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Original Article

A novel minimum cost maximum power algorithm for future smart home energy management

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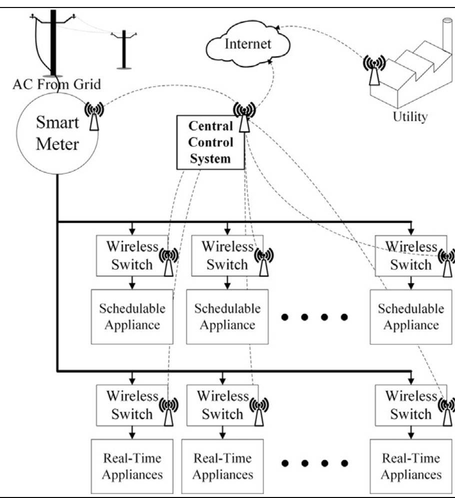
GRAPHICAL ABSTRACT



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ABSTRACT

With the latest development of smart grid technology, the energy management system can be efficiently implemented at consumer premises. In this paper, an energy management system with wireless communication and smart meter are designed for scheduling the electric home appliances efficiently with an aim of reducing the cost and peak demand. For an efficient scheduling scheme, the appliances are classified into two types: uninterruptible and interruptible appliances. The problem formulation was constructed based on the practical constraints that make the proposed algorithm cope up with the real-time situation. The formulated problem was identified as Mixed Integer Linear Programming (MILP) problem, so this problem was solved by a step-wise approach. This paper proposes a novel Minimum Cost Maximum Power (MCMP) algorithm to solve the formulated problem. The proposed algorithm was simulated with input data available in the existing method. For validating the proposed MCMP algorithm, results were compared with the existing method. The compared results prove that the proposed algorithm efficiently reduces the consumer electricity consumption cost and peak demand to optimum level with 100% task completion without sacrificing the consumer comfort.

Introduction

In this new era, the usage of electricity has increased tremendously due to the development of new modern technologies. This

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excessive use of electricity tends to increase in power demand and frequent peak demand [1,2]. As per the report of United States Energy Information Administration (USEIA), 24% of power demand will be increased in the following decades for residential consumer [3]. Recently, India and North America have confronted severe blackouts due to the inability of coping up with the required power demand [4]. The inability to cope up with the required power demand within the available generated power is due to the unavailability of proper Demand Side Management (DSM) and Demand Response (DR) programs. Implementation of proper DSM and DR program can be achieved with the help of smart grid technology. The smart grid technology modifies the traditional grid into a modern grid by providing two-way communication between the utility and the end user [1]. In addition, the smart grid technology upgrades the traditional grid by providing smart features like Advanced Metering Infrastructure (AMI), Wide-Area Monitoring, Protection and Control system (WAMPAC) [5]. The peak demand can be controlled by implementing efficient DR program with the help of smart grid [6]. With the efficient DR program, both the consumer and utility would be economically benefited. If peak demand is reduced by DR program, then the utility can avoid spending additional generation cost during peak hours. The consumer would get incentive and reduction in electricity bill from the utility by avoiding the use of appliances during peak hours [7]. The DR program can be efficiently achieved with the implementation of smart Home Energy Management (HEM) at consumer premise. The HEM system will monitor and control the home appliances with the aim of reducing the consumption cost and shifting some of the appliances from peak hours to off-peak hours. This will help both the consumer and utility. The core challenge in implementing the HEM system lies in the ability to differentiate the type of appliances, since the working process of certain appliances may get affected when it is turned off during its operation time while shifting the load with respect to time. So this type of uninterruptable appliances should not be turned off by HEM. In addition, the HEM should not affect the total work done by the interruptible appliances by turning them off with an aim of reducing the demand. In recent years, many researchers had concentrated to contribute efficient HEM algorithms to overcome the peak demand and to reduce the consumer electricity cost [2]. Mohsenian-Rad et al. [8] described an incentive-based scheduling of home appliances with an aim to reduce the cost of electricity. This scheduling scheme concentrates only on peak demand reduction and the percentage of work done by appliances with respect to the scheduling scheme is not considered and it will affect the consumer comfort levels. Demand response scheduling for multi-residence by using a distributed algorithm was introduced by Gatsis and Giannakis [9], however in this work, bulk information sharing was required between utility and end-user. With an aim of reducing the monthly electricity bill, an optimization algorithm for scheduling the home appliances was proposed [10]. In this work, the algorithm works based on the target value of monthly bill fixed by the consumer. The monthly bill is reduced by compromising the percentage of total work done by the appliances and it will affect the consumer comfort level. An Artificial Neural Network (ANN) based HEM algorithm is proposed with the aim to reduce the consumption cost and peak load [11]. This algorithm has a high computational process so it is complex for practical implementation. A new Binary Backtracking Search Algorithm was used for real-time optimal schedule control of home appliances with an aim to reduce energy consumption and peak demand [12]. The results show the reduction of peak demand but the per-day total demand of consumer is reduced to 21.07% for weekday and 26.1% for the weekend. This will affect the consumer comfort by not scheduling the appliances with their needed demand. New system architecture with battery and photovoltaic is described with an aim of reduction of electricity consumption cost [13]. This study works based on the cost of electricity with respect to time. During the low-cost time slot, the system will charge the battery and the appliances will be supplied by the grid. During high-cost time slot, the appliances will be supplied by the battery. The results show a reduction in cost, but the system is not valid if the battery is drained during the high-cost time slot. Some other HEM algorithms with an aim of reducing the peak demand and electricity consumption cost with the integration of renewable energy are presented in the literature [14–16]. The integration of renewable energy with HEM system efficiently reduces the consumption cost and peak demand, but the implementation cost is high. Basit et al. [17] used a step-wise approach to solve MILP problem for scheduling the home appliances to minimize the cost. The time slot based price model is considered in this work to enhance the user to choose their convenient time slot to operate their appliances, so as to attain economic benefits. The work was simulated with 4 different load scenarios. The results show that in some scenarios, the resultant scheduling scheme has not completed the appliance's task by 100% which causes low comfort level for the consumers. On the contrary, the appliances work more than the required task; this makes unwanted power loss and leads to consumer economic loss.

Almost no studies in the literature provide a HEM algorithm by considering about 100% of task completion of the appliances during load scheduling with an aim of reduction in peak demand and consumption cost. Most of the HEM methods in literature are based on an evolutionary algorithm, which makes the system complex and its affect the system response time.

By considering the pros and cons from the literature, a novel Minimum Cost Maximum Power (MCMP) algorithm was proposed in this paper. The main contributions of this study are;

- A novel MCMP algorithm which reduces the consumer electricity consumption cost more efficiently when compared with the existing methods.
- The proposed algorithm efficiently reduces the peak demand in comparison with existing methods.
- The proposed algorithm schedule all home appliances with 100% task completion even after reduction in cost and peak demand.
- The system response of the proposed MCMP algorithm is less when compared with the existing methods. This makes the proposed MCMP simpler and the same can implemented in real time systems as the computation process is also less.
- Most of the HEM methods presented in the literature are related to an already available algorithm or modified version of the available algorithm. But the approach of the proposed MCMP algorithm is novel to literature which is uniquely designed for the HEM system applications.

