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IESR: Instant Energy Scheduling Recommendations for Cost Saving in Smart Homes

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ABSTRACT The exponential increase in energy demands continuously causes high price energy tariffs for domestic and commercial consumers. To overcome this problem, researchers strive to discover effective ways to reduce peak-hour energy demand through off-peak scheduling yielding low price energy tariffs. Efficient off-peak scheduling requires precise appliance profiling to identify a scheduling recommendation for peak load management. We propose a novel off-peak scheduling technique that provides instant energy scheduling recommendations by monitoring appliances in real-time following user-devised criteria. Once an appliance operates during a peak hour and fulfills the user criteria, a real-time scheduling recommendation is presented for users' approval. The proposed technique utilizes appliance energy consumption data, user-devised criteria, and energy price signals to identify the recommendation points. The energy cost-saving performance of the proposed technique is evaluated using two publicly available real-world energy consumption datasets with four price signals. Simulation results show a significant cost-saving performance of up to 84% for the experimented datasets. Moreover, we formulate a novel evaluation metric to compare the performance of various off-peak scheduling techniques on similar criteria. Comparative analysis indicates that the proposed technique outperforms the existing methods.

INDEX TERMS Energy cost saving recommendations, off-peak scheduling, peak demand optimization, energy consumption awareness.

I. INTRODUCTION

The increase in energy consumption raises the energy production cost, and the increase in energy cost significantly affects the economic growth of a country [1]. The domestic energy demands are growing eventually due to the increase in population and technological advancements for enhanced user comfort [2], [3]. Nowadays, smart homes are user-friendly, assistive, and more comfortable due to the increased number of automatic appliances that put a significant load on smart grids [4], [5]. Recent studies on energy management in smart home recommender systems for energy saving present a summary of well-known energy and cost optimization techniques [6]–[8]. The increased energy demand on smart grids elevates the cost of energy production for suppliers. Thus, compelling industry and academia to find efficient ways to minimize energy demand while maintaining cost-effective energy prices.

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A. PROBLEM STATEMENT

Various off-peak scheduling techniques are proposed to balance energy demand and reduce energy costs [7], [9]–[14]. An off-peak scheduling technique identifies an energy-consuming appliance in peak hours and recognizes the type of the appliance as shiftable or non-shiftable load. Then, it examines the division of peak and off-peak hours in the energy price signal provided by the energy suppliers for scheduling the target appliance. Finally, it suggests a scheduling recommendation for that appliance to the user, who might accept or ignore it. For these recommendations, existing off-peak scheduling techniques disregard the real-time user preferences during appliance identification for scheduling, i.e., the user cannot decide how to monitor an appliance once it starts operating. However, it would be crucial for users to monitor appliances on-the-fly. Moreover, existing techniques consider off-peak scheduling only as an optimization problem [15] neglecting the significance of a user's choices during the process of scheduling decisions.

An essential step in off-peak scheduling is analyzing the energy price signals. Various price signals offer different distributions of peak and off-peak hours, which affects the cost-saving performance. In the price signal, if the duration of peak hours is more than off-peak hours, the cost-saving performance increases. This relationship is because, with more peak hours, the scheduling distributes more load to off-peak hours. To offer flexibility to the smart homes equipped with advanced metering infrastructure, the energy suppliers introduce several energy price signals, among which flat pricing, real-time pricing (RTP), critical peak pricing (CPP), and time-of-use (ToU) are well-known [16], [17]. In flat pricing, the energy rate remains constant for 24 hours; on the other hand, in RTP, the rate of energy for every hour is different. Furthermore, in ToU, the energy rate of a day is divided into two or three different rates among various hours. CPP is somewhat similar to ToU as in CPP, the rate of a few hours (usually one or two) can be very high as compared to other hours, and this happens for some days in a year [18].

B. CONTRIBUTIONS AND ORGANIZATION

In this study, we propose an Instant Energy Scheduling Recommendation (IESR) technique that monitors appliances' energy usage in real-time according to user-defined criteria, i.e., the user specifies parameters for targeting an appliance for scheduling. It instantly presents off-peak scheduling recommendations to the user when an appliance's energy consumption begins in peak hours and fulfills the user-defined criteria. When a user receives a recommendation for off-peak scheduling, the appliance can be shifted to the nearest off-peak hour on acceptance or continues to function if the user ignores the recommendation. In the latter case, no energy-saving can be achieved. However, if the recommendations are accepted, the user has a valuable energy-saving opportunity. The originality of the IESR resides in the fact that it detects the energy consumption of an appliance in real-time, exhibiting an opportunity for the user to gain control of current energy consumption and achieve energy cost-saving, which might motivate the user to comply with the suggested reschedulings.

