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Application of Two-Phase Simplex Method (TPSM) for an Efficient Home Energy Management System to Reduce Peak Demand and Consumer Consumption Cost

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ABSTRACT Superabundant utilization of electricity in the residential sector is one of the major reasons for frequent peak demand. Hence, power sector necessitates an appropriate solution to control and monitor the peak demand. In this regard, implementation of an appropriate home energy management system becomes mandatory at customer premises to have an effective control over peak demand. Thus, in this research a simple home energy management using Two-Phase Simplex Method (TPSM) is proposed with an objective to (i) reduce peak demand, (ii) reduce consumer consumption cost, and (iii) conserve consumer comfort level. Further, the research proposes detailed investigations on the smart energy-home management model monitored by IoT. For simulations, different load scenarios are considered and the results are compared with the existing benchmarks available in the literature. On validations, the proposed TPSM method is found simple, reliable and efficient. More importantly, the multipurpose objectives has certainly given better results in consumer consumption cost that can give better control to peak demand. Furthermore, the usage of lucid simplex method has almost reduced the computational complexity to fasten the response time. In this regard, consumer comfort is served here is considered as a major accomplishment with the proposed work.

INDEX TERMS Smart grid, Demand-side management, Home energy management, Demand response, Appliance scheduling

I. INTRODUCTION

Modernization with recent technology driven by the advancement in power electronics has made the common mankind to utilize the electronic home appliances in regular routines. Thus, excess power usage via modernized and convetional electric home appliances primes to an increase in power demand and periodic peak demand [1], [2]. Besides, the productive advancements in electric vehicle technology is considered as one of the probable inclusions in home energy management for battery charging. This again increases the burden on utility to raise the power demand and peak demand. Hence, burden on utility becomes monumnetal to supply the actual power demand for consumers. This uncertain power demand forces the utility to create frequent power outages for consumers. To attenuate the problem, an effective Home – Energy Management (HEM) system is needed. In particular, the self automated HEM is more aprrorpriate to serve for this purpose [3]. Note that HEM is not only beneficial for utility but also to the consumer from an economic perspective. Implementation of much effective HEM can be achieved with the assistance from smart grid technology. It is important ot mention here that smart grid system has the provision to merge distributed renewable energy sources with conventional power grid. Further, wise usage of smart grid technology and HEM system, balances the ratio between power demand and avaiable power generation to attain bidirectional communication feature [4]. In recent years, many researches has handled this problem to build an efficient HEM system

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that can overcome peak demand and reduce consumer electricity cost [2]. Scholarly research in [5] has proposed an Incentive-based scheduling for home appliances in [5]. Albeit the algorithm has reduced the cost of operation, the algorithm was not successful to bring out 100% task completion by the day-end to affect the consumer comfort. With a primary objective to provide HEM for multi-residential consumers, a demand scheduling scheme was introduced in [6]. However, this method needs to share bulk information data between consumers and utility and hence it requires expensive communication infrastructure for implementation. Inspired by the ability to handle multimodal problems, optimization algorithm was introduced in [7] to reduce the monthly electricity consumption cost. Being a non-conventional method, this algorithm has a target value fixed by the consumer. Later, the consumption cost is reduced by compromising the work of appliances. This certainly affects the consumer satisfaction with task completions by the appliance.

The HEM algorithms with the integration of renewables are the recent research attractions found in literature [8]–[10] to reduce peak demand and there cost. But then, integration of renewable sources and HEM results in reduction of consumption cost and monumental increase in installation cost. In [11], a stepwise approach for a Mixed Integer Linear Programming (MILP) problem-based HEM is proposed. Though the method results in successful day-wise scheduling scheme for the home appliances, 100% task completion is not attained yet. Similar to [7], Optimization based approach with a blend of hybrid bacterial forging and particle swarm optimization algorithm was proposed in [12] for demand side management. Further, the method uses a heuristic algorithm-based framework to achieve better task completion. With the advent of optimization, many scholarly researches has applied their scheduling algorithm for demand response [13]–[20]. However, all the methods has certainly fall in to any of the following drawbacks (i) Incomplete task completion (ii) failure in reducing the consumption cost, (iii) complex coding structure and (iii) poor performance in peak demand. Thus, there exist a necessity for a simple, reliable and robust mathematical model for home energy management system. On analyzing the merits and demerits of the scholarly research in literature, a simple Two-Phase Simplex Method (TPSM) is proposed for HEM. Further, it is seen that usage of simplex methods is found more appropriate since it is lucid, robust and easy to implement. It is worth to mention here that the proposed scheme utilizes two-phase lightweight approach for implementing an automated demand response program. Application of IoT to monitor and interface with real-time pricing scheme is a notable contribution of this research. Few of the major research contributions that are vital to meet the research objectives are given in the following:

(i) A novel and simple HEM system with TPSM is introduced to reduce the consumption cost.
(ii) HEM system is interfaced to have a compatibility to control offline and online.
(iii)The task completion of the home appliances by the proposed method is 100%.
(iv)The system response time is very less compared to other methods.

The remainder of this paper is organized as follows: Section II describes the system model considered for the study and the practical implementation of the proposed TPSM based HEM. Section III gives the details about problem formulation; constraint definition; problem statement. Section IV explains the problem solutions and steps involved in the proposed TPSM-HEM. Section V set formulation for the simulation and detailed comparison results. Section VI gives the conclusion.

II. SYSTEM MODEL

In order to present an accurate system model, an actual real-time pricing scheme was considered to impement the proposed TPSM based HEM. Further, a smart grid infrastructure at consumer permises is needed to implement the automated demand response program. Therefore, a HEM systems with Wireless Home Area Network (WHAN) and cloud computing is considered at the consumer's premise for applying the proposed TPSM. Block diagram of the proposed HEM infrastructure is shown in Fig. 1. The infrastructure is designed to execute the proposed algorithm by getting input from utility and consumer. Note that Central Control System (CCS) acts as a brain for the entire system. For communication, the ethernet is connected between CCS and utility. Further, the overall power consumption of every individual home is measured with an IoT based smart meter and the details are communicated to the utility. This enables the server to collect the power consumption data from all consumers to identify the peak demand hours. With this available information on servers, a common day-ahead electricity cost for the different time slot is generated by the utility and transmitted to its entire consumer's CCS. It is important to note here that CCS connects all home appliances in every individual home to an individual wireless switch via ZigBee to facilitate wireless ON/OFF control of home appliances. The keypad at CCS provides consumers to enter or edit appliance details with their demand. Furthermore, a display is enabled to monitor the traffic and consumption cost.