To validate the proposed MCMP algorithm, the results are compared with existing methods and the results are presented in this paper. The results prove that the proposed algorithm completes 100% task with minimum cost by comparing other existing works. The response time of proposed MCMP algorithm is less when compared to the existing methods. The peak demand is reduced efficiently when compared to the existing method available in the literature. Rest of this paper is organized as follows: Section 'System model' describes the system model considered for the study and about practical implementation of the proposed MCMP algorithm. Section 'Problem formulation' gives the details about problem formulation; constraint definition; problem statement. Section 'Problem solution' explains the problem solutions and steps involved in the proposed MCMP algorithm. Section 'Proposed schemes for stated problem' explains about set formulation for the simulation, detailed comparison results. Section 'Simulation result' gives the conclusion.

System model

A HEM system at consumer end is considered for the implementation of proposed demand-side management algorithm. The HEM system is shown in Fig. 1. This system is designed to monitor, control, and manage the electric energy of home appliances. A smart meter is connected at starting terminal of AC supply to calculate the overall home energy consumption at every time instant. The Central Control System (CCS) is the heart of the proposed system, where all the communication and decision-making is done. The CCS contains a microcontroller which is connected to a display unit, a keypad module, and communication modules include ethernet and zigbee. The microcontroller is programmed with the proposed algorithm to execute the algorithm in real time. The execution of microcontroller includes, receiving the power consumption data from smart meter through zigbee and transmitting the power consumed data to utility through internet/ethernet; Receiving day-ahead pricing information from utility by internet/ ethernet (The day-ahead electricity pricing can be fixed by utility with respect to power consumed data received from all consumers); Getting the input data from consumer through keypad module and displaying the consumer entered value through display unit. The information from consumer includes, list of home appliances connected to End Device (ED) Zigbee with its respective Personal Area Network ID (PAN ID); type of each appliance connected (explanation about zigbee network and types of appliances are given below in this section); power ratings of each appliance in kW and number of time slots required to complete the task of each appliance. After receiving the inputs from utility and consumer, the microcontroller will make the decision to turn-on or turn-off the appliances with respect to time. The appliances turn-on and turn-off is done by wireless home area network through zigbee module. The wireless home area network is built by connecting each zigbee module separately to all home appliances and it acts as ED. The zigbee module at CCS acts as Coordinator (C). The power supply to the appliances is made through a relay which is controlled by ED zigbee with reference to the signal it has received from CCS. According to consumer home size or distances between the appliances located in the home, the zigbee network can be designed by any one of cluster tree topology, mesh topology, or star topology. In the proposed work the authors categorize the home appliances into two types, schedulable appliances and real-time appliances (uninterruptable appliances). The appliances that are unaffected by turn-off during its time of operation are categorized as schedulable appliances. Schedulable appliances can be turned-off during the high-cost phase of electricity. Later the appliances are turned-on to complete its task during the low-cost phase of electricity. This is due to the schedulable appliances' flexibility of operation. The appliances which are affected by turn-off during its operation are categorized as real-time appliances. Real-time appliances cannot be turned-off due to its low degree of flexibility.

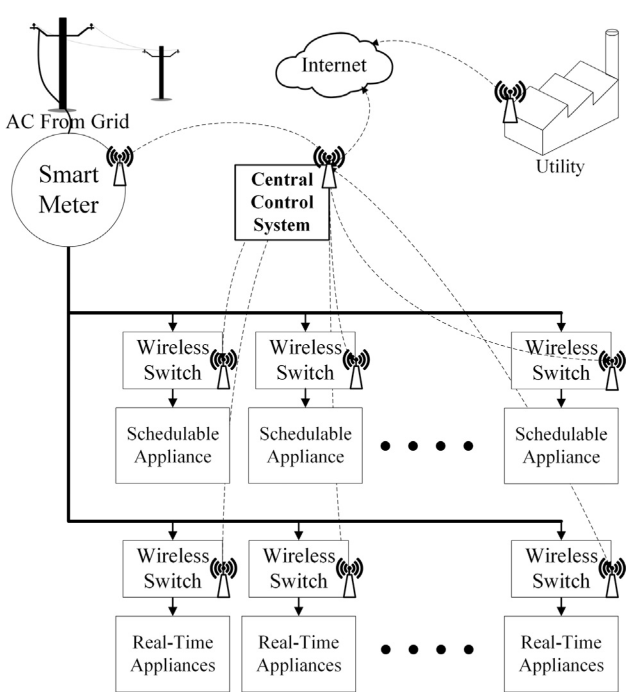

Fig. 1. Proposed Home Energy Management system.

Problem formulation

The main goal of the proposed work is to reduce the consumer's electricity consumption cost without sacrificing their comfort. This can be achieved by scheduling the schedulable appliances during the low-cost time slot. The real-time appliances should not be turned-off. In each time slot, the electricity consumption should not lead to a peak in the demand curve. Let, $T = \{t_1, t_2, t_3 \ldots t_N\}$ be the set of N time slots, where t_n denotes the nth time slot. Cost of electricity for each time slot is given by set $C = \{c_1, c_2, c_3 \ldots c_N\}$, where c_n represents the per unit cost of electricity at t_n. The total number of schedulable appliances are SA and the total number of real-time appliances is RA. The total number of all home appliances is, TA = SA + RA. Set of schedulable appliances is given by $S = \{a_1, a_2, a_3 \ldots a_{SA}\}$ and set of real-time appliances is given by $R = \{b_1, b_2, b_3 \ldots b_{RA}\}$. To simplify the mathematical formulation, two binary variables $v_{i,n}$ and $z_{j,n}$ are introduced in Eqs. (1) and (2). The '*i*' in Eq. (1) represents the *i*th appliances in S set and '*j*' in Eq. (2) represents the *j*th appliance in R set. If the *i*th appliances in S set is scheduled at t_n, then $v_{i,n} = 1$, otherwise 0. If the *j*th appliances in R set is scheduled at t_n, then $z_{j,n} = 1$, otherwise 0.

$$v_{i,n} = \begin{cases} 1, & \text{if ith device is ON in time } t_n \\ & \forall i = 1 \ldots SA, n = 1 \ldots N, \\ 0, & \text{if ith device is OFF in time } t_n \end{cases} \tag{1}$$

$$z_{j,n} = \begin{cases} 1, & \text{if jth device is ON in time } t_n \\ & \forall j = 1 \ldots RA, n = 1 \ldots N, \\ 0, & \text{if jth device is OFF in time } t_n \end{cases} \tag{2}$$

Power consumed by *i*th appliance at time t_n is $P_{i,n}$. Power consumed by *j*th appliance in time t_n is $Q_{j,n}$. P_{tn} is the power consumed by total home appliances at any time slot. Eq. (3) gives the total power consumed by all appliances in home per day.

