Multi-class Appliance Scheduling for Cost-effective Energy Management with Constraint and User Preferences

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Abstract: For decades, the electrical power grid worldwide has transformed from traditional to the smart power grid, focusing on its transparency to both utility and consumer. The energy management systems play a substantial part in demand response within the smart power grid umbrella, enabling demand-side management at the residential level. These systems generate the consumption profile of appliances and reduce the burden on end-user in scheduling appliances operations. With these consumption profiles of past usage, there is a possibility to generate a time window containing user preferable time slots for appliance operation for the next day. Using this time window, one can generate a cost-effective schedule-pattern autonomously. In this regard, this article proposes a home energy-demand management scheme consisting of a time window generator and a schedule-pattern generator to generate a cost-effectively comfortable schedule-pattern with demand threshold constraint. Multi-class appliances home enabled with a net-meter demonstrate the proposed approach's effectiveness. The simulation results showcase that the proposed approach helps the user to save electricity bills with constraint preserving comfort.

Keywords: ANN, home energy management, multi-class appliance, net-meter, pattern-generation algorithm, user comfort.

1. Introduction

Energy management systems (EMS) find their suitability both at the grid and consumer side. The EMS at the grid side aims for efficient generation, transmission, and distribution, and at the consumer side aims for cost-effective planning, monitoring, and scheduling energy needs [1]. The demand-side, mostly the residential area, consumes a substantial portion of the power generated in contrast with commercial and industrial [2]. A smart power grid combined with demand response enables demand-side management in residential areas to balance the grid supply and consumer demand [3]. This balance avoids blackouts and brownouts during peak hours and also avoids underutilization of power during off-peak hours. The demand response in residential areas makes demand management possible, not only at the grid level via direct load control mechanism (in real-time) but also at the residence level via appliances scheduling (day-ahead) [4], [5], [6]. This appliance scheduling provides end-user/consumers with an opportunity to cost-effectively operate appliances under a dynamic pricing scheme via home energy management (HEM) systems. The cost-effective operation of appliances allows individuals to reduce electricity bill (EB) with full or no comfort by shifting the operation of appliances through scheduling algorithms [7], [8], [9], [10].

Scheduling appliances operations via algorithms have attracted significant attention in recent years enabling end-users to control appliances concerning time-varying electricity tariffs. The scheduling algorithms incorporate utility updates (day-ahead electricity tariff) with rooftop photovoltaic (PV) information and end-user preferences to plan home appliances operations [11], [12], [13]. The numerous models and algorithms for appliance scheduling, including variable tariffs and thresholds on power, draw from the grid with different pricing schemes or demand management approaches addressing either EB reduction or uncompromised user's comfort, are observed in the literature as discussed below.
In [9], the authors' proposed appliances scheduling using load shifting techniques to reduce EB. Such demand shifting techniques may discomfort the user due to operational delays. In [10], the authors presented a mathematically developed model to schedule appliances using a linear programming technique for EB reduction. In [11], the authors proposed the heating-ventilation-air-conditioning model for the HEM system using mixed-integer nonlinear programming to reduce EB. However, the model considers only EB minimization. In [12], the authors presented linear programming models for appliance scheduling to minimize EB. In [13], the authors designed a HEM system compromising user comfort for EB reduction via appliance scheduling. In [14], the authors defined the objectives and constraints functions mathematically to reduce EB. However, the function considers only EB minimization as an objective. In [15], the authors presented a scheduling algorithm to control an appliance's operational time and energy consumption using mixed-integer nonlinear programming for reducing EB. The authors in [9], [10], [11], [12], [13], [14], and [15] do not consider demand peaks and operational delays that may arise due to shifting demand at off-peak hours or during low tariff hours while reducing EB.

In [16], the authors proposed the HEM algorithm using a mathematical model of home appliances to minimize user discomfort and EB. In [17], the authors proposed a mathematical model of optimization using mixed-integer nonlinear programming and heuristic algorithms to minimize EB and discomfort. In [18], the authors presented the mathematical formulation of the objective function and algorithm for EB reduction with comfort, considering the limited number of appliances. In [19], the authors presented a flexible load control strategy to schedule appliances for reducing EB and discomfort. In [20], the authors proposed appliance scheduling under day-ahead pricing using integer linear programming to reduce EB comfort. In [21], the authors presented a decentralized HEM framework to minimize EB while preserving user preferences. In [22], the authors proposed appliance scheduling for HEM, including renewable energy sources using demand shifting techniques to reduced energy consumption, thereby reducing EB with user comforts. In [23], the authors proposed a bottom-up approach for HEM using smart plugs to reduced EB, maintaining user comfort. The authors in [16], [17], [18], [19], [20] [21], [22], and [23] do not consider demand peaks that may develop during EB reduction while preserving user comfort.

From the literature review, an observation is that the reported HEM schemes generate a day-ahead schedule pattern for appliances to reduce either EB by shifting appliance operation to a non-preferable hour, thereby compromising the end user's comfort. Some HEM schemes entirely prefer to address user comfort alone. In both cases, the schemes do not consider demand peaks that may raise while reducing EB with user comfort. Thus, our observation is that an area needs immediate addressing for cost-effective energy management with user comforts and demand threshold constraints via scheduling appliances operations. However, if past consumption profiles of appliances operations are available, a time window containing user preferable time slots for an appliance operation can be generated. The user or the utility can set a demand threshold or grid power draw constraint to maintain a demand below a level, thereby suppressing demand peaks without curtail. If the cost-effective schedule-pattern gets
generated from these windows autonomously, considering constraints, then cost-effective energy management with user comfort and constraint is possible. Therefore, this article proposes a HEM scheme consisting of a time window generator, a schedule-pattern generator, a demand threshold, and a grid power draw constraint to generate a cost-effectively comfortable schedule-pattern.

A home with multi-class appliances enabled with a net-meter and demand threshold constrained demonstrate the proposed approach's effectiveness. The simulation results showcase the proposed approach comparing the outcomes of full comfort schedule-pattern and cost-effectively comfortable schedule-pattern, thereby concluding EB's savings with comfort and constraint. In the rest of the article, section 2 presents an overview of the HEM system model. Section 3 formulates and defines both time window and schedule-pattern generation algorithms. The demonstration of simulation results is in Section 4. Section 5 concludes the proposed algorithms with the benefits of the user.

2. Home Energy Management System Model

This section presents a HEM scheme for a net-meter enabled home with entities like multi-class appliances demand, grid-tied rooftop PV power information, day-ahead electricity tariff from the utility, grid power constraint, and hourly demand threshold constraint, as shown in Fig. 1.