III. PROBLEM FORMULATION

The problem formulation is made to reduce power consumption cost of customers without compromising the consumer comfort. Notably, reduction of cost in peak demand is wisely handled to resolve the burden impound on utility and consumers. In general, the power consumption cost is reduced by shifting the residential electrical load from peak to the off-

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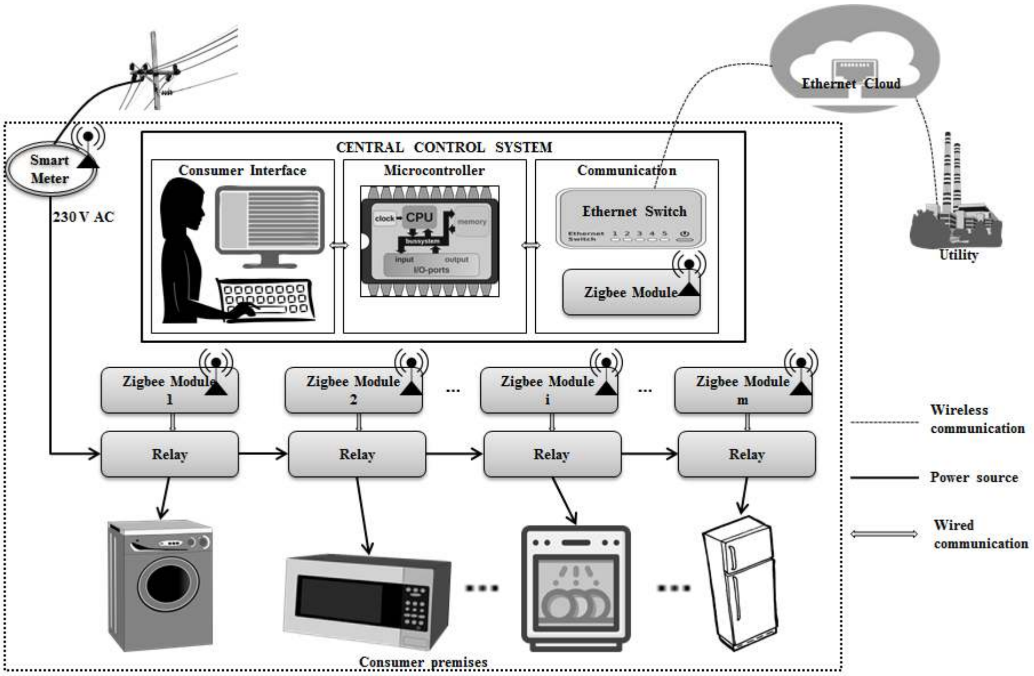

FIGURE 1. **Proposed home energy management system.**

peak time slot by considering that the electric utility (power provider). Note that this is an existing scheme implemented in real-time pricing of the consumers connected to smart grid technology. To maintain demand in limits, load shifting must be carried out in such a way that all necessary appliances (non-shiftable or non- schedulable or real-time appliances) are ensured to not get affected during its working process. Also, the appliance (shiftable or schedulable) involved in load shifting must complete its 100% task between any time of that day; with or without break. Nonetheless, it is also important to avoid consumer dissatisfaction. One of the usual problems that arise in the implementation of real time- demand response program is that every consumer tends to shift their electric load from a high-cost time slot to a low-cost time slot to reduce the power consumption cost. But then, new peak demand is created due to the aforementioned load shifting. Therefore, it is necessary to allot total electrical demand within a limited range to neglect the needless peak demand. To accomplish the task, a target value constant E is assigned to maintain peak to average ratio in a limited range and hence the peak demand is restricted. This ensures the maximum electrical load per house is limited and not getting exceeded to the target value E. It is important to note that the target value is assigned by the electric utility depending upon the climate or seasonal or festival condition of their consumer. Nevertheless, this target value E may not change frequently hence, the authors considered E as constant. By considering the prerequisite objectives and constraints, the authors formulated a mathematical model for a residential consumer. Let, set $(A) = \{A_1, A_2, A_3, \cdots, A_i, \cdots, A_M\}$, be the set of M number of home appliances, where A_i denotes the i^{th} appliance. Set $(D) = \{DA_1, DA_2, DA_3, \cdots, DA_i, \cdots, DA_M\}$, be the set of the rated power of appliances, where DA_i denotes the rated power of i^{th} appliances in kW. The total demand needed by individual appliances to complete its 100% task per day is given inset $(L) = \{L_1, L_2, L_3, \cdots, L_i, \cdots, L_M\}$, such that the total power consumed by DA_i of the appliance must be equal to L_i to complete its 100% task. Set $(T) = \{T_1, T_2, T_3, \cdots, T_j, \cdots, T_N\}$, be the set of '$N$' number of time slots and cost set $(C) = \{C_1, C_2, C_3, \cdots, C_j, \cdots, C_N\}$ in cents/kW for time slots. For mathematical formulation, $M * N$ decision variable $(V_{i,j})$ are introduced in (1). In equation (1), the variables $'i'$ denote appliances and 'j' represents respective time slot. If the i^{th} appliance is scheduled to 'ON' at j^{th} time slot then $V_{i,j} = 1$, otherwise $V_{i,j} = 0$.

$$\begin{matrix} V_{1,1} & V_{1,2} & \cdots & V_{1,j} & \cdots & V_{1,N} \\ V_{2,1} & V_{2,2} & \cdots & V_{2,j} & \cdots & V_{2,N} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ V_{i,1} & V_{i,2} & \cdots & V_{i,j} & \cdots & V_{i,N} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ V_{M,1} & V_{M,2} & \cdots & V_{M,j} & \cdots & V_{M,N} \end{matrix} \tag{1}$$

Power consumed by the i^{th} appliance at j^{th} time slot can be found by using $(DA_i) \times (V_{i,j})$ and the total power consumed by all appliances at j^{th} time slot (PT_j) can be referred in equation (2). The total power consumed by the i^{th} appliance at day-end (PA_i) is given in equation (3).