$$P_{tn} = \sum_{i=1}^{SA} (P_{i,n})(v_{i,n}) + \sum_{j=1}^{RA} (Q_{j,n})(z_{j,n}) \ \forall n \tag{3}$$

Constraint definitions

Constraints for the proposed algorithm are given mathematically from Eqs. (4)–(8). To confirm that, during peak hours the demand is not increasing largely, the total power consumed by all home appliances at any time slot must be kept under a target value E. Because within a single time slot if large demand of appliances are scheduled or turned-on then it will affect the demand curve and leads to peak demand. This constraint is given in Eq. (4). For real-time implementation, the value of E is fixed by the electric utility. The target value, E can be fixed based on the conditions like utility generation capacity, climate condition and consumers regional festival season. The E value may vary between consumers with respect to their tariff plan. The utility may increase or decrease the E value by comparing the seasonal generation capacity and consumers demand profile. The timely update of E value is communicated to every consumer's CCS by the utility through internet. The effects of different target value E with the proposed algorithm are given in the simulation result section.

$$P_{tn} \leqslant E, \ \forall n \tag{4}$$

As mentioned early, the real-time appliances should not be turned-off. So the sum of turned-on appliances in set 'R' should be equal to a total number of real-time appliances 'RA' for all time slots or the sum of turned-on appliances in set 'R' should be equal to a total number of the time slot. This constraint is mathematically given in Eq. (5).

$$\sum_{j=1}^{b_{RA}} (z_{j,n}) = RA, \quad \forall n; \quad \sum_{n=1}^{N} (z_{j,n}) = N, \quad \forall j \tag{5}$$

Schedulable appliances have high operational flexibility. At any time slot, the devices in set S can be turned-on or turned-off according to the power demand of real-time appliance. If the power demand of real-time appliances per time slot is greater than E, then all schedulable appliances should be turned-off. If the power demand of real-time appliances is smaller than E, then some of the Schedulable appliances or all schedulable appliances can be turned-on, but the overall power demand on a home should be lesser than or equal to E. This constraint is given by mathematical form in Eqs. (6)–(8).

$$\sum_{i=1}^{a_{SA}} (v_{i,n}) = SA', \quad \forall n; \quad \sum_{n=1}^{N} (v_{i,n}) \leqslant N, \forall i \tag{6}$$

where $SA' = SA$

$$\text{If}: \sum_{i=1}^{SA} (P_{i,n})(v_{i,n}) \leqslant E - \sum_{j=1}^{RA} (Q_{j,n})(z_{j,n}) \tag{7}$$

where $SA' \subset SA$

$$\text{If}: \sum_{i=1}^{SA} (P_{i,n})(v_{i,n}) > E - \sum_{j=1}^{RA} (Q_{j,n})(z_{j,n}) \tag{8}$$

Problem statement

The proposed optimization algorithm aims to find optimum scheduling scheme to reduce the total cost of electricity consumption per day without violating the stated constraints. The problem statement is given by, "The sum of power consumed cost by schedulable appliances and real-time appliance per day should be minimized by optimum scheduling scheme". This optimization problem is defined mathematically in Eq. (9).

$$\min_{v_{i,n}, z_{j,n}} \sum_{n=1}^{N} \left(\sum_{i=1}^{SA} (P_{i,n})(v_{i,n}) c_n + \sum_{j=1}^{RA} (Q_{j,n})(z_{j,n}) c_n \right) \tag{9}$$

Problem solution

The problem statement in Eq. (9) is a mixed binary integer programming problem. This type of problem has high computational complexity in finding the optimal solution. So the stated problem in Eq. (9) is divided into two sub-problems [17]. The first sub-problem finds N sets of all possible combinations for scheduling the appliances to a single time slot without violating the stated constraints. The second sub-problem provides the optimum appliances scheduling scheme by allotting suitable combination set in the first sub-problem to its optimum time slot or the second sub-problem search the suitable combination sets in first sub-problem to schedule it to its respective time slots so that the overall cost at the end of the day is optimum without violating the stated constraints.

Sub-Problem 1

The aim of sub-problem 1 is to generate N number of sets. The generated sets contain all possible ways of scheduling the appliances per time slot. Let the generated sets be Y_1, Y_2, $Y_3 \ldots Y_N$. Each set Y_x, $x = 1, 2, 3 \ldots N$ is subset of $S \bigcup^R$. Let $y_{m,x}$ denotes the m-th device in x-th set with demand of $\hat{P}_{m,x}$. Each set is generated by satisficing the constraint stated in Eq. (10). The real time appliances must be presented in all generated Y sets; as it is given in Eq. (11). The schedulable appliance may or may not be presented in generated Y sets; as shown in Eq. (11).

$$\sum_{m=1}^{|Y_x|} \widehat{P}_{m,x} \leqslant E, \ \forall x \tag{10}$$

where $|Y_x|$ is cardinality of the set Y_x

$$0 \leqslant \sum_{x=1}^{N} \alpha_{m,x} \leqslant N, \ \forall m, and\ y_{m,x} \in S; \sum_{x=1}^{N} \alpha_{m,x} = N, \ \forall m, and\ y_{m,x} \in R \tag{11}$$

where $\alpha_{m,x}$ is binary variable, $\alpha_{m,x} = 1$ if mth device is presented in xth set.

Sub-Problem 2

The sub-problem 2 selects the generated Y_x set to schedule in any one of the time slots to minimize the total cost. A binary variable $\mu_{x,n}$ is introduced in Eq. (12). If set Y_x is scheduled to time t_n then the value of $\mu_{x,n}$ is 1, otherwise it is 0. Then the rest of the optimization problem for sub-problem 2 is given in Eq. (13). If the set Y_x is scheduled once to a time slot, then the same Y_x should not schedule again to any remaining time slot. This constrain is given in Eqs. (14).

$$\mu_{x,n} = \begin{cases} 1, & \textit{if set } Y_x \textit{ is scheduled to time } t_n \\ & \forall x = 1 \ldots N, n = 1 \ldots N, \\ 0, & \textit{if set } Y_x \textit{ is not scheduled to time } t_n \end{cases} \tag{12}$$

$$\min_{\mu_{x,n}} \sum_{n=1}^{N} C_n \left(\sum_{x=1}^{N} \left(\sum_{m=1}^{|Y_x|} \widehat{P}_{m,x} \right) \mu_{x,n} \right) \tag{13}$$

$$\sum_{\boldsymbol{x}=1}^{\boldsymbol{N}} \boldsymbol{\mu}_{\boldsymbol{x},\boldsymbol{n}} \leqslant 1, \quad \forall \boldsymbol{x}; \sum_{\boldsymbol{n}=1}^{\boldsymbol{N}} \boldsymbol{\mu}_{\boldsymbol{x},\boldsymbol{n}} \leqslant 1, \quad \forall \boldsymbol{n}, \tag{14}$$

Proposed schemes for stated problem

The solution for Sub-problem 1 and 2 is given in this section. The optimum results from these two sub-problems give the solution for the stated optimization problem in Eq. (9).

