2016; 74:286–92.
6. AngeloMA, Pedrasa P, Ted D,SpoonerS, Iain F, MacGill M. Scheduling of demand side resources using binary particle swarm optimization. IEEE Transactions on Power Systems. 2009; 24(3):1173–81.
7. Khomami HS, Javidi MH. An efficient home energy management system for automated residential demand response. 28th International Power System Conference, 2013 Nov 4–6, Tehran,Wroclaw; 2013. p. 303–12.
8. Du P, Lu N. Appliance commitment for household load scheduling. IEEE Transactions on Smart Grid. 2011; 2(2):411–19.
9. Salinas S, Li M, Li P. Multi-objective optimal energy consumption scheduling in smart grids. IEEE Transactions on Smart Grid. 2013; 4(1):341–8.
10. Hu XM,Zhan ZH,Lin Y,Gong YJ,Yu WJ,Hu YX,Zhang J. Multiobjective genetic algorithm for demand side management of smart grid. IEEE Symposium on Computational Intelligence in Scheduling (CISched),Singapore; 2013. p. 14–24.
11. Saber A, Venayagamoorthy G. Resource scheduling under uncertainty in a smart grid with renewables and plug-in vehicles. IEEE Systems Journal. 2012; 6(1):103–9.
12. Zhang D, Shah N, Lazaros G, Papageorgiou P. Efficient energy consumption and operation management in a smart building with microgrid. Energy Conversion and Management. 2013; 74:209–22.
13. Chavali P, Yang P, Nehorai A. A distributed algorithm of appliance scheduling for home energy management system. IEEE Transactions on Smart Grid. 2014; 5(1):282–90.
14. Mohsenian-Rad A,Vincent WS, Wong W,JatskevichJ,-Schober R,Leon-Garcia A. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. IEEE Transactions on Smart Grid. 2010; 1(3):320–31.
15. Fathi M, Bevrani H. Adaptive energy consumption scheduling for connected microgrids under demand uncertainty. IEEE Transactions on Power Delivery. 2013; 28(3):1576–83.
16. Ezhilarasan S,Palanivel P, Sambath S. Design and development of energy management system for DG source allocation in a micro grid with energy storage system. Indian Journal of Science and Technology. 2015 Jul; 8(13):1–9.
17. Rouhi F, Effatnejad R. Unit commitment in power system by combination of dynamic programming, genetic algorithm and particle swarm optimization. Indian Journal of Science and Technology. 2014 Jan; 7(12):2056–63.
18. Moghimi SM, Hosseinian SH, Elahimanesh A, Sarlak G. Multi-objective control, management and optimization of

micro-grid energy in the presence of DG and energy storage by a Smart Energy Management System (SEMS). Indian Journal of Science and Technology. 2015 Dec; 8(35).
19. Shangai S, Xian X, Colchester C. Multiobjective evolutionary algorithms: A survey of the state of the art, swarm and evolutionary computation. Swarm and Evolutionary Computation. 2011; 1(1):32–49.
20. ZitzlerE, Thiele L. Multiobjective evolutionary algorithms:A comparative case study andthe strength pareto approach. IEEE Transactions onEvolutionary Computation.1999; 3(4):257–71.
21. Christopher O, Adika A, Wang L. Autonomous appliance scheduling for household energy management. IEEE Transactions on Smart Grid. 2014; 5(2):673–83.
22. Chiang MK,Li KSM. Intelligent home management in the smart grids.2012 IEEE Asia Pacific Conference on Circuits and Systems (APCCAS); 2012.p. 567–70.
23. Samadi P, Mahsenian-Rad H, Vincent WS, Wong W,-Schober R. Tackling the load uncertainity challenges for energy consumption scheduling in smart grid. IEEE Transactions on Smart Grid.2013; 4(2):1–10.