IESR works as a middleware between the smart home appliance controller and the user. IESR integrates with the smart home appliance controller to read the appliance energy consumption data to monitor the appliance in real-time and fetches the energy price signal from the energy provider. By operating on these data, IESR generates energy cost-saving recommendation points based on the appliance energy usage patterns and price signals. The user receives a notification of appliance scheduling if the recommendation points identified by IESR are falling in peak hours. If the user chooses to schedule an appliance for an off-peak hour, IESR sends a signal to the appliance controller to schedule the appliance. The integration of IESR with the smart home is presented in Fig. 1, where IESR communicates with the smart home to receive consumption data and reads the energy price signals from the smart grid to produce cost-saving recommendations.

In a nutshell, the main contributions of our study are summarized as follows:

1) We propose a novel technique to provide real-time energy-saving recommendations on user-defined appliance monitoring criteria.
2) We investigate the influence of energy price signals and appliance energy consumption patterns on the cost-saving performance of off-peak scheduling techniques.
3) We formulate a novel evaluation metric to compare the cost-saving performance of various techniques.

The rest of the paper is organized as follows. Section II presents other off-peak scheduling techniques discussed in the literature. In Section III, we briefly explain the proposed methodology of our IESR technique. Then, we present experimental studies and results in Section IV. In Section V, we discuss outcomes and gained insights. Finally, we conclude the study with future work directions in Section VI.

II. RELATED WORK

This section discusses existing off-peak scheduling techniques, their achievements, and their main limitations.

Day-ahead prediction of energy demand assists in energy scheduling during peak hours. A stochastic-based predictor has been proposed to forecast the next day's energy demand (24h ahead) since the energy price market provides energy tariffs for the next day in advance [19]. The peak shaving approach reduces the energy load during peak hours to a predefined threshold [20]. An energy-saving recommender system analyzes the energy consumption pattern of the user, monitors the price signal, and takes energy consumption information from appliances to provide off-peak hour scheduling recommendations [21].

A reinforcement learning algorithm based on human appliance interaction takes into account user behaviors while generating off-peak scheduling recommendations [9]. However, a user's interaction with the system is limited as the recommendation provided to the user is based on appliance interaction behavior only. The authors do not consider that a user may require to target some specific appliances in real-time as they start operating. Also, an energy efficiency framework detects micro-moments using various sensors in a household and produces an energy-saving recommendation by observing the user behavior based on micro-moments [10], [22]–[24]. The micro-moments describe an appliance's energy consumption pattern and a user's energy usage behavior in a household. Nevertheless, they do not address the problem of how the user can choose to target specific appliances while producing energy efficiency recommendations.