Solution for Sub-problem 1

The solution in sub-problem 1 gives N number of sets, each set contains the possible combination of appliances in set S and R. The following steps are presented to achieve proposed solution for sub-problem 1.

Step 1: Generate $(2^{TA}-1)$ Number of Y_x sets ($\forall x = 1, 2, 3\ldots 2^{TA}-1$), by combining all unique possible combination of devices in set R and set S.
Step 2: From the generated Y_x sets, Select the sets which contain all the devices in set R within the combination and remove the remaining sets. Now the constraint $\sum_{x=1}^{N}\alpha_{m,x} = N, \forall m,\ and\ y_{m,x} \in R$ is satisfied.
Step 3. From the remaining Y_x sets, Calculate the total power demand for each set by adding the power demand of individual appliances in Y_x set.
Step 4: From the remaining Y_x sets in Step 2, remove the sets which contain power demand greater than E. Now the remaining Sets in Y_x satisfy the constraint $\sum_{m=1}^{|Y_x|}\widehat{P}_{m,x} \leqslant E, \forall x$.

Solution for Sub-problem 2 (minimum cost maximum power algorithm)

To find the solution for Sub-problem 2, a new Minimum Cost Maximum Power algorithm (MCMP) is proposed. The proposed algorithm solves the scheduling solution in a simple and efficient way. The basic idea of the proposed algorithm is, selecting the Y_x set which has maximum power (P_{max}) and by selecting T_n set with minimum cost (C_{min}) and schedule the P_{max} to C_{min} to yield the optimum Scheduling solution. Fig. 2 explain the proposed MCMP algorithm. In each step of finding P_{max} and C_{min} gives an optimum scheduling for a single time slot. By repeating the steps until all the appliances complete their task, the resultant scheduling scheme is considered to be optimum for minimizing the total cost with 100% task completion. Y_x sets and T_N set should be updated when moving from one step to another step. The update of Y_x sets is done by removing the sets which contain the task completion appliances. The update of T_N is done by removing the time slot which is already allotted in the previous step. The steps for proposed MCMP algorithm are given below.

Step 1: From Y_x sets, Select the set which contains maximum power demand and makes the selected set as P_{max}.
Step 2: From T_N set, select the minimum cost time slot and make the selected time slot as C_{min}.
Step 3: Schedule the P_{max} set to C_{min} time slot.
Step 4: Update the Y_x sets by removing the sets containing the task completed appliances.
Step 5: Update the T_N set by removing Scheduled time slot.
Step 6: From the updated Y_x sets, select the set which contains maximum power demand and makes the selected set as updated P_{max}.
Step 7: From updated T_N set, select the minimum cost time slot and make the selected time slot as updated C_{min}.
Step 8: Schedule the updated P_{max} set to updated C_{min} time slot.

Repeat the step 4 to step 8 until task completion of all devices.

Simulation result

Set formulation for simulation

For validation, the proposed MCMP algorithm is simulated with the residential load. The data for residential electric load and cost

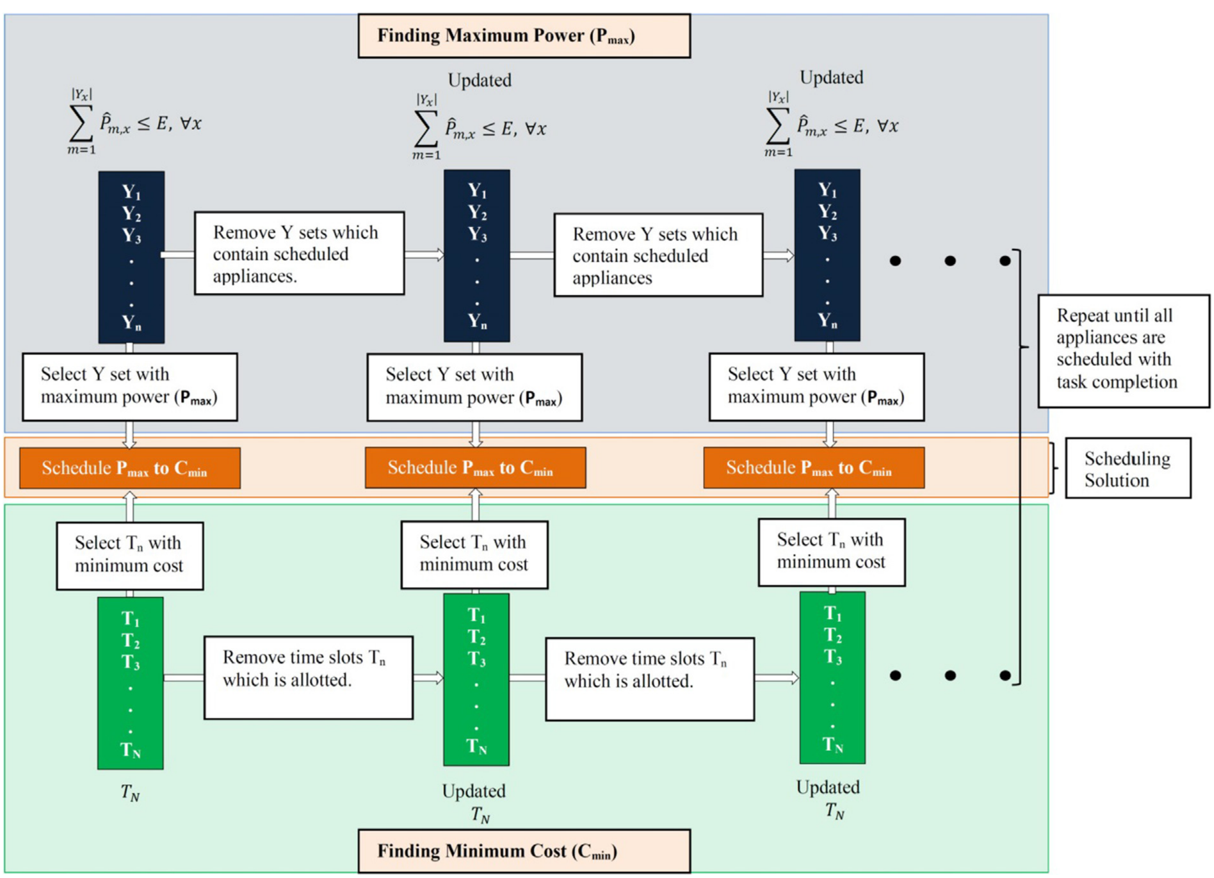

Fig. 2. Proposed Minimum Cost Maximum Power (MCMP) algorithm.