**Entity_1 - Multi-class appliances demand:**

From the literature review, we have predominantly observed that the reported HEM schemes consider two types of load: shiftable and non-shiftable to generate a day-ahead schedule-pattern for appliances operation. Some HEM schemes also assume interruptable and non-interruptible appliances to schedule it in real-time. Our approach is in line with the literature that generates a schedule pattern day-ahead of appliances operation. Therefore, this paper considers a set of multi-class appliances \( A \), classified into two broad categories, based on their demand-type shiftable and non-shiftable as \( \text{Class}_{\text{NA}} \) and \( \text{Class}_{\text{SA}} \), respectively, as shown in equation (1).

\[
A = \{ \text{Class}_{\text{NA}} \cup \text{Class}_{\text{SA}} \} \tag{1}
\]

These appliances are operated at their defined time slots or at an appropriate time slot based on their type. The \( \text{Class}_{\text{SA}} \) appliances get operated at an appropriate time slot of the day, whereas \( \text{Class}_{\text{NA}} \) appliances get operated at user-defined time slots. However, some shiftable appliances get operated one-time in a day (such as kettle, iron, water heater, vacuum cleaner, and well pump), two times in a day (such as rice cooker and electric stove) and one-time for continuous two hours in a day (such as washing machine).

Therefore, \( \text{Class}_{\text{SA}} \) appliances are categorized further into three types as \( \text{Class}_{\text{SO}}, \text{Class}_{\text{ST}} \) and \( \text{Class}_{\text{SC}} \), based on their possibility of being operated once, twice, and once for continuous two hours a day, respectively, as indicated in equation (2).

\[
\text{Class}_{\text{SA}} = \{ \text{Class}_{\text{SO}} \cup \text{Class}_{\text{ST}} \cup \text{Class}_{\text{SC}} \} \tag{2}
\]
The energy-demand analysis for a day (24-hour) is a resolution of one hour as a one-time slot, assuming each hourly slot is 60 minutes. The shortest operational length of an appliance is assumed to be 1 minute. Accordingly, any appliance's operational length should be a multiple of 1 minute that extents from 1 minute to 60 minutes (one hour), or 1 minute to 120 minutes (two hours). Simultaneously, there are possibilities with an actual operational length, which is less than an hour, but in multiples of 1 minute. The proposed approach assumes that the appliance's demand for this kind of operational length exists for an entire hour and should schedule the appliance operation at an appropriate hourly time-slot.

For an appliance \( a \), the assumption is that the demand remains constant during its operation. When the rating of an appliance is \( R_a \), then the demand \( D_a \) per its operational length \( n_a \) is as shown in equation (3).

\[
D_a = \frac{R_a}{60} \ast n_a \quad \forall a \in \{A\}
\]

\[ (3) \]

**Entity_2 - Grid-tied rooftop PV power information:**

A grid-connected rooftop PV is assumed in this article, as a local source of uninterruptable renewable energy, to be available for appliance operation. The \( PV_{day,gen} \) is considered as the summation of \( PV_{h,gen} \), as shown in equation (4).

\[
PV_{day, gen} = \sum_{h=1}^{24} PV_{h, gen}
\]

\[ (4) \]

Assuming an intermittent nature of PV, this paper considers the net-meter features to alleviate the uncertainty of rooftop PVs output power at the residence level. Furthermore, this paper also assumes that the PV installation capacity depends on the user's choice.

**Entity_3 - Day-ahead electricity tariff form utility:**

However, this article assumes that a house's demand cannot be managed all alone with rooftop PV. Therefore, there is a seamless grid power every hour of the day \( GP_h \). The day-ahead hourly tariff information \( T_h \), from the utility, for the grid power is as shown in equation (5).

\[
Tariff = \{T_1, T_2, \ldots, T_{24}\}
\]

\[ (5) \]

The HEM utilizes suitable low tariff hours of the equation (5) to reduce EB.

**Entity_4 - Grid power constraint:**

Operating appliances during low tariff hours can cause demand peaks not appropriate for the grid. Thus, the article considers a constraint on power drawn from the grid to reduce such peaks. An assumption in this article is that the utility limits the user from drawing the grid power based on their rooftop PV installation capacity in such a way that the grid power, drawn, should always be less than or equal to installed \( PV_{peak} \), as listed in equation (6).

\[
GP_h \leq PV_{peak} \quad \forall h \in [1, 2, 3, \ldots, 24]
\]

\[ (6) \]
This consideration enables the utility to be aware of the power requirement that may arise due to the intermittent nature of PV and ensures grid power availability as a standby to avoid demand curtailments.

**Entity 5 - Hourly demand threshold constraint:**

An assumption in this paper is that the demand threshold should be so that even if all non-shiftable appliances operate simultaneously during a particular time slot, they should not get curtailed. Furthermore, the demand threshold should be within grid power limits.

Hence, considering equation (6), $D_{h,threshold}$ is assumed as shown in equation (7),

$$D_{h,threshold} \leq GP_h$$

(7)

The demand threshold is a limit set by the user on the appliance's demand during a time slot due to operation, whereas the grid power is the hourly power available from the grid to the user. To distribute the demand uniformly throughout the day, thereby to reduce demand peaks, equation (6) and equation (7) attempts to limit users from drawing grid power and, in turn, encouraging them towards utilizing renewable energy (PV), thereby benefiting society concerning carbon footprints.

The utility decides the grid power to be drawn by the user and communicates to the HEM day-ahead, which helps users to keep the demand below a threshold, thereby preventing rebound peaks for grid stability. This threshold might delay or curtain specific appliance operation to prevent demand peaks, thereby discomforting users. Hence the users can minimize this trade-off between personal comfort and grid reliability through proper PV installation, taking into account equation (6) and equation (7).

3. **An algorithmic approach for generating cost-effective schedule-pattern with user preferences**

This section defines the user preferred time window generator and schedule-pattern generation algorithms.

3.1 **User preferred time window**

From literature, an observation is that there is a possibility to generate a user-preferred time window using a classifier [24]. The classifier chooses the most preferred time slot by the user over some days and finally considers it a user-preferred time slot—a group of such user-preferred time slots for appliance results in a time window for an appliance.

For example, if a user operates an appliance, say an electric heater, for the first 20 days of the month at 5 am and operates the same for the last 10 days of the month at 6 am, then the classifier considers the user preferred time slots for an electric heater as 5 am and 6 am thereby generating a time window with time slots 5 am and 6 am considering 5 am as the full-comfort time slot. However, concerning the last 10 days of the month's user preference, the full-comfort time slot should be 6 am because the user might have changed his preference for operating the appliance from the 5 am time slot to 6 am. Thus classifier lacks generating the full-comfort time slots considering the recently preferred time slots by the user. In this regard, this article considers an artificial
neural network (ANN) technique based time window generator that generates the user preferred time slots considering the recently used time slots to identify full-comfort time slots.