$$PT_j = \sum_{i=1}^{M} (DA_i) \times (V_{i,j}) \tag{2}$$

$$PA_i = \sum_{j=1}^{N} (DA_i) \times (V_{i,j}) \tag{3}$$

To meet out the objective of consumer comfort, all appliances must complete 100% of the task by day-end. Therefore, the power consumed by i^{th} appliances must be equal to (L_i) as given in the constraint equation (4). To accomplish the comfort, various loads allotted for a single time slot must be lesser than or equal to the target value E. This will confirm that

Set of Appliance (M Numbers)	Set of time slots per day (N Slots)					Total power consumed per appliance at end of the day
	T_1	T_2	T_3	$\cdots$	T_j	
A_1	$(DA_1)\times(V_{1,1})$	$(DA_1)\times(V_{1,2})$	$(DA_1)\times(V_{1,3})$	$\cdots$	$(DA_1)\times(V_{1,j})$	$PA_1=\sum_{j=1}^{N}(DA_1)\times(V_{1,j})$
A_2	$(DA_2)\times(V_{2,1})$	$(DA_2)\times(V_{2,2})$	$(DA_3)\times(V_{3,3})$	$\cdots$	$(DA_2)\times(V_{2,j})$	$PA_2=\sum_{j=1}^{N}(DA_2)\times(V_{2,j})$
A_3	$(DA_3)\times(V_{3,1})$	$(DA_3)\times(V_{3,2})$	$(DA_3)\times(V_{3,3})$	$\cdots$	$(DA_3)\times(V_{3,j})$	$PA_2=\sum_{j=1}^{N}(DA_3)\times(V_{3,j})$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
A_i	$(DA_i)\times(V_{i,1})$	$(DA_i)\times(V_{i,2})$	$(DA_i)\times(V_{i,3})$	$\cdots$	$(DA_i)\times(V_{i,j})$	$PA_i=\sum_{j=1}^{N}(DA_i)\times(V_{i,j})$
	$PT_1=\sum_{i=1}^{M}(DA_i)\times(V_{i,1})$	$PT_2=\sum_{i=1}^{M}(DA_i)\times(V_{i,2})$	$PT_3=\sum_{i=1}^{M}(DA_i)\times(V_{i,3})$	$\cdots$	$PT_j=\sum_{i=1}^{M}(DA_i)\times(V_{i,j})$	Total power consumed per time slot by total appliance
	C_1	C_2	C_3	$\cdots$	C_j	Price in Cents/kW for different time slot.
	$CC_1=PT_1\times C_1$	$CC_2=PT_2\times C_2$	$CC_3=PT_3\times C_3$	$\cdots$	$CC_j=PT_j\times C_j$	Consumed cost per time slot
	$Z=\sum_{j=1}^{N}CC_j$					Total cost at end of the day

Figure 2. **Calculation table for the stated problem statement in equation (1)-(7).**

the demand is shared within the limit for all the time slots. Thus, the demand curve is under control and it will not lead to a peak demand. The constraint for maximum allowed power per time slot by all the sum of appliances per house is given in equation (5).

$$PA_i = L_i, \forall(i = 1,2,\cdots,M) \tag{4}$$

$$PT_j \leq E, \forall(j = 1,2,\cdots,N) \tag{5}$$

The consumption cost at j^{th} time slot$\left(CC_j\right)$ is given in equation (6)

$$\left(CC_j\right) = \left(C_j\right) \times \left(PT_j\right), \forall(j = 1,2,\cdots,N) \tag{6}$$

Therefore, the total cost at the day-end (Z) is given in (7)

$$Z = \sum_{j=1}^{N} CC_j \tag{7}$$

A detailed calculation table for the stated problem formulation is given in Fig. 2. These calculations in above table can be used for implementing any optimization method with similar problem statements. With the obtained mathematical formulation from equations (1)-(7), the problem statement is limited as, "*To minimize the consumption cost by finding optimum values for all decision variables, without violating the stated constraints*". The same problem statement can be mathematically represented as shown in equation (8).

$$min(Z) = \sum_{j=1}^{N}\left(C_j\right) \times \left(PT_j\right) \tag{8}$$

Subject to:

$$PA_i = L_i, \forall(i = 1,2,\cdots,M)$$

$$PT_j \leq E, \forall(j = 1,2,\cdots,N)$$

IV. Application of Two-Phase Simplex Method for demand response system.

As the problem formulation made in equation (8) is a Binary Linear Programming Problem (BLPP), it is much better to solve the problem efficiently via simplex method. simplex method in general finds the optimum value for a Linear Programming Problem (LPP) by using the systematical approach with less computational effect [21]& [22]. However, equation (8) has equality and inequality constraints and thus it may not be solved by a conventional simplex method. Considering the non-linearity with mixed constraints, here Two-Phase Simplex Method (TPSM) is used. The utilized TPSM handles the LPP problem in two phases as phase-I and phase-II. In Phase-I results pertinent to initial basic feasible solution is evolved and later, in phase-II the obtained solution is utilized to obtain an optimal solution. Detailed explanations with mathematical expressions of TPSM method is discussed in the following.

A. Two-phase Simplex method(TPSM)

Since TPSM is an extended version of simplex method, the problem formulation to be made is almost identical to problem formulation made in equation (8). Hence, standard notation of the simplex method is used hereafter for simplicity, and further it is ensured to not affect the original problem statement. The minimization is converted to maximization with 'negative' such that, Max = - (Min).

$$max\ z = -(c_1x_1+c_2x_2+\ldots+c_nx_n) \tag{9}$$

Subject to

$$a_{11}x_1+a_{12}x_2+\ldots+a_{1n}x_n = b_1$$
$$a_{21}x_1+a_{22}x_2+\ldots+a_{2n}x_n = b_2$$
$$\vdots$$
$$a_{m1}x_1+a_{m2}x_2+\ldots+a_{mn}x_n \leq b_m$$
$$\forall x_1,\ldots,x_n \geq 0.$$