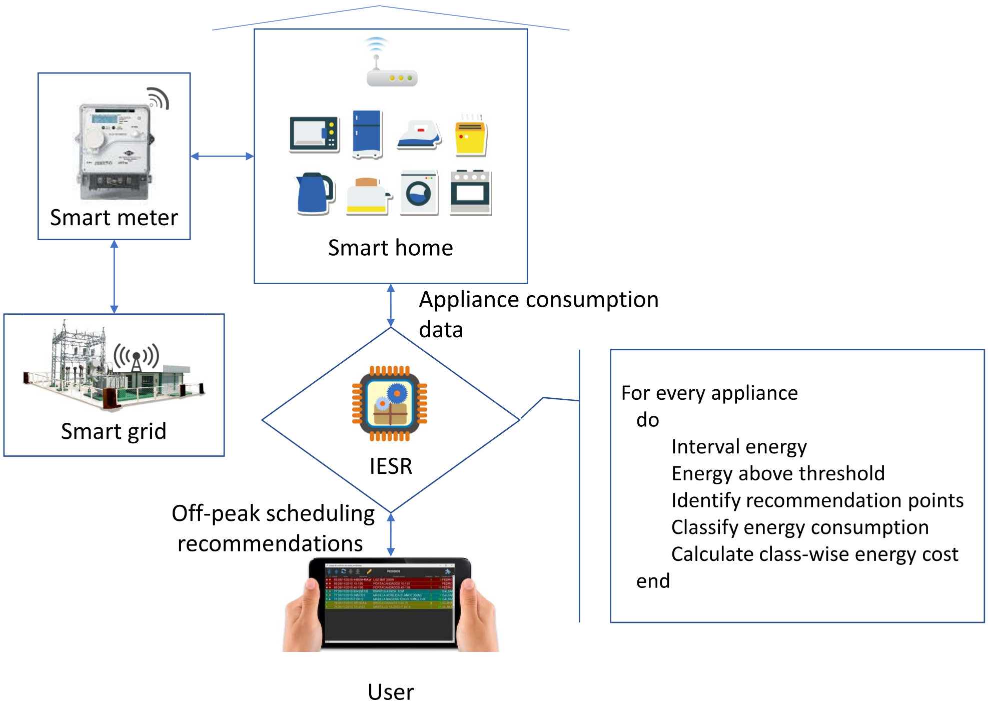


FIGURE 1. Integration of IESR in smart home.

The Hybrid Gray Wolf Differential Evolution (HGWDE) technique was implemented to shift energy load to off-peak hours [3]. This technique achieves an optimal situation between load shifting and user comfort. A hybrid technique reduces energy cost while maintaining user comfort [25]. Priorities are assigned to individual appliances by the user, and the hybrid technique finds an optimal scheduling solution for the appliances. Furthermore, a Home Energy Management System (HEMS) reduces energy demand and cost with the assistance of renewable energy sources and an energy storage system [26]. In addition to this, [27] presents a Hybrid Flower pollination BAT Algorithm (HFBA) for energy, cost, and Peak-to-Average Ratio (PAR) reduction that initially categorizes appliances based on their energy consumption patterns. It includes a fuzzy logic controller for controlling appliances and a heuristic optimization technique for scheduling appliances for energy, cost, and PAR reduction.

There are several meta-heuristic algorithms such as Moth-Flame Optimization (MFO) [31], Whale Optimization Algorithm (WOA) [32], Harris Hawks Optimization (HHO) [33], and Artificial Ecosystem Optimizer (AEO) [28] that consider off-peak scheduling as an optimization problem. These algorithms analyze dynamic patterns in a complex scheduling problem and reach an optimal solution. [34] develops a HEMS for precise scheduling of appliances of a smart home using HHO. Also, [28] presents an AEO algorithm to reduce energy demand and cost. An Energy Management System (EMS) was presented in [29] that monitors the smart home appliances and performs off-peak scheduling. Similarly, [30] proposes a Sustainable Parasitic Energy Management System (SPEMS) that optimizes energy demand, cost, PAR, and user discomfort. SPEMS schedules appliances to decrease peak load and find an optimal solution to resolve conflicting objectives. The system adapts to the user's energy usage behavior and considers previous days' scheduling data to find an optimal solution.

So far, we have examined various off-peak scheduling techniques from the existing literature, accomplishing cost-saving, peak load balancing, energy demand optimization and user appliance interaction-based scheduling, and various HEMS. However, user requirements-based methods to target appliances for scheduling are deficient. There is a scarcity of real-time user decisions for scheduling appliances based on appliances' energy consumption behaviors. The impact of energy price signals on the performance of off-peak scheduling techniques has been rarely investigated. Our research focuses on these identified issues to explore user influence in off-peak scheduling decisions, providing flexibility to the user in targeting appliances for scheduling.

Table 1 presents the summary of related work according to techniques, achievements, price signals, and, most notably, limitations.

III. THE INSTANT ENERGY SCHEDULING RECOMMENDATION TECHNIQUE

In this section, we present a novel instant energy scheduling recommendation (IESR) technique that minimizes the energy cost of a smart home by scheduling energy load to an off-peak hour. The smart home user specifies an appliance monitoring criteria. The monitoring condition comprises rules that

TABLE 1. Summary of related work.