for different time slots are taken from [17]. Four different load scenarios are considered with respect to four different seasonal variations. For simulation purpose, ten appliances (TA = 10) A1 to A10 are fixed as residential loads and 24 h is divided into 8 time slots (T = T1, T2, T3, T4, T5, T6, T7, T8). Two appliances A1, A2 (RA = 2) are considered as real-time appliances out of 10. These two real-time appliances are assumed to be in ON state of all seasons and for all time slots. Remaining eight appliances (SA = 8) A3 to A10 are considered as schedulable appliances. Individual power demand for all 10 appliances for 4 different Load Scenarios (LS1 to LS4) is tabulated in Table 1. (The appliances load given in Table 1 is considered to be constant, because the proposed algorithm calculates the demand with respect to the rated power of appliances which is taken as input from the consumer. Even though in practical application, the home appliances will not have constant power, but the appliances will work within the rated power. So the information about the rated power of each appliance is enough to the successful execution of the proposed algorithm.) The appliances A1 and A2 are allotted to schedule for an entire time slot and for entire load scenario. The Appliances A3 to A10 are scheduled as per Table 2. The set formulation in Table 2 is about, the number of time slot required by each appliance to complete its appliances task (in practical application, this information is given by consumer to CCS). For an instance, at scenario LS1 for appliances, A1 and A2 require all the time slots from T1 to T8 to complete its task. For the appliance A7 at scenario LS3, required four time slots (T1, T3, T4, T5). The proposed algorithm is simulated by considering this data has, number of time slot required to complete the task by schedulable appliances. Considering equal priority for real-time appliances (in practical application, in some cases, the real-time appliances may not be turned-on for all the time slot), in this work, the authors considered the real-time appliances are turned-on for all time slot; this will not harm the proposed algorithm [17]. The associated cost of each time slot and demand required for a single time slot for different load scenarios is given in Table 3. In practice, the time-based cost data in Table 3 is updated daily by the utility to CCS with day-ahead pricing scheme.

Time slot based comparison

Time slot based comparison of proposed MCMP and existing methods for LS1 to LS4 is given in Fig. 3. For LS1 the total demand per day is 63 kW. The demand for real-time appliances is 24 kW and this demand cannot be altered by MCMP. So the remaining demand of 39 kW should be scheduled as per the proposed MCMP optimization algorithm to reduce the cost. The maximum demand per time slot E is fixed to 12 kW. To validate the proposed MCMP algorithm, the results are compared with DijCosMin Algorithm (PRDSol), Low Complexity Algorithm (LCSol), Sub-optimal solution (SOPSol), Optimum Solution (OPTSol) and Particle Swarm Optimization (PSO) which is available in the literature [17]. PRDSol is based on graph search algorithm, and which is used to find the best appliances scheduling scheme to minimize the consumption cost. LCSol and SOPSol are the modified versions of PRDSol with the aim of reducing the complexity. The detailed explanation about OPTSol and PSO is given in [17]. For LS1 the minimum cost time slot is T7 with cost of 2 cents/kW and maximum cost time slot is T6 with the cost of 8 cents/kW. The demand scheduled by MCMP for T7 is 12 kW (which is the maximum load in LS1) and for T6 is 3 kW. This comparison shows that the proposed algorithm schedules maximum demand to a low-cost time slot which leads to a reduction in consumption cost and is economically profitable to the consumer. From the result in LS1, it is observed that at T6 the demand scheduled by SOPCol, LCSol, OPTSol, PRDSol, and PSO are 12 kW, 9 kW, 5 kW, 5 kW and 9 kW respectively. For a maximum cost time slot T6, the existing algorithms scheduled higher demand when compared to the proposed method. So this comparison shows that the existing algorithms have not efficiently scheduled the demand for reduction of consumption cost. In the same way, while comparing all time slots for all 4 scenarios, the proposed algorithm schedules the demand more efficiently than the existing method. In LS2 the results shows that at T3 the OPTSol schedules the demand with 2 kW. But the minimum demand required for every time slot is 3 kW (i.e.,) the demand required for real-time appliances is 3 kW. So, it is observed that the OPTSol violated the

Table 1
Demands for appliances at different Load Scenarios (LS1–LS4) [17].

Appliance	LS1	LS2	LS3	LS4
A1	1.5 kW	1.5 kW	1.5 kW	1.5 kW
A2	1.5 kW	1.5 kW	1.5 kW	1.5 kW
A3	1.5 kW	1 kW	1 kW	0.5 kW
A4	0.5 kW	1 kW	0.5 kW	1 kW
A5	1 kW	1 kW	0.5 kW	1.5 kW
A6	1 kW	1.5 kW	1 kW	1 kW
A7	1 kW	1.5 kW	0.5 kW	1 kW
A8	2 kW	1 kW	0.5 kW	0.5 kW
A9	1 kW	1 kW	0.5 kW	1 kW
A10	1.5 kW	1 kW	1.5 kW	0.5 kW
Total	12.5 kW	12 kW	9 kW	10 kW

Table 2
Set formulation [17].

Load scenario	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
1	T1, T2…T8	T1, T2…T8	T1, T3, T4	T1, T4, T8	T2, T3, T4, T6, T8	T2, T3, T4, T6, T8	T2, T3, T4, T5, T7, T8	T2, T3, T4, T5, T6, T7	T3, T8	T3, T8
2	T1, T2…T8	T1, T2…T8	T1, T3, T7	T1, T3, T8	T1, T3, T4, T8	T3, T4, T5, T8	T3, T4, T5, T8	T1, T3, T4, T6	T1, T3, T5, T6	T3, T4, T8
3	T1, T2…T8	T1, T2…T8	T1, T4, T5	T1, T4, T5	T1, T4, T6, T7, T8	T1, T3, T4, T5	T1, T3, T4, T5	T1, T3, T4, T5	T3, T4, T5	T3, T4, T5, T6, T8
4	T1, T2…T8	T1, T2…T8	T2, T8	T2, T4, T6, T8	T2, T5, T6, T7	T4, T6	T3, T4, T5	T3, T4, T5	T4, T7	T3, T4, T7, T8

Table 3
Cost and total demand for different time slot at different load scenarios [17].

Time slot	Demand in kW				Price in Cents/kW			
	LS1	LS2	LS3	LS4	LS1	LS2	LS3	LS4
T1	5	8	7	3	4	8	5	4
T2	8	3	3	6	5	3	3	9
T3	12	12	6	4	6	9	7	5
T4	10	9	9	8	7	4	9	8
T5	6	7	8.5	5	6	6	8	6
T6	7	5	5	7.5	8	5	4	7
T7	6	4	3.5	6	2	7	4	4
T8	9	9	5	5	5	6	6	6