The above LPP should be in Standard Form (SF). Hence, the LPP in equation (9) can be converted into SF by adding slack variable 'x_s' for the constraints equation having '$\leq$' type. Same slack variables are added to objective function with a product of 'zero', such that '$0x_s$' to make sure that the impact of slack variables is zero with an objective function. Then the SF of the LPP is given in equation (10).

$$max\ z = -(c_1x_1+c_2x_2+0x_{si}+\ldots+c_nx_n) \tag{10}$$

Subject to

$$a_{11}x_1+a_{12}x_2+a_{1s1}x_{s1}\ldots+a_{1n}x_n = b_1$$
$$a_{21}x_1+a_{22}x_2+a_{2s2}x_{s2}\ldots+a_{2n}x_n = b_2$$
$$\vdots$$

$a_{m1}x_1+a_{m2}x_2+a_{msi}x_{si}+\ldots+a_{mn}x_n= b_m\,,\ \forall x_1,x_{si}\ldots,x_n \geq 0.$

Equation (10) in SF, has the vectors *x, b, c*, and from which matrix '***A***' can be introduced as follows.

$$\boldsymbol{A}=\begin{bmatrix} \boldsymbol{a_{11}} & \boldsymbol{a_{12}} & \cdots & \boldsymbol{a_{1n}} \\ \boldsymbol{a_{21}} & \boldsymbol{a_{22}} & \cdots & \boldsymbol{a_{2n}} \\ \vdots & \vdots & \vdots & \vdots \\ \boldsymbol{a_{m1}} & \boldsymbol{a_{m2}} & \cdots & \boldsymbol{a_{mn}} \end{bmatrix}_{\boldsymbol{m\times n}}.$$

The authors assume that the slack variables are present in the vectors *x, c*, and matrix *A*. Hence, the variables are denoted as $x=col(x_1,x_2,\ldots x_n)$, $b=col(b_1,b_2,\ldots,b_n)$, $c=col(c_1,c_2,\ldots,c_n)$. Where, '*x*' is the decision variable of the objective function and '*b*' in LHS (Left Hand Side) of equation (10) is the constraint. The coefficient of the decision variable of the objective function is '*c'* and its coefficient matrix of the constraints equations is *A*. The condition for the aforesaid vectors are given as follows: $x\in\mathbb{R}^n$, $b\in\mathbb{R}^n(\ \forall b\geq 0)$, $c\in\mathbb{R}^n$, $A=(a_{ij})\in\ \mathbb{R}^{m\times n}$, $x_j\ \geq 0, \forall j=1,2,\cdots,$ and Rank $A = m\ (<n)$. Some of the basic notation used for TPSM are given below for understanding the implementation procedure with actual problem formulation. Let, $A=[a^{(1)},a^{(2)},\ldots,a^{(j)},\ldots,a^{(n)}]$ and $a^{(j)}=col(a_{1j},a_{2j},\ldots,a_{mj})$, then $a^{(j)}$ is j^th^ column of matrix *A*. Basic matrix $B=[b^{(1)},b^{(2)},\ldots,b^{(m)}]$, where $b^{(1)},b^{(2)},\ldots,b^{(m)}$ are basic columns. The $(m\times 1)$ vector $x_B=B^{-1}b$ gives *m* basic variables $x_{B1},\ x_{B2},\ldots,\ x_{Bm}$. To find the basic feasible solution for the basic variable, $x_{Bi}=B^{-1}b_i$, the value for objective function $z(x_B)$ is calculated by $z(x_B)=c_B^T x_B$. Where c_B is coefficient column of basic variables $c_B = col(c_{B1},\ c_{B2},\ldots,\ c_{Bi},\ldots,\ c_{Bm})$.

B. Steps involved in TPSM

1) INITIALIZATION

The initialization process starts with obtaining the constraints. To obtain basic matrix B, the constraints in equation (10) should contain $M\times M$ identity matrix. However, equation (10) is a mixed constraint type, and hence there is no possibility of getting the initial identity matrix. Therefore, artificial variables are added to the constraint in equation (10) such that matrix A contains $M\times M$ identity matrix to select it as a basic matrix B [31].

2) TPSM PHASE I

The objective function of phase-I should contain only artificial variables by keeping all main constraints equations with slack and artificial variables. The mathematical expression for phase-I objective function and constraints are given in (11).

$$max\ z_a = -(x_{a1}+x_{a2}+\ldots+x_{ai}) \tag{11}$$

Subject to

$$\begin{gathered} a_{11}x_1+a_{12}x_2+\ldots+a_{1n}x_n = b_1 \\ a_{21}x_1+a_{22}x_2+\ldots+a_{2n}x_n = b_2 \\ \vdots \\ a_{m1}x_1+a_{m2}x_2+a_{ms}x_s+\ldots+a_{mn}x_n+x_{ai}= b_m \\ \forall x_1,x_s\ldots,x_n\,,x_{ai}\geq 0. \end{gathered}$$

Where:

z_a – is the objective function of phase I.

x_{ai} – is the artificial variables.

TABLE I
SIMPLEX TABLEAU

x_B	$y^{(1)}$	$y^{(2)}$	$\cdots$	$y^{(j)}$	$\cdots$	$y^{(n)}$
$x_{B1}=(B^{-1}b)_1$	y_{11}	y_{12}	$\cdots$	y_{1j}	$\cdots$	y_{1n}
$x_{B1}=(B^{-1}b)_2$	y_{21}	y_{22}	$\cdots$	y_{2j}	$\cdots$	y_{2n}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$x_{B1}=(B^{-1}b)_i$	y_{i1}	y_{i2}	$\cdots$	y_{ij}	$\cdots$	y_{in}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$x_{Bm}=(B^{-1}b)_m$	y_{m1}	y_{m2}	$\cdots$	y_{mj}	$\cdots$	y_{mn}
$z(x_B)$	(z_1-c_1)	(z_2-c_2)	$\cdots$	(z_j-c_j)	$\cdots$	(z_n-c_n)

a) First iteration

From equation (11), identify the matrix *A*, basic matrix *B* (identity matrix) and calculate the values $\forall\ x_{Bi,}y^{(j)},\ z(x_B)$. The value of $y^{(j)}$ in Table I is given by $B^{-1}a^{(j)},\ \forall\ (j=1,2,\ldots,n)$ and the scalars $(z_j\text{-}c_j)$ is relative cost coefficients $(z_j-c_j)=c_B^T y^j-c_j$. As simplex tableau is given in Table I with the calculated values. After filling the simplex tableau, the sign of relative cost coefficient (z_j-c_j) will help the method to wisely select the current basic feasible (optimal) solution x_{Bi}.. However, the search for existence of a new $\widehat{x_{Bi}}$ such that $z(\widehat{x_B})>z(x_B)$ is also performed. The conditions for optimal value and existing optimal value are given below.