### 3.1.1 An ANN technique for generating a time window:

The ANN network receives the input signals and then multiplies it with the corresponding weights. A linear combiner output is generated by summing up all the weighted inputs, as shown in equation (8).

\[
\text{Linear combiner output} = \sum_{i=1}^{n} [\text{input}_i \times \text{weight}_i] \tag{8}
\]

To generate the time window past 30 days of consumption profiles containing the ON and OFF states of appliances at particular time slots are taken into consideration. The state of an appliance \(a\), as shown in equation (9) at a particular time slot, for a particular day is considered as inputs to the ANN.

\[
\text{App}_{\text{state}}_{TS,d} = \begin{cases} 
0; & \text{OFF State} \\
1; & \text{ON State}
\end{cases} \tag{9}
\]

The weights of the ANN network are arbitrarily selected, as shown in equation (10).

\[
W_d = \frac{d}{100} \tag{10}
\]

Therefore considering the inputs from equation (9) and weights from equation (10), the weighted input of the ANN is, as shown in equation (11).

\[
\text{weighted } \text{input}_{TS,d} = \text{App}_{\text{state}}_{TS,d} \times W_d \tag{11}
\]

Concerning equation (8), equation (9), equation (10), and equation (11), the linear combiner output of ANN is as shown in equation (12).

\[
\text{Linear combiner output} = \sum_{d=1}^{30} \left[ \text{weighted } \text{input}_{TS,d} \right] \tag{12}
\]

If linear combiner output at a particular time slot \(TS\) is non-zero, then \(TS\) is the preferred time slot by the user for an appliance operation. On the other hand, if the output is zero, then \(TS\) is considered as a non-preferred time slot by the user for an appliance operation. A particular time slot with the highest linear combiner output value is the highest priority time slot, also known as a full-comfort time slot in this article.

### 3.1.2 An algorithmic approach for generating a time window using the ANN technique:

The time window generator provides the flexibility to generate user preferred time slots ahead of scheduling appliances' operation considering equation (8), equation (9), equation (10), equation (11), and equation (12), as discussed in algorithm 1.
Algorithm 1: Time window generation algorithm

Input: $\text{App\_state}_{TS,d}, \text{weighted\_input}_{TS,d}$.
Output: $\text{PTW}_a$.
1. Initialize $\text{PTW}_a = \{\};$ ///* Empty time window*/
2. for each appliance $a$ in a set of appliances $A$
3. for each time slot $TS$ from 1 to 24:
4. Sum = 0
5. for each day $d$ from 1 to 30:
6. Calculate input $\text{App\_state}_{TS,d}$ using equation (9)
7. Calculate the weight $W_d$ using equation (10)
8. Calculate the weighted input $\text{weighted\_input}_{TS,d}$ using equation (11)
9. Sum = Sum + weighted input
10. if: Sum = 0 then $TS$ is user preferred time slot
11. Include $TS$ in time window $\text{PTW}_a$ as a user-preferred time slot for an appliance $a$
12. The time window for all appliances.

The generated time window containing these preferred time slots is termed as the preferred time window for an appliance $a$, as shown in equation (13), and discussed in algorithm 1.

$$\text{PTW}_a = \{TS_1, TS_2, ..., TS_{24}\} \quad (13)$$

An appliance gets operated with user ease during an appropriate time slot within this generated time window. For $\text{Class}_{\text{NA}}$ appliances, the time window contains a list of must run time slots, whereas, for $\text{Class}_{\text{SA}}$ appliances, it contains the range of optional operational time slots.

3.2 Cost-effective schedule-pattern generation algorithms

This section defines the pattern-generation algorithms considering entity_1, entity_2, entity_3, entity_4, entity_5, and generated user preferred time window. In this algorithmic approach, an assumption is that initially $GP_{h,\text{avai}}$ is equal to $GP_h$, and $PV_{h,\text{avai}}$ is equal to $PV_{h,\text{gen}}$.

3.2.1 The scheduling-pattern generation algorithm for $\text{Class}_{\text{NA}}$ appliances:

The demand $D_a$ is calculated using equation (3) for an appliance, $a \in \text{Class}_{\text{NA}}$. However, it is assumed that $D_a$ is non-shiftable and remains constant, existing for all time slots of $\text{PTW}_a$ defined by the user.

The $\text{Class}_{\text{NA}}$ appliances get scheduled for their operation to their respective defined time slots that belong to $\text{PTW}_a$, as discussed in Algorithm 2.

Algorithm 2: $\text{Class}_{\text{NA}}$ appliances schedule-pattern generation algorithm

Input: $D_a, \text{PTW}_a, PV_{h,\text{gen}}, GP_h, D_{h,\text{threshold}}$.
Output: $D_{h,\text{NA}}$.
1. Initialize $D_{h,\text{total}} = 0, D_{h,\text{NA}} = 0, PV_{h,\text{avai}} = PV_{h,\text{gen}}, PV_{h,\text{avai}} = PV_{h,\text{gen}}$;
2. for each appliance $a \in \text{Class}_{\text{NA}}$
   ///Step (3)-(5), identifying an operational time-slot for an appliance operation with demand $D_a$///
3. for: $(h = 1; h \leq 24; h++)$
4. if: $h \in \text{PTW}_a$ and $D_{h,\text{total}} + D_a \leq D_{h,\text{threshold}}$ then
5. $h$ is an operational time-slot for an appliance $a$
6. if: $D_a \leq PV_{h,\text{avai}}$ then
   ///Step (7), updates PV available power///
7. $PV_{h,\text{avai}} = PV_{h,\text{avai}} - D_a$;
8. 
else:
   ///Step (9), updates available grid power\\/
9. \( GP_{h,avail} = GP_{h,avail} - D_a \)
   ///Steps (10), updates ClassNA and total, hourly demand\\/
10. \( D_{h,NA} = D_{h,NA} + D_{h,total}, D_{h,total} = D_{h,total} + D_{h,NA} \).
11. Schedule-pattern for ClassSA appliances operation.

After generating the schedule-pattern for ClassNA, the ClassSA appliances are arranged in order, priority wise and class-wise (ClassSO, ClassST, and ClassSC), as discussed in Algorithm 3.

After sorting, the ClassSA appliances, their schedule-pattern is generated, as per arranged order, one after the other sequentially as discussed below. The proposed schedule-pattern generation algorithms for shiftable appliances check all appropriate time-slots with sufficient PV energy to meet the demand or low tariffs. Accordingly, it schedules the appliance’s operation at a suitable time slot, with minimum tariff or maximum renewable energy utilization.

**Algorithm 3: ClassSA appliances sorting algorithm**

**Input**: \( D_a, PTW_a \)

**Output**: Sorted Appliances.

///Step (2)-(4), sorts ClassSO appliances ///
1. for appliances \( \text{\epsilon ClassSO} \)
2. Assign the highest priority to an appliance with less number of time slots in \( PTW_a \) and with the lengthiest demand.
3. Sort the appliances based on priority from high to low.

///Step (5)-(7), sorts ClassST appliances ///
4. for appliances \( \text{\epsilon ClassST} \)
5. Assign the highest priority to an appliance with less number of time slots in \( PTW_a \) and lengthiest demand.
6. Sort the appliances based on priority from high to low.

///Step (8)-(10), sorts ClassSC appliances ///
7. for appliances \( \text{\epsilon ClassSC} \)
8. Assign the highest priority to an appliance with less number of time slots in \( PTW_a \) and lengthiest demand.
9. Sort the appliances based on priority from high to low.
10. Appliances sorted for scheduling.