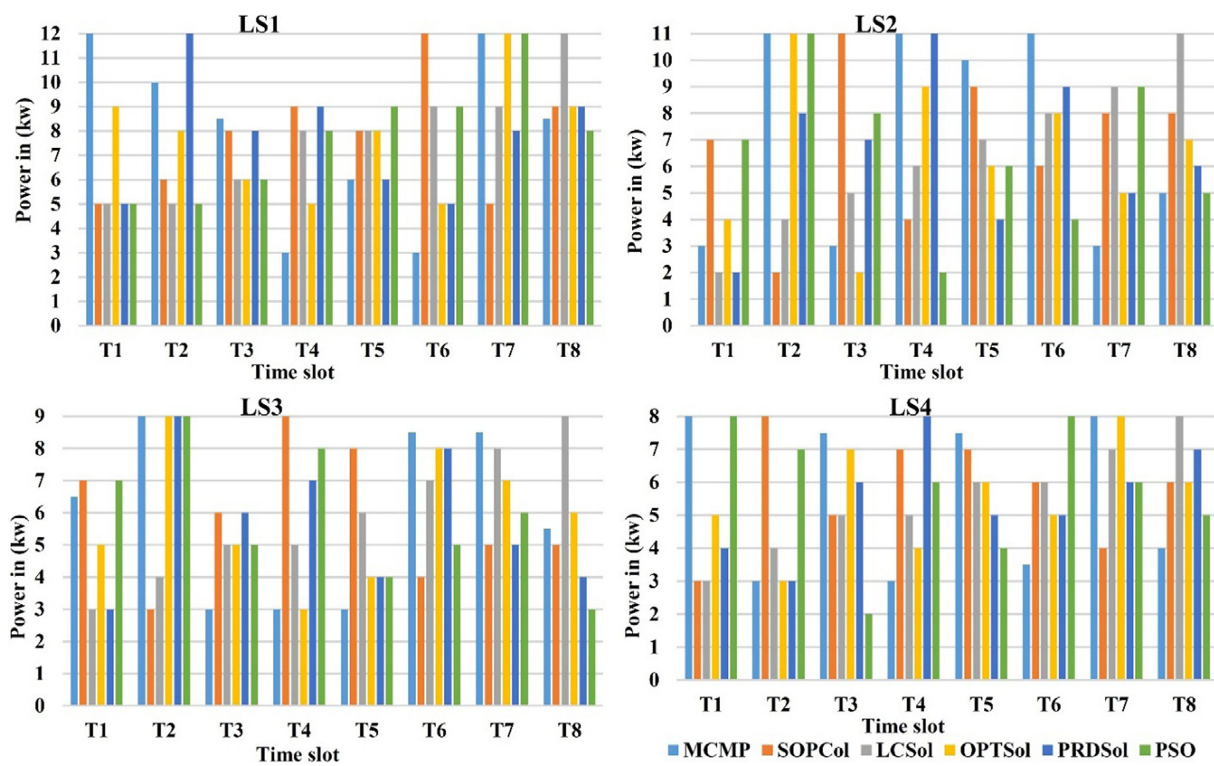

Fig. 3. Demand Scheduling for LS1–LS4.

stated constraint of real-time appliances by not scheduling demand of 1 kW of real-time appliances at T3. This will cause discomfort to the consumer. But the proposed MCMP algorithm has not violated any stated constraints. Fig. 4 shows the detailed analysis of how the individual appliances are scheduled for each time slot, LS1 to LS4 by the proposed MCMP algorithm. Fig. 4 can be taken as proof of the result shown in Fig. 3. From Fig. 4, at LS3 time slot 1, the appliances A1, A2, A5, A7, A8, A9, and A10 have a demand of 1.5 kW, 1.5 kW, 0.5 kW, 0.5 kW, 0.5 kW, 0.5 kW, and 1.5 kW respectively. So the sum of total demand at time slot 1 is 6.5 kW. From Fig. 3, the demand at LS3 for time slot 1 is also 6.5 kW. This comparison confirms the scheduling scheme in Fig. 4 is a proof for results.

For detailed analysis on load scheduling by the proposed algorithm, the cost per time slot versus the descending order of time slot with respect to cost is compared with the existing method for LS1 is given in Fig. 5. In Fig. 5 the maximum cost time slot is T6, and the next upcoming time slots in x-axis are in descending order. While comparing the results, the proposed MCMP algorithm schedules the appliances uniquely when compared to the existing methods and also the total consumption cost is also low from other existing methods. The average per time slot cost of the proposed MCMP algorithm is 37.0265 cents. For SoPCol, LCSol OPTsol, PRDSol, and PSO the average per time slot cost are 45 cents, 41.875 cents, 38 cents, 41 cents, 40.875 cents respectively.

Task completion comparison

Task completion Percentage of proposed MCMP algorithm is compared with existing work and the results are shown in Table 4. For LS1, by comparing the task completion results, MCMP schedules all 63 kW (100% of task completion) demand at the day end, but SoPSol, LCSol, OPTSol, PRDSol, and PSO schedules only 62 kW (98.41%) of demand at the end of the day. The remaining 1 kW is not scheduled by existing algorithms. This shows that MCMP schedules the total demand as per the needs of the consumer. Similarly, while comparing the task completion the proposed algorithm schedules the demand to 100% at the end of the day for all 4 scenarios.

For LS4, by comparing the task completion results, MCMP schedules all 44.5 kW demand at the day end. But the task completion by LCSol, OPTSol, PRDSol is 44 kW (98.88%), which is lesser than the total demand needed per day for LS4. The task completion of SOPCol and PSO in LS4 is 103.37%, (i.e.) above 100%. Which