(i) If all $(z_j-c_j)\geq 0$ then the current x_{Bi} is optimal.

(ii) If some $(z_j-c_j)<0$ and for that some $yij>0$ then there exists a new $\widehat{x_{Bi}}$ such that $z(\widehat{x_B})>z(x_B)$. If the second condition is satisfied, then go for pivoting iteration to obtain the new $\widehat{x_{Bi}}$.

b) Pivoting iteration 1

The new $\widehat{x_{Bi}}$ is obtained by pivoting the simplex tableau such that, taking one column out of *B* and entering it by another column of *A* which is not already a basic column. The rule for which column $a^{(k)}$of *A,* should be entered in *B* and which column $b^{(r)}$ of *B,* should be taken out by following the set of rules as given below [31].

-- Rule 1. Column to enter (pivot $a^{(k)}$)

Choose $a^{(j)}$ which has the most negative value of (z_j-c_j) which at least one $y_{ij}>0$.

Such that,$(z_k-c_k)=\min\limits_j\{(zj-cj):<\ 0, and\ some\ y_{ij}>0\}$.

-- Rule 2. Column to leave the basis (pivot $b^{(r)}$)

If the pivoting column is $a^{(k)}$, then $x_{Br}=\min\limits_i\left\{\frac{x_{Bi}}{y_{ik}}:\ y_{ik}>0\right\}$

After calculating the (z_k-c_k) and x_{Br} values, update the $\widehat{B}$ matrix. Later using $\widehat{B}$ compute $\forall x_{Bi,}y^{(j)},\ z(x_B)$, and$(z_j-c_j)$.

The above pivoting iteration must be continued until the optimal solution is reached.

3) TPSM PHASE II

In phase I, the optimal solution must be 'zero' since the objective function only has artificial variables. Hence, the value of 'x_B'at the final iteration of phase-I must be the basic feasible solution for the first iteration of phase-II of TPSM. Thus, by keeping the original objective function and final $\widehat{B}$ in phase-I, compute $\forall x_{Bi,}y^{(j)},\ z(x_B)$, and$(z_j-c_j)$ by following the

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same procedure of phase-I. Repeat the procedure until optimal solution in phase-II is arrived. Now, the resultant solution in phase-II is the optimal value of the original objective function given in equation (9). The TPSM can be applied to equation (8) for getting an optimized scheduling scheme without violating the formulated constraints. For better understanding, the flowchart for TPSM applied for home energy management system is given in Fig.3.

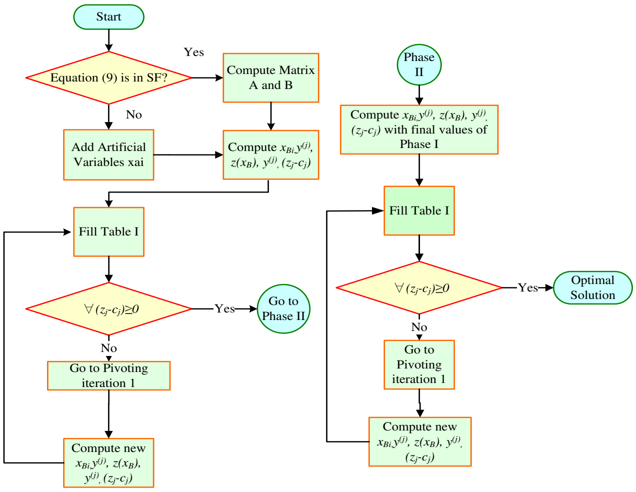

Figure 3. **Flowchart for TPSM applied home energy management system**

V. Simulation result

A) Set formulation for the simulation

To validate the efficiency of TPSM, an exclusive mathematical equation formulated for residential application in section 4 is utilized. For simulations, four various load profiles namely LS1, LS2, LS3 and LS4 are considered and the mandatory data subset like residential load profile and its corresponding time schedule are referred from [11]. From the data subset, it is inferred that 10 home appliances (M=10) and at 8 various time slots (N=8) are considered. Thus, 3 hours of continuous operation constitute a slot to obtain (8×3) 24 hours in a day. Details of various load scenarios with the power demand of individual home appliances and its time duration are given in Table II and Table III respectively. According to the data, the subset $A = \{A_1, A_2, \cdots, A_{10}\}$, home appliances corresponding to and the subset $T = \{T_1, T_2, \cdots, T_8\}$, time slot are wisely determined. Based on the appliance parameters, the rated power is calculated and presented in Table II. For brevity, the subset for '*D*' in kW of LS1 is alone presented as follows *D* = {1.5, 1.5, 1.5, 0.5, 1, 1, 1, 2}. Further, basic understanding with table III can be inferred as: The assigned load A1 of LS1 only needs 8 optimal slots in a day whereas A10 require only 2 slots to complete the task. In other words, A1 has to turned on for all 24 hours and A10 just requires any 6 hours in 2 slots. According to the problem formulation, all the scheduled load should achieve 100% task within the given slots '*L*'. i.e., the scheduled load of LS1 $D = \{1.5, 1.5, 1.5, 0.5, 1, 1, 1, 2\}$ should optimally achieve its 100% task in the time slot $L = \{8, 8, 3, 3, 5, 5, 6, 6, 2, 2\}$. It is worth to mention here that any excess time consumption will lead to customer discomfort in terms of peak demand and excess energy consumption.

Since the dataset has 10 home appliance with 8 time slots ($M = 10$ and $N = 8$), 80 decision variable are found in set formulation $(V_{M=10,N=8})$. These decisions are crucial to determine the optimal load scheduling and the problem statement in equation 8 is expected to return this variable for its wise operation. The control various via TPSM are expected to possess a better trade-off between normal and peak load. For the given input dataset, the cost in cents are estimated and it is presented in Table IV. Similarly, the total power required at the day end for different LS is also calculated and tabulated in Table V.