The PV appropriate hour is a suitable time slot within \( PTW_a \) with sufficient minimum PV power to accommodate the demand of an appliance \( a \), during its operation, as shown in equation (14).

\[
PV_{mn} = \min \{ PV_{h,gen} | h \in PTW_a \}
\] (14)

The idea behind the definition of PV appropriate time slots is to maximize the utilization of available renewable energy by accommodating the demand of an appliance within the available energy at a specific time slot and allowing greater demands to use other higher energy time slots. The concept provides an opportunity to utilize renewable energy to its maximum and allows the end-user to maximize EB savings.

Similarly, the appropriate utility hour is a time slot within \( PTW_a \), as shown in equation (15), which has minimum tariff and grid power, enough to meet an appliance’s demand during its operation.

\[
T_{mn} = \min \{ T_h | h \in PTW_a \}
\] (15)

The schedule-pattern generation for non-shiftable appliances considering scheduling appliances operations independently or
simultaneously is the same. Whereas for shiftable appliances, scheduling appliances simultaneously through optimization techniques help us to reduce EB with user comforts, but at the same time, it may draw power from girds during hours with low tariffs and sell the PV power during hours with high tariffs. The proposed scheme’s motivation is to drive the end-user to utilize renewable for the benefits of the user, grid, and society. Concerning this, we proceeded with the schedule-pattern generation for shiftable appliances independently, thereby achieving a reduction in EB with user comfort drawing less power from the grid.

3.2.2 The schedule-pattern generation algorithm for ClassSO appliances:

For scheduling the operation of an appliance, \( a \in \text{Class}_{SO} \), operated ones a day, its demand \( D_a \) is calculated using equation (3). Based on this \( D_a \), the pattern generation algorithm schedules the appliance operation at an appropriate hour of PV or utility, represented in equation (14) and equation (15).

Likewise, \( \text{Class}_{SO} \) appliances operations are scheduled subsequently with user preferences, as discussed in Algorithm 4.

Algorithm 4: ClassSO appliances schedule-pattern generation algorithm

| Input | \( D_a, \text{PTW}_a, PV_{h,gen}, GP_h, D_{h,threshold}, PV_{h,avail}, GP_{h,avail}, PV_{mn}, T_h, T_{mn}, D_{h,NA}, D_{h,SO} \) |
|-------|---------------------------------------------------------------|
| Output| \( D_{h,SO} \). |

1. Initialize \( D_{h,SO} = D_{h,NA}, D_{h,SO} = 0 \);
2. for each appliance \( a \in \text{Class}_{SO} \)
   ///Step (3)-(6) identifying an appropriate time slot of PV for an appliance operation///
   3. for: \( h = 1; h \leq 24; h++ \)
      4. if: \( h \in \text{PTW}_a \) and \( D_{h,total} + D_a \leq D_{h,threshold} \) then
      5. if: \( D_a \leq PV_{h,avail} \) and \( PV_{h,avail} = PV_{mn} \) then
      6. \( h \) is an operational time-slot for an appliance \( a \);
   ///Step (7), updates PV available power///
   7. \( PV_{h,avail} = PV_{h,avail} - D_a; \) goto step 13;
   ///Step (8)-(11) identifying an appropriate time slot of utility tariff for an appliance operation ///
   8. for: \( h = 1; h \leq 24; h++ \)
      9. if: \( h \in \text{PTW}_a \) and \( D_{h,total} + D_a \leq D_{h,threshold} \) then
     10. if: \( D_a \leq GP_{h,avail} \) and \( T_h = T_{mn} \) then
     11. \( h \) is an operational time-slot for an appliance \( a \);
   ///Step (15) updates available grid power///
   12. \( GP_{h,avail} = GP_{h,avail} - D_a; \)
   ///Steps (13)-(14), updates ClassSO and total, hourly demand///
   13. \( D_{h,SO} = D_{h,SO} + D_a; \)
   14. \( D_{h,total} = D_{h,total} + D_{h,SO}; \)
   15. goto step 2 for next appliance;
16. Schedule-pattern for ClassSO appliances operation.

After generating the schedule-pattern for ClassSO appliances, ClassST appliances schedule-pattern gets generated (using Algorithm 5) concerning the updated, available PV and grid power (from Algorithm 4).

3.2.3 The schedule-pattern generation algorithm for ClassST appliances:

For scheduling the operation of an appliance, \( a \in \text{Class}_{ST} \) operated twice a day, its demand \( D_a \), is calculated using equation (3), assuming that this appliance is operated two times a day at different time slots with the same operational length. Based on this demand \( D_a \), the appliance gets scheduled for two turns of operation (first turn and then the second turn) subsequently to appropriate time slots, as discussed in Algorithm 5.
Algorithm 5: ClassST appliances schedule-pattern generation algorithm

Input: \( D_o \), \( PTW_o \), \( PV_{h, gen} \), \( GP_o \), \( D_h, \text{threshold} \), \( PV_{h, \text{avail}} \), \( GP_{h, \text{avail}} \), \( PV_{mn} \), \( T_h \), \( T_mn \), \( D_h, \text{NA} \), \( D_h, \text{SO} \), \( D_h, \text{total} \).

Output: \( D_h, \text{ST} \).
1. Initialize \( D_h, \text{total} = D_h, \text{NA} + D_h, \text{SO} \); \( D_h, \text{ST} = 0 \);
2. for each appliance \( a \in \text{ClassST} \)
   3. for each turn of an appliance \( a \)
      /////Step (4)-(7) identifying an appropriate time slot of PV for an appliance operation /////
      4. for: \((h = 1; h \leq 24; h++)\)
         5. if: \( h \in PTW \) and \( D_h, \text{total} + D_a \leq D_h, \text{threshold} \)
         6. if: \( D_a \leq PV_{h, \text{avail}} \) and \( PV_{h, \text{avail}} = PV_{mn} \)
         7. \( h \) is an operational time-slot for an appliance \( a \);
      /////Step (8), updates PV available power/////
      8. \( PV_{h, \text{avail}} = PV_{h, \text{avail}} - D_a \); 
      goto 14;
      /////Step (9)-(12) identifying an appropriate time slot of utility tariff for an appliance operation /////
      9. for: \((h = 1; h \leq 24; h++)\)
         10. if: \( h \in PTW \) and \( D_h, \text{total} + D_a \leq D_h, \text{threshold} \)
         11. if: \( D_a \leq GP_{h, \text{avail}} \) and \( GP_{h, \text{avail}} = PV_{mn} \)
         12. \( h \) is an operational time-slot for an appliance \( a \);
      /////Step (13) updates available grid power/////
      13. \( GP_{h, \text{avail}} = GP_{h, \text{avail}} - D_a \);
      /////Steps (14)-(15), updates ClassST and total, hourly demand/////
      14. \( D_h, \text{ST} = D_h, \text{ST} + D_h, a \);
      15. \( D_h, \text{total} = D_h, \text{total} + D_h, \text{ST} \);
      16. goto step 3 for the next turn;
17. Schedule-pattern for ClassST appliances operation.

Likewise, ClassST appliances operations are scheduled subsequently for each turn, as discussed in Algorithm 5.

After generating the schedule-pattern for ClassST appliances, ClassSC appliances schedule-pattern gets generated (using Algorithm 6) concerning the updated, available PV, and grid power (from Algorithm 5).