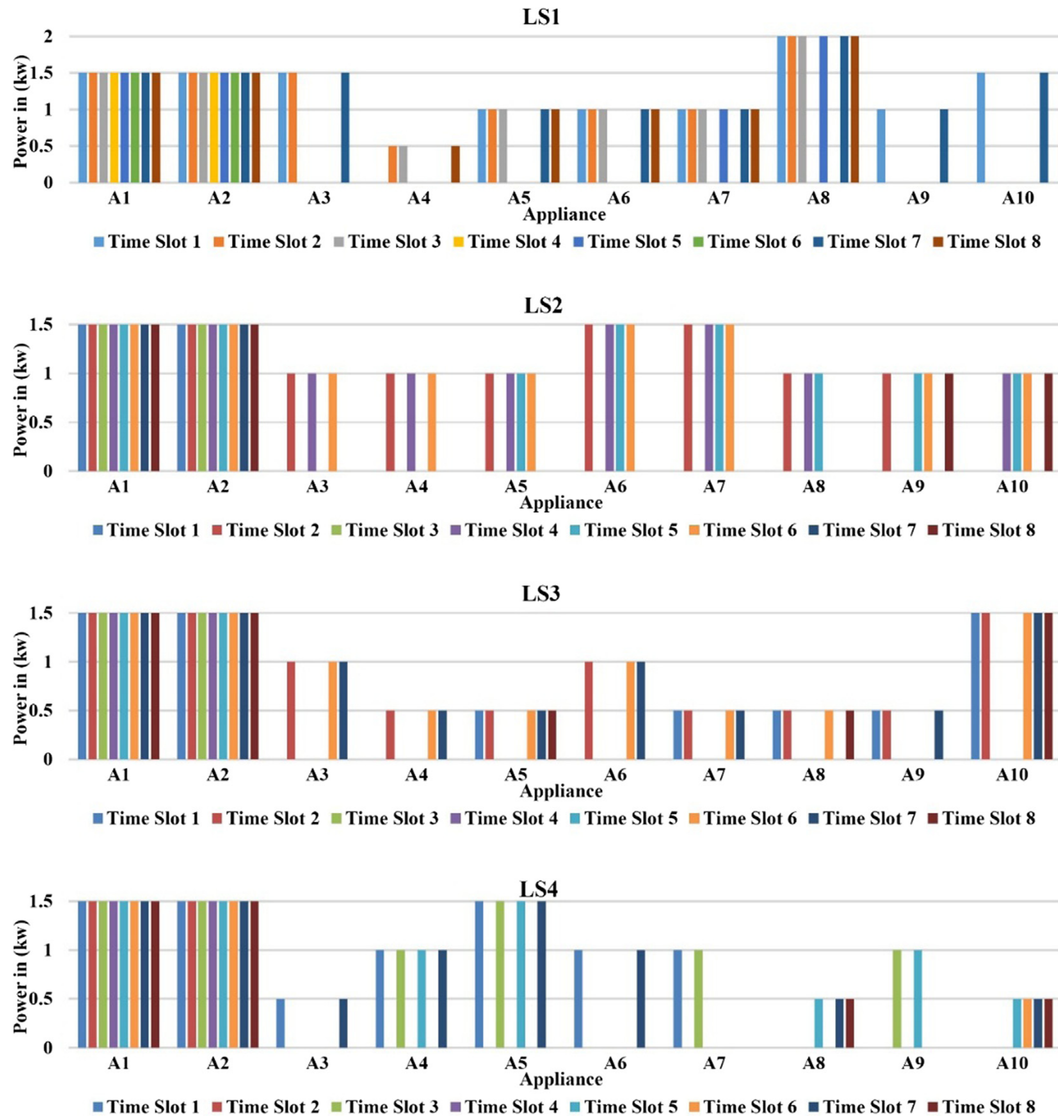

Fig. 4. Appliances scheduled scheme by MCMP algorithm for LS1–LS4.

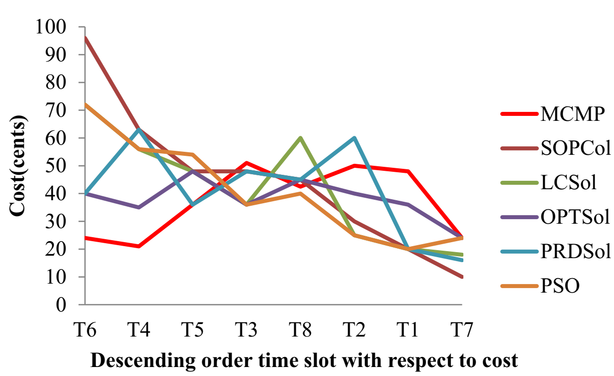

Fig. 5. Descending order price comparison for LS1.

Table 4
Comparison of task completion in percentage.

Algo	LS1	LS2	LS3	LS4
MCMP	100.00	100.00	100.00	100.00
SOPCol	98.41	96.49	100.00	103.37
LCSol	98.41	91.23	100.00	98.88
OPTSol	98.41	91.23	100.00	98.88
PRDSol	98.41	91.23	97.87	98.88
PSO	98.41	91.23	100.00	103.37

means the total demand of LS4 is 44.5 kW, but the SOPCol and PSO scheduled the appliances up to 46 kW. So these algorithms scheduled the appliances more than the consumer's requirement which leads to unwanted wastage of power and increase the consumption cost. But the proposed MCMP algorithm exactly schedules the appliances as consumer need for all LS1 to LS4.

Comparison of cost

Total cost for consumed energy per day for the proposed MCMP algorithm is compared with existing work is shown in Fig. 6. In Table 5 the cost difference between proposed MCMP algorithm to existing algorithm is compared and the results are tabulated in percentage. In Table 5, the results are given in such a way that, the cost of SOPCol at LS1 is 17.64% greater than the proposed MCMP algorithm. From all 4 scenarios, the cost of proposed MCMP algorithm is lower than the other existing algorithm. In LS2, the percentage of cost differences for OPTSol and PRDSol is given by −8.09% and −2.44%; which means, the cost for OPTSol and PRDSol

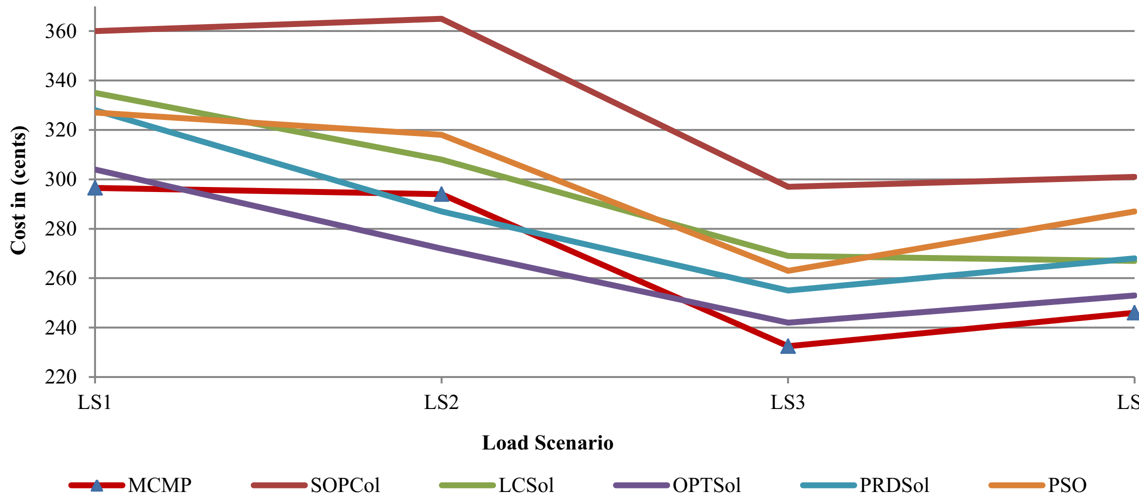

Fig. 6. Cost comparison of MCMP with existing method.

Table 5
Percentage of cost different from MCMP to existing method.

Algo	LS1	LS2	LS3	LS4
SOPCol	17.64	19.45	21.72	18.27
LCSol	11.49	4.55	13.57	7.87
OPTSol	2.47	-8.09	3.93	2.77
PRDSol	9.60	-2.44	8.82	8.21
PSO	9.33	7.55	11.60	14.29

Table 6
Comparison of response time.

Algo	Time (sec)
MCMP	0.362
SOPSol	0.538
LCSol	0.483
PRDSol	8.599
OPTSol	179
PSO	18.58

is 8.09% and 2.44% lesser than the proposed MCMP algorithm respectively. But while comparing task completion in Table 4, OPTSol and PRDSol complete only 91.23% of total demand required per day. This shows that the cost of proposed MCMP algorithm is little higher than the OPTSol and PRDSol but it is important to note that the proposed MCMP algorithm complete its 100% task. Except for OPTSol and PRDSol in LS2, all remaining 4 scenarios LS1, LS2 (Except OPTSol and PRDSol), LS3, and LS4 are higher in cost while comparing to proposed MCMP algorithm.