TABLE II
DEMANDS FOR APPLIANCES AT DIFFERENT LOAD SCENARIOS (LS1-LS4) [11]

Appliances	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

TABLE III
APPLIANCES WORKING DURATION (LS1-LS4) [11]

Appliances	(No. of Time slots)			
	LS1	LS2	LS3	LS4
A1	8	8	8	8
A2	8	8	8	8
A3	3	3	3	2
A4	3	3	3	4
A5	5	4	5	4
A6	5	4	3	2
A7	6	4	4	2
A 8	6	4	4	3
A9	2	4	3	2
A10	2	3	5	4

B) Results and discussion

The data set available in Tables I-IV are utlized to calculate the datas of table shown in Fig. 2. Further, TPSM is applied to get an optimized scheduling scheme for all four LS. The resultant scheduling scheme obtained by TPSM is given in Table VI. Note that Table VI only possess only a binary value according as given in equation (1) to indicate the load turn on and off during the time slot. From the resultant scheduling scheme, it is possible to calculate/analyze different parameters like task completion, total cost, response time and peak demand. For comprehensive comparison, all the aforesaid parameters are compared with popular methods available in literature like DijCosMin Algorithm (PRDSol), Low Complexity Algorithm (LCSol), Sub-optimal solution (SOPSol), Optimum Solution (OPTSol), and Particle Swarm Optimization (PSO).

TABLE IV
COST AT DIFFERENT TIME SLOT (LS1 LS4) [11]

Time Slot	Price in Cents/kW			
	LS1	LS2	LS3	LS4
T1	4	8	5	4
T2	5	3	3	9
T3	6	9	7	5
T4	7	4	9	8
T5	6	6	8	6
T6	8	5	4	7
T7	2	7	4	4
T8	5	6	6	6

TABLE V
TOTAL POWER REQUIRED TO COMPLETE 100 % (LS1-LS4)

Appliance	Total power (kW)			
	LS1	LS2	LS3	LS4
A1	12	12	12	12
A2	12	12	12	12
A3	4.5	3	3	1
A4	1.5	3	1.5	4
A5	5	4	2.5	6
A6	5	6	3	2
A7	6	6	2	2
A8	12	4	2	1.5
A9	2	4	1.5	2
A10	3	3	7.5	2
Total power for 100 % task.	63	57	47	44.5

TABLE VI
SCHEDULING SCHEME BY TPSM FOR ALL FOUR LS.

TPSM Resultant Scheduling scheme for LS1								
Appliance	Time Slot							
	T 1	T 2	T 3	T 4	T 5	T 6	T 7	T 8
A1	1	1	1	1	1	1	1	1
A2	1	1	1	1	1	1	1	1
A3	1	1	0	0	0	0	1	0
A4	1	1	0	0	0	0	0	1
A5	1	1	1	0	0	0	1	1
A6	1	1	1	0	0	0	1	1
A7	1	1	1	0	1	0	1	1
A8	1	1	1	0	1	0	1	1
A9	1	0	0	0	0	0	1	0
A10	0	0	0	0	0	0	1	1

TPSM Resultant Scheduling scheme for LS2								
Appliance	Time Slot							
	T 1	T 2	T 3	T 4	T 5	T 6	T 7	T 8
A1	1	1	1	1	1	1	1	1
A2	1	1	1	1	1	1	1	1
A3	1	1	0	0	0	0	1	0
A4	1	1	0	0	0	0	0	1
A5	1	1	1	0	0	0	1	1
A6	1	1	1	0	0	0	1	1
A7	1	1	1	0	1	0	1	1
A8	1	1	1	0	1	0	1	1
A9	1	0	0	0	0	0	1	0
A10	0	0	0	0	0	0	1	1

TPSM Resultant Scheduling scheme for LS3								
Appliance	Time Slot							
	T 1	T 2	T 3	T 4	T 5	T 6	T 7	T 8
A1	1	1	1	1	1	1	1	1
A2	1	1	1	1	1	1	1	1
A3	1	1	0	0	0	0	1	0
A4	1	1	0	0	0	0	0	1
A5	1	1	1	0	0	0	1	1
A6	1	1	1	0	0	0	1	1
A7	1	1	1	0	1	0	1	1
A8	1	1	1	0	1	0	1	1
A9	1	0	0	0	0	0	1	0
A10	0	0	0	0	0	0	1	1

TPSM Resultant Scheduling scheme for LS4								
Appliance	Time Slot							
	T 1	T 2	T 3	T 4	T 5	T 6	T 7	T 8
A1	1	1	1	1	1	1	1	1
A2	1	1	1	1	1	1	1	1
A3	1	1	0	0	0	0	1	0
A4	1	1	0	0	0	0	0	1
A5	1	1	1	0	0	0	1	1
A6	1	1	1	0	0	0	1	1
A7	1	1	1	0	1	0	1	1
A8	1	1	1	0	1	0	1	1
A9	1	0	0	0	0	0	1	0
A10	0	0	0	0	0	0	1	1

1) Comparison of Appliances task completion

To evaluate the proposed method and its effectiveness, it is necessary to compare the results of proposed method other popular literature works. By utilizing the mathematical formulations via TPSM scheduling, the actual power consumed at each time slot is wisely calculated and compared with various algorithms as shown in Table VII. For comparison, the results of methods like SOPcol, LCsol, OPTsol, PRDsol and PSO are also considered and its data is presented in Table VII. It is worth mentioning here that the suitability of any of the methods is preferred only based on 100% task completion. From Table VII, it can be seen TPSM has achieved 100% task completion for LS1, LS2, LS3 and LS4 with a total power consumption 63KW, 57KW and 44.5KW respectively. Detailed discussion pertinent to Table VII is given in the following.

i. For LS1, except TPSM, all the methods has scheduled only 62KW as total power which is a notable conclusion in regard to the methods failing to attain 100% task completion.
ii. For LS2, TPSM has wisely allocated the load to make the home appliances to consume the optimal power of 57KW. However, SOPcol has consumed only 55KW while the remaining methods has consumed 52KW. This again gives the evidence of methods failing to achieve 100% task completion.
iii. On contrary to LS1 and LS2, all the methods in comparison has achieved 100% task completion except PRDsol.
iv. With respect to LS4, the power consumed by LS4 via TPSM is found 44.5KW whereas, the PSO and SOPcol methods has found to allocate excess load to produce 46KW as power consumption. However, LCSol, OPTSol and PRDSol methods has consumed only 44KW to match the accuracy of TPSM method.