3.2.4 The schedule-pattern generation algorithm for ClassSC appliances:

Appliances in this classification are non-preemptive in operations, and their total operation gets scheduled as a whole during two suitable continuous time slots where there exists sufficient PV power or low tariffs. In a case where there does not exist sufficient PV or low tariffs for two consecutive time slots, then the combination of suitable time slots of PV and grid should be preferred. For scheduling the operation of such appliance, \( a \in \text{ClassSC} \) operated ones a day for continuous two hours (between 60 and 120 minutes), its demand \( D_a \) is calculated using equation (3). Since we have assumed energy demand management using hourly time slots of 60 minutes each, \( D_a \) segregated into demands \( D_{a,1} \) and \( D_{a,2} \) for first and second, 60 minutes, respectively, as shown in equation (16).

\[
D_a = D_{a,1} + D_{a,2} \forall a \in \text{ClassSC}
\]  

Based on the demands \( D_{a,1} \) and \( D_{a,2} \) the appliance operation is scheduled, at appropriate hours of PV or utility or combination of both, as discussed in Algorithm 6.

Algorithm 6: ClassSC appliances schedule-pattern generation algorithm

Input: \( D_o \), \( PTW_o \), \( PV_{h, gen} \), \( GP_o \), \( D_h, \text{threshold} \), \( PV_{h, \text{avail}} \), \( GP_{h, \text{avail}} \), \( PV_{mn} \), \( T_h \), \( T_mn \), \( D_h, \text{NA} \), \( D_h, \text{SO} \), \( D_h, \text{total} \).

Output: \( D_h, \text{SC} \).
1. Initialize \( D_h, \text{total} = D_h, \text{NA} + D_h, \text{SO} + D_h, \text{ST}; \)
2. for each appliance \( a \in \text{ClassSC} \)
/*Step (3)-(6) identifying an appropriate time slot of PV for an appliance operation //*/
3. for: (h = 1; h ≤ 24; h++) and if: h, h+1 ∈ PTWa
4. if: Subroutine_a and Subroutine_b then
5.  if: Subroutine_c and Subroutine_d then
6.  if: PVh,avail = = PVmin then h, h+1 are consecutive operational time-slots for an appliance a;
/*Step (7), updates PV available power//*/
7.  do Subroutine_1 and Subroutine_2; then goto step (34);
/*Step (9)-(12) identifying an appropriate time slot of PV for an appliance operation //*/
8. for: (h = 1; h ≤ 24; h++) and if: h, h+1 ∈ PTWa
9. if: Subroutine_a and Subroutine_b then
10. if: Subroutine_c and Subroutine_d then
/*Step (7), updates PV available power//*/
11. if: PVh+1,avail = = PVmin then h, h+1 are consecutive operational time-slots for an appliance a;
12. do Subroutine_1 and Subroutine_2; then goto step (34);
/*Step (15)-(18) identifying an appropriate time slot of PV for an appliance operation //*/
13. for: (h = 1; h ≤ 24; h++) and if: h, h+1 ∈ PTWa
14. if: Subroutine_a and Subroutine_b then
15. if: Subroutine_c and Subroutine_d then
16. if: PVh,avail = = PVmin then h, h+1 are consecutive operational time-slots for an appliance a;
/*Step (19), updates PV and grid available power//*/
17. do Subroutine_1 and Subroutine_4; then goto step (34);
/*Step (21)-(24) identifying an appropriate time slot of PV for an appliance operation //*/
18. for: (h = 1; h ≤ 24; h++) and if: h, h+1 ∈ PTWa
19. if: Subroutine_a and Subroutine_b then
20. if: Subroutine_e and Subroutine_d then
21. if: PVh+1,avail = = PVmin then h, h+1 are consecutive operational time-slots for an appliance a;
/*Step (25), updates grid and PV available power//*/
22. do Subroutine_3 and Subroutine_2; then goto step (34);
/*Step (27)-(30) identifying an appropriate time slot of utility tariff for an appliance operation //*/
23. for: (h = 1; h ≤ 24; h++) and if: h, h+1 ∈ PTWa
24. if: Subroutine_a and Subroutine_b then
25. if: Subroutine_e and Subroutine_d then
26. if: Th = = Tmin then h, h+1 are consecutive operational time-slots for an appliance a;
/*Step (31), updates grid available power//*/
27. do Subroutine_3 and Subroutine_4; then goto step (34);
/*Step (33)-(36) identifying an appropriate time slot of utility tariff for an appliance operation //*/
28. for: (h = 1; h ≤ 24; h++) and if: h, h+1 ∈ PTWa
29. if: Subroutine_a and Subroutine_b then
30. if: Subroutine_e and Subroutine_d then
31. if: Th+1 = = Tmin then h, h+1 are consecutive operational time-slots for an appliance a;
/*Step (31), updates grid available power//*/
32. do Subroutine_3 and Subroutine_4; then goto step (34);
33. if: operation of an appliance a is scheduled then
/*Steps (40)-(43), updates ClassSC and total, hourly demand//*/
34. Dh,ClassSC = Dh,ClassSC + Dα₁;
35. Dh+1,ClassSC = Dh+1,ClassSC + Dα₂;
36. Dh,total = Dh,total + Dh,ClassSC;
37. Dh+1,total = Dh+1,total + Dh+1,ClassSC;
38. Schedule-pattern for ClassSC appliances operation.

Subroutine_a: Dh,total + Dα₁ ≤ Dh,threshold;
Subroutine_b: Dh+1,total + Dα₂ ≤ Dh+1,threshold;
Subroutine_c: Dα₁ ≤ PVh,avail;
Subroutine_d: Dα₂ ≤ PVh+1,avail;
Subroutine_e: Dα₁ ≤ GP,h,avail;
Subroutine_f: Dα₂ ≤ GP,h+1,avail;
Subroutine_1: PV,h,avail = PV,h,avail - Dα₁;
Subroutine_2: PV,h+1,avail = PV,h+1,avail - Dα₂;
Subroutine_3: GP,h,avail = GP,h,avail - Dα₁;
Subroutine_4: GP,h+1,avail = GP,h+1,avail - Dα₂;
An assumption for such a class of appliance is that its operational length varies from more than 60 minutes to less than or equal to 120 minutes (i.e., $60 < n_a \leq 120$ minutes). From the literature, an observation is that most of the appliances’ operational length does not exceed 120 minutes [25]. For example, the washing machine operates for 90 minutes, and since energy demand management in this article is hourly, 90 minutes split into 60 minutes and 30 minutes. The demand for the first 60 minutes, and then for 30 minutes, is calculated, and then the appliance operations are scheduled for two consecutive hourly time slots. Therefore the authors assume that demand for such an appliance exists for two continuous hours (between 0 and 120 minutes).

Likewise, $Class_{SC}$ appliances operations are scheduled subsequently with user comfort, as discussed in Algorithm 6.

The HEM scheme defined via Algorithm 1, Algorithm 2, Algorithm 3, Algorithm 4, Algorithm 5 and Algorithm 6, can be summarized as, for a given set of multi-class appliances, past consumption data, demand threshold and grid-power draw constraint, PV and utility information day-ahead, the algorithms find appropriate time slots to schedule appliances for next-day operations for cost-effective energy-operations of appliances with comforts and constraint.