Technique(s)	Achievement(s)	Price signal(s)	Limitation(s)
Stochastic predictor [19]	Peak load reduction	N/A	Real-time energy scheduling is not considered.
Peak shaving [20]	Reduce load during peak hours	N/A	Different price signals are not considered.
Reinforcement Learning [9]	Energy conservation and peak load reduction	ToU	Lacks CPP price signal analysis.
Energy efficiency using Micro-Moments [10], [24]	Energy- and cost-saving	N/A	Lacks price signal analysis.
HGWDE [3]	Cost-saving and PAR reduction	RTP and CPP	Real-time user requirements are not addressed.
Hybrid technique [25]	Improve user comfort, cost-saving, and PAR reduction	DA-RTP and CPP	Cost-saving vs. user-comfort trade-off is not addressed.
HEMS [26]	Cost reduction with renewable energy sources and energy storage system	ToU, CPP	Execution time
Multi-agent recommendation system [21]	Recommendation of shifting load to off-peak hours	RTP	User comfort and different price signal types (ToU, CPP) are not considered for experimentation
HFBA [27]	Energy and cost reduction by off-peak scheduling	RTP, ToU	Operational complexity for the smart home user
AEO [28]	Reduce energy cost and PAR	RTP, CPP	User comfort and cost reduction trade-off overlooked
EMS [29]	Cost reduction	ToU	Complexity for implementation in a real environment
SPEMS [30]	Optimization of energy demand, cost and PAR	ToU	CPP and RTP price signals are overlooked during experimentation

identify the high energy consumption of appliances in peak hours. When an appliance meets the user-specific criteria, IESR recommends shifting the appliance to an off-peak hour. The appliances can be shifted to the nearest off-peak hour identified in different price signals. The distribution of peak, mid-peak, and off-peak hours in a price signal affects the performance of IESR. The performance of IESR with different price signals will be investigated in Section IV-C. In subsequent sections, we explain the functionality of IESR in detail. The flow chart of IESR's functional operation is shown in Fig. 2.

A. ENERGY PRICE MODELS

Off-peak scheduling depends on the energy price models as the distribution of hourly pricing yields an off-peak to peak hour ratio. An hour can be a peak hour in one price model, whereas it may be an off-peak hour in another price model. The price models shown in Fig. 4 depict this distribution phenomenon. Therefore, the scheduling mechanism needs to identify peak price hours from energy tariffs to distinguish between peak, mid-peak and off-peak usage. The energy price model illustrates the hourly energy tariff offered by the energy supplier. The hourly energy price is different in RTP, ToU, and CPP.

In the CPP model, the energy price at certain hours is very high compared to the rest of the hours. Also, it is usually used by commercial consumers. In contrast to CPP, ToU is variable as it comprises different energy prices for different time intervals. ToU models are widely used for domestic consumers. RTP is an entirely dynamic price model as energy prices for every hour change every day. CPP, RTP, and ToU pricing signals are shown in Fig. 4. RTP and CPP price signals are commonly used in existing studies [26], [28] whereas ToU is an averaged signal extracted from RTP by using the method depicted in Fig. 3. We specify three price ranges for distribution of hours into off-peak (8.10 - 14.51), mid-peak (14.52 - 20.92) and peak (20.93 - 27.35) hours presented in Fig. 3.

It can be noted from Figs. 4a and 4b that there are three main categories of energy hours, i.e., peak, mid-peak, and off-peak. Peak corresponds to high price hour, mid-peak (sometimes termed as shoulder peak) corresponds to medium price hour, and off-peak corresponds to low price hour. If an appliance consumes energy in mid-peak or peak hours, IESR technique generates a recommendation for off-peak scheduling. The different categories of price hours assist in finding the off-peak to peak energy consumption ratio, which we use during comparative analysis of different techniques in Section IV-D. Based on the off-peak to peak ratio, we measure the energy cost-saving performance of various off-peak scheduling techniques in Section IV-D.

B. INTERVAL ENERGY

The appliance energy consumption data is required for the identification of energy scheduling recommendations. From the appliance energy consumption data, the proposed IESR finds patterns of energy used in peak hours according to the pricing model's hourly peak, mid-peak, and off-peak distribution already discussed in Section III-A. The appliance level energy consumption data is provided by various publicly available datasets [35], [36] in different frequencies. For IESR, we consider appliance level energy consumption data provided at a 1-second interval (1 Hz). In this type of data, there are certain short time intervals where the appliance is temporarily not using any energy or the energy value is missing due to any reason. This type of short interval can mislead IESR to ignore it for recommendation identification. To cope with this problem, we convert the 1-second's data into interval data (i.e., 1 to 10-second interval) so that the missing energy values adjust in these intervals. The value of the interval will be selected by the smart home user while defining IESR criteria. The pseudo-code to convert 1-second consumption data