Thus, on overall the mathematical intelligence in TPSM is experimented in all cases to prove its ability to schedule home appliance as per customer need. For clarity, the power consumed by appliances via TPSM in each slot pertinent to various load schedule given in Fig. 4.

TABLE VII
COMPARISON OF TOTAL POWER CONSUMED BY THE DIFFERENT SCHEDULING SCHEME

Time Slot	**Total power consumed by all appliances at jth time slot Equation (2) for LS1 in (kW)**					
	TPSM	**SOPCol**	**LCSol**	**OPTSol**	**PRDSol**	**PSO**
T1	11	5	5	9	5	5
T2	10	6	5	8	12	5
T3	8	8	6	6	8	6
T4	3	9	8	5	9	8
T5	6	8	8	8	6	9
T6	3	12	9	5	5	9
T7	12	5	9	12	8	12
T8	10	9	12	9	9	8
Total Power (kW) at day end	**63**	**62**	**62**	**62**	**62**	**62**
Time Slot	**Total power consumed by all appliances at jth time slot Equation (2) for LS2 in (kW)**					
	TPSM	**SOPCol**	**LCSol**	**OPTSol**	**PRDSol**	**PSO**
T1	3	7	2	4	2	7
T2	11	2	4	11	8	11
T3	3	11	5	2	7	8
T4	11	4	6	9	11	2
T5	10	9	7	6	4	6
T6	11	6	8	8	9	4
T7	3	8	9	5	5	9
T8	5	8	11	7	6	5
Total Power (kW) at day end	**57**	**55**	**52**	**52**	**52**	**52**

Time Slot	Total power consumed by all appliances at jth time slot Equation (2) for LS3 in (kW)					
	TPSM	**SOPCol**	**LCSol**	**OPTSol**	**PRDSol**	**PSO**
T1	6	7	3	5	3	7
T2	9	3	4	9	9	9
T3	3	6	5	5	6	5
T4	3	9	5	3	7	8
T5	3	8	6	4	4	4
T6	9	4	7	8	8	5
T7	9	5	8	7	5	6
T8	5	5	9	6	4	3
Total Power (kW) at day end	**47**	**47**	**47**	**47**	**46**	**47**
Time Slot	**Total power consumed by all appliances at jth time slot Equation (2) for LS4 in (kW) in (kW)**					
	TPSM	**SOPCol**	**LCSol**	**OPTSol**	**PRDSol**	**PSO**
T1	8	3	3	5	4	8
T2	3	8	4	3	3	7
T3	8	5	5	7	6	2
T4	3	7	5	4	8	6
T5	8	7	6	6	5	4
T6	3	6	6	5	5	8
T7	8	4	7	8	6	6
T8	3.5	6	8	6	7	5
Total Power (kW) at day end	**44.5**	**46**	**44**	**44**	**44**	**46**

2) Cost comparison

As performance analysis, the total consumption cost per day by different algorithms is calculated by using equation (7) and the obtained results are tabulated in Table VIII. For better understading, the cost corresponding to all the mthods are plotted in Fig.5. From the analysis, the consumption cost of TPSM is found comparatively lower than all other algorithms except in LS2. In this case, it is notable that cost of OPTSol and PRDSol is lesser as 272 cents and 287 cents since, the methods has not scheduled 100% task. Therefore, TPSM scheduling scheme is found profitable for the consumer compared to other methods available in comparison.

TABLE VIII
COST COMPARISON (LS1-LS4)

LS	**Cost in Cents**					
	TPSM	SOPCol	LCSol	OPTSol	PRDSol	PSO
LS1	**297**	360	335	304	328	327
LS2	**294**	365	308	272	287	318
LS3	**231**	297	269	242	255	263
LS4	**245**	301	267	253	268	287