4. Simulation Results and Discussions

This section discusses simulation results using proposed algorithms by assuming $Class_{NA}$ and $Class_{SA}$ appliances, as listed in Table 1. Table 2 lists $Class_{NA}$ appliances, and Table 3, Table 4, and Table 5 list $Class_{SA}$ appliances with their operational length $n_a$ in minutes, generated preferred time window, and demand during operation. An assumption is that Table 3, Table 4, and Table 5 list appliances as per priority, i.e., the appliance with a smaller time window and lengthiest demand at the top of the list, and vice versa using Algorithm 3.

The user defines the operational length of an appliance, and the time window generator defines the preferred time slots for an appliance, respectively, as listed in Table 2, Table 3, and Table 4. For $Class_{NA}$ appliances, the preferred time slots are must run hours, whereas, for $Class_{SA}$ appliances, they are optional operating hours. The operational length defines the number of minutes that an appliance must run during its turn of operation.

For simplicity, we divided each time slot into 60 minutes, and the minimum operational length of an appliance is 1 minute. Also, for the demonstration of the proposed approach, an assumption is that the PV capacity, demand threshold, and grid power limit values are 1.5 kW (peak), 1.5 kWh, and 1.5 kWh, respectively, satisfying the equation (6) and equation (7). However, the PV capacity, demand threshold, and grid power limit values can be varied based on the user’s willingness, considering equation (6) and equation (7). The article assumes a dynamic electricity tariff from [26].

4.1 Scheduling appliances operations using the proposed algorithmic approach

The proposed algorithmic approach schedules $Class_{NA}$ appliances operations to their preferred time slots, as stated in Algorithm 2; and $Class_{SA}$ appliances operations to appropriate time slots, as stated in Algorithm 4 to Algorithm 6.
4.1.1 Scheduling ClassNA appliances operations

For scheduling ClassNA appliances, the demand $D_a$ for an appliance $a$, is calculated using equation (3), and listed in Table 2. Using Algorithm 2, all theses ClassNA appliances operations are scheduled sequentially to their respective, user-defined preferred time slots, as shown in Fig. 2.

4.1.2 Scheduling ClassSA appliances operations

For scheduling ClassSA appliances operations, the demand $D_a$ is calculated using equation (3) for each appliance $a \in$ ClassSA and tabulated in Table 3, Table 4, and Table 5. Algorithm 4, Algorithm 5, and Algorithm 6 scheduled all these ClassSA appliances operations to their respective appropriate hours of either PV or utility, respectively, as shown in Fig. 3, Fig. 4 and Fig. 5.

As discussed in the proposed approach, the appliances listed in Table 2, Table 3, Table 4 and Table 5 are scheduled as per user preferences, as shown in Fig. 6.

4.2 Demonstration of the effectiveness of the proposed HEM scheme

The HEM approach proposed in this article is an analytical method to minimize EB with an hourly demand threshold, including user comfort.

4.2.1 Demonstrating the effectiveness of ANN-based time window generation technique

We considered full-comfort based time slots for demonstrating the effectiveness of the time window generator. Full-comfort time slots are the highest priority time slots from the generated time window. We have compared the proposed ANN technique based generated full-comfort time slots with a classifier technique based generated full-comfort time slots as listed in Table 6.

In a full-comfort scenario, the user operates appliances with 100% comfort and no operational delay, calculated using equation (17) and equation (18).

$$\text{Operational delay} = \left\lceil \left(\text{Comfortable hour}\right) - \left(\text{Scheduled hour}\right) \right\rceil$$  \hspace{1cm} (17)

$$\text{Percentage of comfort} = \left(\frac{24 - \text{Operational delay}}{24}\right) \times 100$$  \hspace{1cm} (18)

An observation from the comparison is that there is an operational delay of 0 to 4 hours with a comfort ranging between 83.33% to 100 % for the classifier based full-comfort time slots concerning ANN-based full-comfort time slots. This discomfort is because the classifier considers the most preferred time slot as a user-preferred time slot, and ANN considers the recently used time slots over some recent days as user preferred time slots. However, comfort should always be 100% with no operational delay when it comes to full-comfort. In this regard, the ANN-based time window generation technique overrules the classifier based time window generation technique.

4.2.2 Demonstrating the effectiveness of proposed cost-effective schedule-pattern generation algorithms

We considered the scheduling of appliances operations with a full-comfort scenario and a cost-effective scenario for
demonstrating the proposed schedule-pattern generation algorithms’ effectiveness. In a full-comfort scenario, the user prefers full-comfort time slots only to schedule appliances operations with 100% comfort and no constraints. In a cost-effective scenario, the user prefers to schedule appliances with a certain comfort level considering constraints.

Figure 7 presents these scenarios considering scheduled appliances’ operational demand for full-comfort time slots generated by the classifier and ANN technique and the cost-effective schedule-pattern generated using time window by the schedule-pattern generation algorithms. The presented scenarios are assessed for a day on different parameters as listed in Table 7 calculated using equation (19), equation (20), equation (21), equation (22), equation (23), equation (24), equation (25), equation (26), equation (27), and equation (28).

\[
Total \ demand = \sum_{h=1}^{24} \left( D_{h,NA} + D_{h,SA} \right)
\]  \hspace{1cm} (19)

Where \( D_{h,SA} = D_{h,SO} + D_{h,ST} + D_{h,SC} \)

\[
Total \ PV \ generated = \sum_{h=1}^{24} PV_{h,gen}
\]  \hspace{1cm} (20)

\[
Total \ PV \ power \ used = \sum_{h=1}^{24} \left( PV_h - PV_{h,avail} \right)
\]  \hspace{1cm} (21)

\[
Total \ grid \ power \ drawn = \sum_{h=1}^{24} \left( GP_h - GP_{h,avail} \right)
\]  \hspace{1cm} (22)

\[
Total \ electricity \ buy \ bill = \sum_{h=1}^{24} \left[ \left( GP_h - GP_{h,avail} \right) * T_h \right]
\]  \hspace{1cm} (23)

\[
Total \ electricity \ sell \ bill = \sum_{h=1}^{24} \left[ \left( PV_{h,avail} \right) * T_h \right]
\]  \hspace{1cm} (24)

\[
Total \ electricity \ bill = \text{Total buy bill} - \text{Total sell bill}
\]  \hspace{1cm} (25)

\[
Peak \ demand = \max(demand \ of \ the \ day)
\]  \hspace{1cm} (26)

\[
Overall \ average \ comfort = \text{average} \left( \text{percentage \ of \ comfort \ of \ all \ shiftable \ appliances} \right)
\]  \hspace{1cm} (27)

\[
CO_2 \text{ emission} = \text{Total grid power drawn} * k
\]  \hspace{1cm} (28)

Where \( k = 0.4483 \) (calculated from carbonfund.org)

Table 7 shows that cost-effective scheduling compared with the ANN-based full-comfort scenario increases PV utilization from 6.44 kWh to 7.75 kWh. This increment in PV utilization reduces power drawn from the grid from 17.06 kWh to 15.76 kWh. Furthermore, it minimizes the total electricity net bill from 54.32 rupees to 53.28 rupees. Moreover, an observation from Table 7 is that cost-effective scheduling reduces the peak demand from 1.88 kWh to 1.46 kWh. The reduction in net EB while preserving...
user preferences considering constraints is achieved, with an average overall comfort of 93.18%, as listed in Table 7. The decrease in power drawn from the fossil fuel-based grid benefits the user and grid, and the society concerning carbon footprints as the cost-effective scheduling reduces carbon emission from 7.65 kg to 7.06 kg, as listed in Table 7.