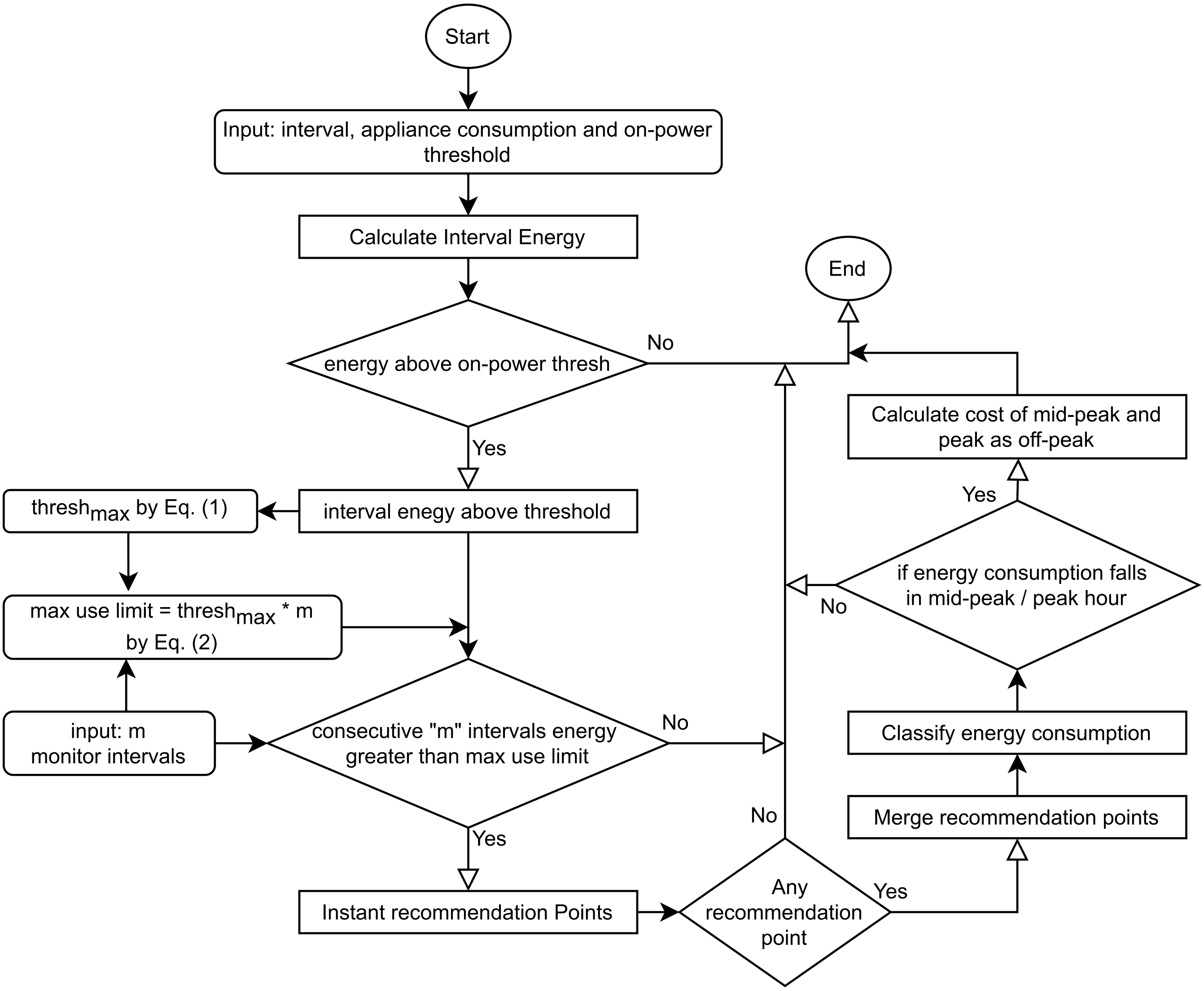


FIGURE 2. Flow chart of the proposed method.

FIGURE 3. RTP to ToU converter.

into interval-based consumption is presented in Algorithm 1. An example output of the Algorithm 1 is shown in Table 2.