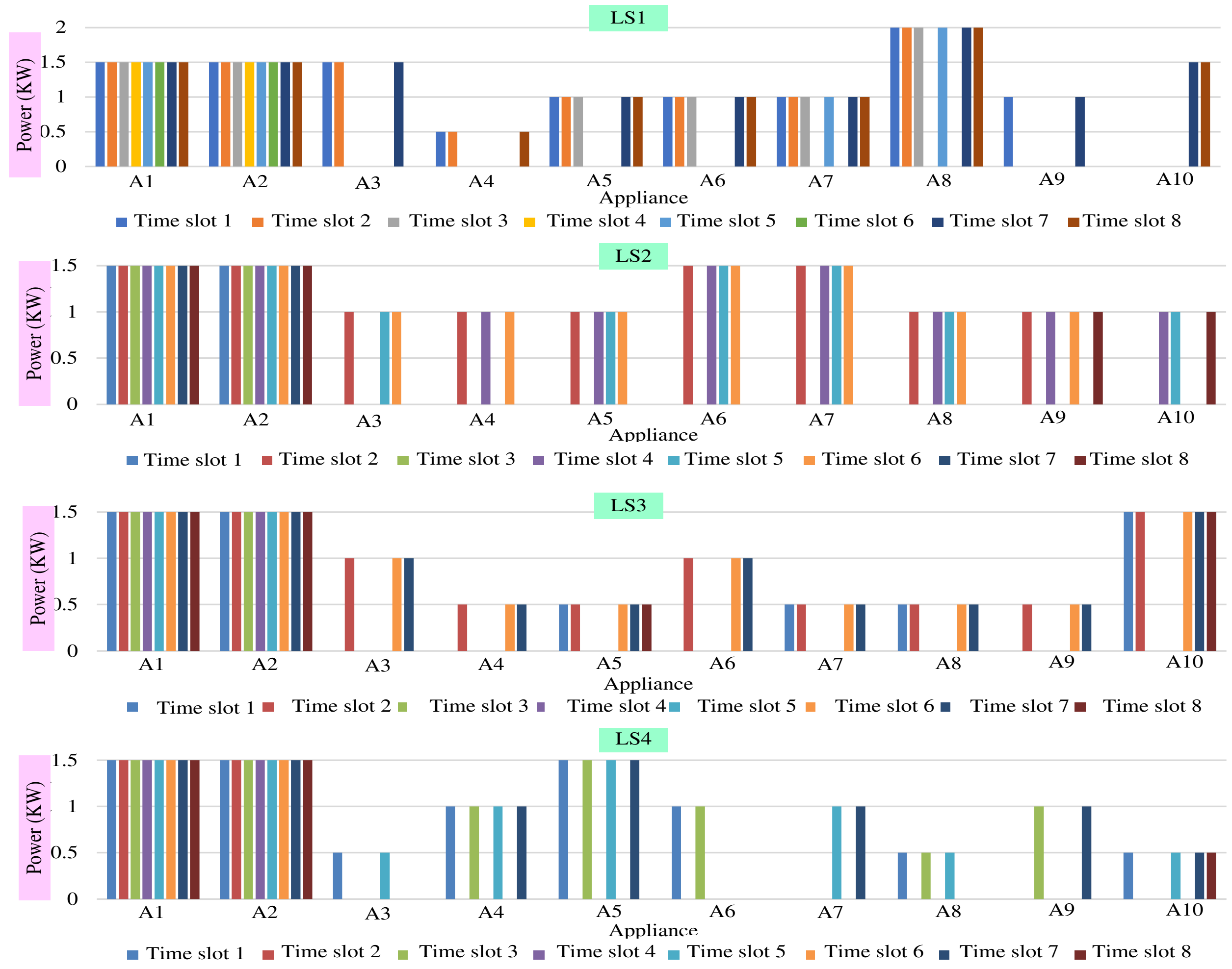

Figure 4. Appliances scheduling split-up (scheme) by TPSM for LS1-LS4

3) Response time comparison.

System response time is one of the important factors for HEM. So the response time of the proposed TPSM is compared with the existing algorithm and the results are tabulated in Table VI. The response time of the proposed TPSM is 0.047s, which is the lowest response time compared to any other algorithms in comparison. Note that the response time listed in Table IX is the time taken to find an optimum scheduling scheme by the algorithm. In practical application, the factors for response time include communication time, the distance between the central control system and appliances, the speed of the internet, ZigBee topology, etc.

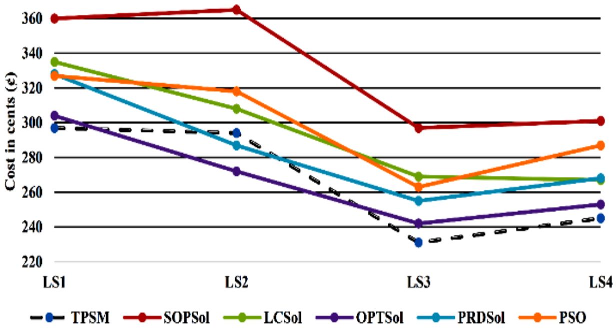

Figure 5. Cost comparison graph

TABLE IX
RESPONSE TIME COMPARISON (LS1-LS4)

Algorithm	Computational Time (s) for LS1
TPSM	0.047
SOPSol	0.534
LCSol	0.483
PRDSol	8.599
OPTSol	179
PSO	18.58

4) Peak demand and peak-to-average ratio reduction comparison

To experiment the ability of TPSM in handling peak demand and reduction in peak to average ratio, the case study of peak demand is performed by considered only TPSM and other existing algorithms for LS1. For better clarity, the peak demand reduction comparison of LS1 pertinent to TPSM ann other algorithms are shown in Fig. 6. In general, the cost of electricity is high during peak hours and low during off-peak hours. Therefore, the peak demand can be reduced by shifting the load from a high-cost time slot (peak hours) to low cost time (off-peak hours). To expalin the fact, the In Fig. 5, the time slots are arranged ascending order to cost. The T6 is the highest cost time slot and T7 is the lowest cost time slot. From the figure, it is seen that the load scheduled by TPSM is low at T6 and it's gradually increasing for consecutive time slots. Further, the highest demand is scheduled by TPSM is found at T7. The gradual increase in demand shows the effectiveness of proposed TPSM in reducing the peak demand and the peak-to-average ratio. On the other, it is crcial to point that several other algorithms in comparison are certainly faling to maintain the peak demand.

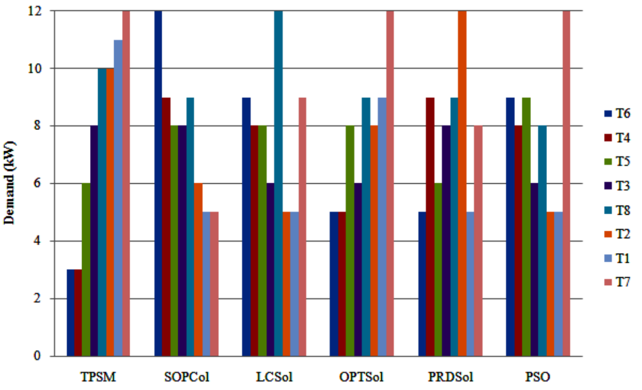

Figure 6. Peak demand reduction comparison for LS1.

VI. Conclusion

This research proposes a new TPSM based demand response program for residential customers (i) to reduce peak demand, (ii) to reduce the electricity consumption cost, (iii) to maintain consumer comfort, and (iv) to reduce the computational time. Further, detailed system model is experimented to implement the proposed TPSM in real-time. For experimentations, four different load scenarios are considered and the demand response program was found highly successful. The results of TPSM method has less consumption cost for load LS1, LS3, and LS4 in comparison with the existing methods. Meanwhile, only for LS2 the consumption cost by TPSM is negligibly higher than OPTSol and PRDSol. But then, the task completion of the methods is not up to 100%. On simulations, the response time of the proposed TPSM is 0.047 s, which is the lowest among all other algorithms. Based on exclusive numerical analysis, the proposed TPSM is highly effective to handle peak demand with better peak-to-average ratio. Further more, implementation of proposed TPSM scheme is also recommended for industrial energy management based on real-time implementation constraints.

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