The benefits listed and highlighted in Table 7 are because PTW has given the degree of freedom for scheduling the operations of appliances to appropriate hours (PV available hours or low tariff hours), and the threshold on hourly demand limits the peaks. Therefore, the inference from these results is that a reduction in EB is possible with a certain degree of comforts and constraints while preserving user preferences.

5. Conclusion

This article proposes a heuristic approach for cost-effective energy management without compromising user comforts while considering constraints via scheduling appliances operations for a home with multi-class appliances. An ANN technique based time window, termed as a user-preferred time window (PTW) concept, is applied for comforts. A threshold on hourly demand is also considered in this approach to prevent rebound-peaks at low tariff hours. The proposed approach addresses the trade-off between EB and comfort by scheduling appliances, taking into account user preferences, a day-ahead tariff, grid-power draw and hourly demand threshold constraints, and rooftop PV.

We have compared the proposed ANN technique-based generated full-comfort time slots with a classifier-based generated full-comfort time slots and observed that the ANN-based time window generation technique overrules the classifier based time window generation technique. We considered the scheduling of appliances operations with a full-comfort scenario and a cost-effective scenario for demonstrating the proposed schedule-pattern generation algorithms' effectiveness. The inference from the obtained simulation results through cost-effective scheduling is that we can reduce EB through increment in PV utilization, including reducing demand peaks and CO2 emission with maximum possible comfort. Therefore the proposed approach benefits the user by reducing EB and benefits the grid by reducing demand peaks while still preserving user comforts. These benefits are because PTW has given the degree of freedom for scheduling appliances to appropriate hours (PV available hours or low tariff hours), and the threshold on hourly demand limits the peaks. Therefore, the inference from these observations is that the reduction in EB is possible with a certain degree of comforts. This article concludes that the proposed heuristic approach can be a feasible choice for multi-class appliance scheduling for cost-effective energy demand management with user easess.
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Nomenclature

\( a \)  
Appliance.

\( A \)  
Set of appliances.

\( \text{App\_state}_{TS,d} \)  
State of an appliance \( a \) at a particular time-slot \( TS \) of the day \( d \).

\( CEF \)  
Cost-effective.

\( \text{Class}_{NA} \)  
Non-shiftable appliances.

\( \text{Class}_{SA} \)  
Shiftable appliances.

\( \text{Class}_{SC} \)  
One time in a day for continuous two hours operated shiftable appliances.

\( \text{Class}_{SO} \)  
One time in a day operated shiftable appliances.

\( \text{Class}_{ST} \)  
Two times a day operated shiftable appliances.

\( \text{COM} \)  
Comfort.

\( d \)  
Day \([1, 2, 3, \ldots, 30]\)

\( D_a \)  
Demand of an appliance (kWh).

\( D_{a,1} \)  
Demand of an appliance during the first 60 minutes of continuous two hours of operation (kWh).

\( D_{a,2} \)  
Demand of an appliance during the second 60 minutes of continuous two hours of operation (kWh).

\( D_{h,a} \)  
Demand of an appliance during an hour (kWh).

\( D_{h,SA} \)  
Total demand of \( \text{Class}_{SA} \) appliances during an hour \( h \).

\( D_{h,SC} \)  
Total demand of \( \text{Class}_{SC} \) appliances during an hour \( h \).

\( D_{h,SO} \)  
Total demand of \( \text{Class}_{SO} \) appliances during an hour \( h \).

\( D_{h,ST} \)  
Total demand of \( \text{Class}_{ST} \) appliances during an hour \( h \).
| Symbol     | Description                                                                 |
|------------|-----------------------------------------------------------------------------|
| $D_{h, \text{threshold}}$ | Threshold on hourly demand (kWh).                                            |
| $D_{h, \text{total}}$     | Total hourly demand (kWh).                                                  |
| $GP_h$        | Grid power during an hour of the day (kWh).                                 |
| $GP_{h, \text{avail}}$    | Hourly available grid power (kWh).                                          |
| $n_a$         | Operational length of an appliance (minutes).                               |
| $\text{OpD}$   | Operational delay (hours).                                                  |
| $\text{PoC}$   | Percentage of comfort (%).                                                  |
| $PTW_a$       | Preferred time window for an appliance operation with time slots $TS_1$, $TS_2$, ..., $TS_{24}$. |
| $PV_{\text{day, gen}}$  | PV power generated for the day (kWh).                                       |
| $PV_{h, \text{avail}}$   | Hourly available PV power (kWh).                                            |
| $PV_{h, \text{gen}}$     | PV power generated hourly (kWh).                                            |
| $PV_{\text{min}}$        | Minimum PV power (kWh).                                                     |
| $PV_{\text{peak}}$       | Peak power of PV (kWp).                                                     |
| $R_a$         | Rating of an appliance (kWh).                                               |
| $T_h$         | Hourly electricity tariff (Rupees/kWh).                                    |
| $T_{\text{min}}$        | Minimum electricity tariff (Rupees/kWh).                                    |
| $TS$          | Time slot $[1, 2, 3, ..., 24]$                                              |
| $W_d$         | Corresponding weight for a state of an appliance $a$ at a particular time-slot $TS$ of the day $d$. |
| $\text{weighted\_input}_{TS,d}$ | Weighted input for a state of an appliance $a$, at a particular time-slot $TS$ of the day $d$. |
Figure Captions:

Fig. 1. Household energy management model.

Fig. 2. $Class_{NA}$ appliances scheduled pattern using Algorithm 1.

Fig. 3. $Class_{SO}$ appliances scheduled pattern using Algorithm 3.

Fig. 4. $Class_{ST}$ appliances scheduled pattern using Algorithm 4.

Fig. 5. $Class_{SC}$ appliances scheduled pattern using Algorithm 5.

Fig. 6. Multi-class appliances scheduled pattern with user comfort.

Fig. 7. ANN full-comfort, Naïve Bayes full-comfort, and cost-effective comfort based scheduled pattern of multi-class appliances.
Table Captions:

Table 1 List of appliances with their rating for 1 bedroom-hall-kitchen home classified as Class NA and Class SA, further sub-classified as Class SO, Class ST, and Class SC.

Table 2 Class NA appliances with their respective operational length, preferred time slots and demand per hour.

Table 3 Class SO appliances with their respective operational length, preferred time slots and demand per turn.

Table 4 Class ST appliances with their respective operational length, preferred time slots and demand per turn.