C. ENERGY ABOVE APPLIANCE ON-POWER THRESHOLD

After appliance interval-based energy consumption is obtained from Algorithm 1, the next step is to identify energy consumption greater than or equal to the appliance on-power threshold. The appliance on-power threshold determines the appliance's active or inactive state. The algorithm detects all intervals that having energy greater than or equal to an appliance on-power threshold. The pseudo-code for finding energy above the appliance on-power threshold is presented in Algorithm 2. An example output of the Algorithm 2 is shown in Table 3 considering $4W$ appliance on-power threshold.

For the identification of scheduling recommendation points, there is a need for an energy consumption monitoring threshold called threshold for maximum use defined by the user for every appliance. During experimentation and simulations, we will consider the average energy consumption calculated from the interval energy of an appliance as the threshold for maximum use. The threshold for max usage can be calculated by (1).

$$thresh_{max} = \frac{\sum_{i=1}^{n} intEnergy_p^i}{n} \tag{1}$$

where $intEnergy_p^i$ represents the power value at i^{th} index of $intEnergy$ and n denotes the length of $intEnergy$.

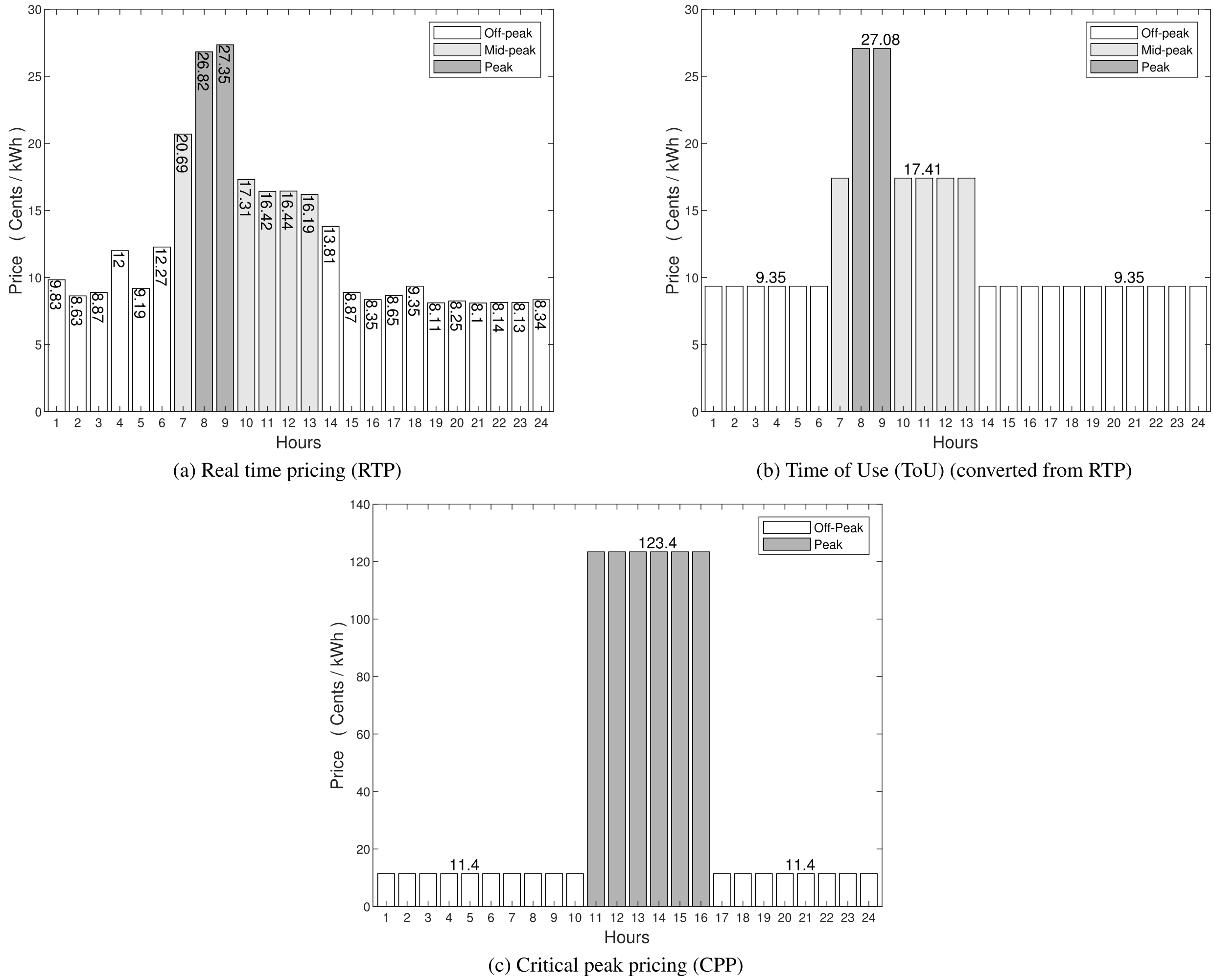


FIGURE 4. **Energy price models.**

D. INSTANT RECOMMENDATION POINTS

Recommendation point identification is the core operation of IESR in which it identifies the starting point of the recommendation. The user formulates criteria for appliance monitoring, i.e., the user specifies the maximum energy level an appliance could reach and a limit of time in which the appliance is constantly consuming more energy than the allowed energy level. When an appliance is turned on, IESR starts monitoring it according to user-defined monitoring criteria. IESR provides off-peak scheduling recommendations only when the user-defined criteria are fulfilled and the energy consumption time lies in peak or mid-peak energy hours. If the energy consumption time does not lie in peak or mid-peak hour, IESR keeps monitoring the appliance until it is turned off or enters peak or mid-peak hour. The pseudo-code for the identification of the starting point of a recommendation is presented in Algorithm 3. The two-parameters *monitorUptoIntervals* and *maxUseLimit* specified by the user control the response of the Algorithm 3. The *maxUseLimit* can be calculated by (2).

$$maxUseLimit = thresh_{max} \times monitorUptoIntervals \quad (2)$$