Comparison of response time

For home energy management system it is important to consider the total response time. So the response time for the proposed MCMP algorithm is compared with the existing method and the results are shown in Table 6. The response time of the proposed MCMP algorithm is 0.326 s which is the lowest response time while comparing with existing algorithm. However, the response time in Table 6 shows only the simulation run time but in reality, the total response time includes the sum of the time taken by communication devices and processing time of the algorithm. In addition, the system response time will vary with respect to the speed of the internet connection and also based on the zigbee topology used in the residence. Other factors which affect the time response are a total number of appliances in the home, obstacles, and the distance between C zigbee and ED zigbee. Even though there are practical factors which affect the response time, run time of the proposed algorithm is less when compared to the existing method. So by implementing the proposed MCMP algorithm in real time systems the total response time will also be less than other methods.

Comparison results with different E value for LS1

The load scenario LS1 is simulated with different Target value E, to examine the impact of E value with the proposed system. The minimum E value is chosen as 4 kW because the total demand for a non-schedulable appliance is 3 kW. So the target value cannot be fixed lesser than 3 kW. The results with different target value from 4 kW to 14 kW are shown in Table 7. From the result, the impact by different E value over total cost and percentage of work done is shown. The results show that for a minimum target value of 4 kW, the proposed algorithm schedules appliances with task completion of 50.79% and the total cost is 172 cents. The percentage of task completion is increased by increasing the E value. By comparing the E values of 10 kW, 11 kW and 12 kW the algorithm schedules the appliances with 100% of task completion but the total cost is lesser for 12 kW. For 13 kW and 14 kW, the results are same with 98.41% task completion at a cost of 289 cents. The overall results in Table 7 show that the algorithms work better with E value which is near to the sum of the rated power of total appliance. The total demand for LS1 is 12.5 kW as shown in Table 1 and best E value of for LS1 is 12 kW. However as stated earlier, the

Table 7
Comparison of results with different E values.

Target value E	Task completed demand (kW)	Total cost (cents)	Percentage of work done (%)
4	32	172	50.79
5	40	215	63.49
6	48	258	76.19
7	53	280	84.13
8	61	321.5	96.83
9	62	318.5	98.41
10	63	308.5	100.00
11	63	300	100.00
12	63	296.5	100.00
13	62	289	98.41
14	62	289	98.41

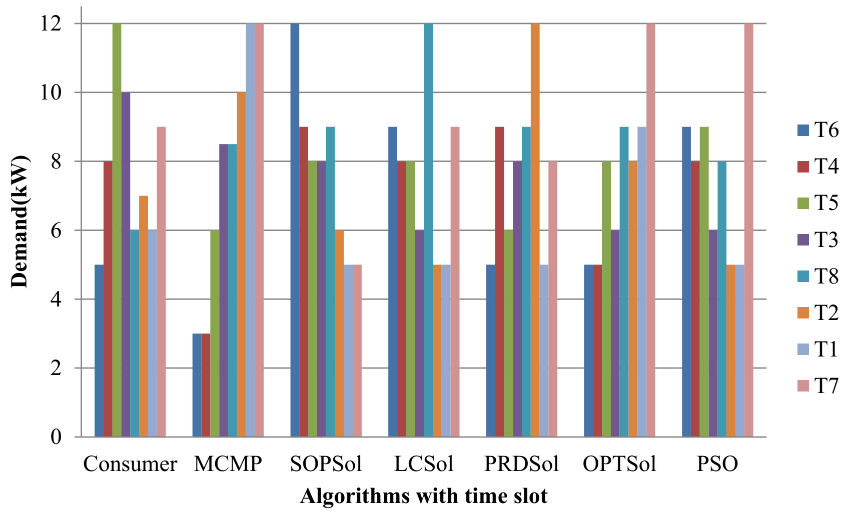

Fig. 7. Comparison of peak demand reduction for LS1.

E value is fixed by the utility by considering the generation capacity, climatic condition and consumers regional festival season. In addition to it, the utility should consider the average load demand of the consumers with respect to their tariff plan. Fixing the E value by considering the average load of consumers will improve the algorithm performance by completing 100% task of appliances with low consumption cost.

Comparison of peak demand reduction

The comparison of peak demand reduction by the proposed MCMP algorithm with the existing method is shown in Fig. 7 for LS1. In the graph, the total load scheduled with respect to a single time slot by proposed algorithm and other existing algorithms are given. The time slot is arranged in descending order such that, the first time slot has higher cost and next respective time slots have lesser cost than the previous one. For LS1, descending order of time slot with respect to cost can be given as T6 > T4>T5 > T3>T8 > T2>T1 > T7. If the utility fixed a time slot with higher cost, then that time slot must have peak power demand. Here T6 have the highest cost so T6 is the highest peak demand and T7 is the lowest peak demand for LS1. So for reducing the peak demand, the algorithm must schedule minimum load to the highest peak demand. By comparing the results shown in Fig. 7, the proposed MCMP algorithm scheduled lowest demand of 3 kW to T6 and T4, later the algorithm increases the load demand for a low-cost time slot. So when the highest load is shifted to low-cost time slots, it means the highest loads are shifted from peak hours to off-peak hours. From the results, it clearly shows that the reduction of peak demand by other existing methods is not efficient when comparing to the proposed MCMP algorithm. Because, existing algorithm cannot efficiently shift the highest load demand to the low-cost time slot. Hence the results in Fig. 7 proves that the proposed algorithm reducing the peak demand very effectively. The 'customer' mentioned in the x-axis is based on the set formulation which is given in Table 2. The results of 'consumer' in x-axis show that how the loads are scheduled by the consumer without any algorithm. In other words how the consumer using the load with respect to time slots without any algorithm.

Conclusions

In this paper, an energy management system is presented for implementing optimum scheduling scheme to minimize the electricity cost and peak demand. A novel MCMP algorithm is proposed to solve the problem. The detailed system model is given for practical implementation of the proposed algorithm. In order to validate the MCMP algorithm four different load scenarios are considered for simulation. The results show that the consumption cost of the proposed algorithm is low for LS1, LS3, and LS4 in comparison with the existing methods. Meanwhile for LS2 the consumption cost by MCMP is slightly higher than OPTSol and PRDSol but the task completion are not up to 100%. The response time of the proposed algorithm is 0.326 s which is low when compared with the existing methods. The peak demand reduction by the proposed MCMP is more efficient with 100% of task completion. So by comparing all the results, it is concluded that the proposed algorithm gives better results in terms of electricity consumption cost, peak demand reduction, task completion and response time. The present work focused towards the home energy management and future study of this work can be extended to industrial energy management systems.

Conflict of interest

The authors have declared no conflict of interest.

Compliance with Ethics Requirement

This article does not contain any studies with human or animal subjects.

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