Table 5 Class SC appliances with their respective operational length, preferred time slots and demand per turn per hour.

Table 6 Outcomes of Class SA appliances in terms of operational delay and percentage of comfort concerning the full-comfort time slots identified by ANN and Naïve Bayes classifier.

Table 7 Assessed parameters for full-comfort and cost-effective based scheduling appliances operations.
Fig. 1.

Fig. 2.

Demand and Energy (kWh)

Time of the day (Hours)
Fig. 6.

One Time Demand for Continuous Two Hours
Two Times Demand
One Time Demand
Fixed Demand
Grid Power Available
PV Power Available
Electricity Tariff

Fig. 7

ANN Full-comfort
Naïve Bayes Full-comfort
Cost-effective Comfort
Grid
PV
Electricity Tariff
### Table 1:

| Room     | Appliance     | Rating     | Class<sub>NA</sub> | Class<sub>SA</sub> | Class<sub>SO</sub> | Class<sub>ST</sub> | Class<sub>SC</sub> |
|----------|---------------|------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Bed Room | CFL_1         | 0.018 kWh  | ✓                  |                    |                    |                    |                    |
|          | Tube_1        | 0.036 kWh  | ✓                  |                    |                    |                    |                    |
|          | Fan_1         | 0.5 kWh    | ✓                  |                    |                    |                    |                    |
| Living Room | CFL_2       | 0.018 kWh  | ✓                  |                    |                    |                    |                    |
|          | Tube_2        | 0.036 kWh  | ✓                  |                    |                    |                    |                    |
|          | Fan_2         | 0.5 kWh    | ✓                  |                    |                    |                    |                    |
|          | TV            | 0.1 kWh    | ✓                  |                    |                    |                    |                    |
|          | Iron          | 1.1 kWh    | ✓                  |                    |                    |                    |                    |
|          | Vacuum Cleaner| 1.3 kWh    |                    | ✓                  |                    |                    |                    |
| Kitchen  | Tube_3        | 0.036 kWh  | ✓                  |                    |                    |                    |                    |
|          | Refrigerator  | 0.15 kWh   | ✓                  |                    |                    |                    |                    |
|          | Kettle        | 1.5 kWh    | ✓                  |                    |                    |                    |                    |
|          | Rice Cooker   | 1.3 kWh    | ✓                  |                    |                    |                    |                    |
|          | Electric Stove| 0.9 kWh    | ✓                  |                    |                    |                    |                    |
| Bath Room | Water Heater  | 1.5 kWh    | ✓                  |                    |                    |                    |                    |
|          | Well Pump     | 0.9 kWh    | ✓                  |                    |                    |                    |                    |
|          | Washing Machine| 2 kW *    | ✓                  |                    |                    |                    |                    |

* Rated maximum power during their term of operation;
✓ : Represents that an appliance belongs to a particular class

### Table 2:

| Class<sub>NA</sub> | $n_a$ per hour (mins) | $PTW_a$ (hours) | $D_a$ per hour (kWh) |
|--------------------|-----------------------|-----------------|----------------------|
| CFL_1              | 60                    | 1~6, 23~24      | 0.018                |
| Tube_1             | 60                    | 19~21           | 0.036                |
| Fan_1              | 60                    | 1~6, 19~24      | 0.5                  |
| CFL_2              | 60                    | 1~6, 22~24      | 0.018                |
| Tube_2             | 60                    | 7~8, 18~21      | 0.036                |
| Fan_2              | 60                    | 7~21            | 0.5                  |
| TV                 | 60                    | 17~21           | 0.1                  |
| Tube_3             | 60                    | 6~7, 18~20      | 0.036                |
| Refrigerator       | 60                    | 1~24            | 0.15                 |

### Table 3:

| Class<sub>SA</sub> | $n_a$ during each turn of operation (mins) | $PTW_a$ (hours) | $D_a$ during its turn of operation (kWh) |
|--------------------|--------------------------------------------|-----------------|-----------------------------------------|
| Class<sub>SO</sub> |                                            |                 |                                         |
| Kettle             | 20                                         | 7~8             | 0.5                                     |
| Iron               | 15                                         | 7~8             | 0.275                                   |
| Water Heater       | 10                                         | 5~6             | 0.25                                    |
| Vacuum Cleaner     | 30                                         | 6~10            | 0.65                                    |
| Well Pump          | 30                                         | 4~10            | 0.45                                    |
### Table 4:

| ClassSA | $n_a$ during each turn of operation (mins) | $PTW_a$ (hours) | $D_a$ during its turn of operation (kWh) |
|---------|------------------------------------------|-----------------|------------------------------------------|
|         |                                          | 1st Turn | 2nd Turn |                                        |
| ClassST | Rice Cooker                              | 30       | 6~9      | 15~17                                   | 0.65                         |
|         | Electric Stove                           | 25       | 6~9      | 14~16                                   | 0.375                        |

### Table 5:

| ClassSC | Time slots (hours) | $n_a$ during the turn of operation (mins) | $D_a$ during the turn of operation (kWh) | $PTW_a$ (hours) |
|---------|-------------------|------------------------------------------|------------------------------------------|-----------------|
|         |                   |                                          |                                          | 5 ~ 12          |
| Washing Machine | First-time slot | 60                                       | 0.779                                    |                 |
|         | Second-time slot | 30                                       | 0.138                                    |                 |

### Table 6:

| Parameters            | Kettle | Iron | Water Heater | Vacuum Cleaner | Well Pump | Rice Cooker | Electric Stove | Washing Machine |
|-----------------------|--------|------|--------------|----------------|-----------|-------------|----------------|-----------------|
|                       | 1st    | 2nd  | 1st          | 2nd            | 1st       | 1st         | 1st            | 2nd             |
| Full-comfort time slot (hour) | ANN    | 7    | 8            | 6              | 10        | 8           | 17             | 9               |
|                       | Naïve Bayes | 8    | 7            | 5              | 7         | 6           | 8              | 16              |
| Operational delay (hours) | 1      | 1    | 1            | 3              | 4         | 0           | 1              | 1               |
| Percentage of comfort (%) | 95.83  | 95.83| 95.83        | 87.5           | 83.33     | 100         | 95.83          | 95.83           |

### Table 7:

| Parameters            | ANN | Naïve Bayes | CEF |
|-----------------------|-----|-------------|-----|
| Total demand (kWh)    | 23.50 | 23.50       | 23.50 |
| Total PV generated (kWh) | 9.28  | 9.28     | 9.28 |
| Total PV used (kWh)   | 6.44  | 6.85       | 7.75 |
| Total grid power draw (kWh) | 17.06  | 16.66      | 15.76 |
| Total buy bill (Rupees) | 63.25 | 62.19      | 57.98 |
| Total sell bill (Rupees) | 8.63  | 7.43       | 4.69 |
| Total electricity bill (Rupees) | 54.62 | 54.76 | 53.28 |
| Peak Demand (kWh)     | 1.88  | 2.21       | 1.46 |
| Overall average comfort (%) | 100.00 | 93.94     | 93.18 |
| CO₂ emission (kgs)    | 7.65  | 7.47       | 7.06 |