An example of a user-defined rule could be if an appliance energy usage goes above $500W$ for more than 5 minutes, recommend off-peak scheduling. Considering this example rule, the parameters for appliance monitoring are:

1) Threshold for max use ($thresh_{max}$) = $500W$
2) Monitor time: 5m (*300s*)

From these parameters, it is important to note that the total monitoring time is 5 minutes which is *300s*. This monitor time can be achieved by two combinations of *interval* and *monitorUptoIntervals* parameters and the results for both of the simulations will be slightly different.

1) $interval = 10s$, $monitorUptoIntervals = 30s$
2) $interval = 30s$, $monitorUptoIntervals = 10s$

The *interval* parameter will be an input to Algorithm 1 and the *monitorUptoIntervals* parameter will be an input

Algorithm 1 Interval Energy

Input: $interval, P^A$ ▷ P^A appliance A power consumption at 1 Hz
Output: $intEnergy$

$S \leftarrow 86{,}400$ ▷ total seconds in one day $24 \times 60 \times 60 = 86{,}400$
$sum \leftarrow 0$
$c \leftarrow 1$
for $s \leftarrow 1, S$ **do**
  if $P^A_{s_i} > 0$ **then**
    $sum \leftarrow sum + P^A_{s_i}$ ▷ appliance A power value at s_i second
  end if
  $b \leftarrow s_i \bmod interval$ ▷ interval specified by user, i.e., 10, 20, …
  if $b = 0$ **then**
    $intEnergy_s \leftarrow s_i - interval + 1$ ▷ start of the interval
    $intEnergy_e \leftarrow s_i$ ▷ end of the interval
    $intEnergy_p \leftarrow sum/interval$ ▷ total power of the interval
    $c \leftarrow c + 1$
    $sum \leftarrow 0$
  end if
end for

Algorithm 2 Energy Above Appliance On-Power Threshold

Input: $intEnergy$, th_{app} ▷ interval energy from Algorithm 1, appliance on-power threshold
Output: $intEnergy$
Hint: The subscripts s, e, and p denote start, end, and power of an interval respectively

$n \leftarrow$ length $intEnergy$
for $i \leftarrow 1, n$ **do**
  if $intEnergy^i_p < th_{app}$ **then** ▷ $intEnergy^i_p$ = power of interval i
    delete $intEnergy^i_s, intEnergy^i_e, intEnergy^i_p$ ▷ deleting interval
  end if
end for

to Algorithm 3 to achieve any monitoring time defined by the user. Suppose the value for *interval* is 10, *monitorUptoIntervals* value is 3, the $thresh_{max}$ is $4W$ so the *maxUseLimit* becomes $12W$. The result of Algorithm 3 is shown in Table 4.

1) MERGE RECOMMENDATION POINTS

When the recommendation points are identified, there is a possibility that the recommendation points are continuous as the appliances operate continuously for a certain period. After the identification of recommendation points, we merge such continuous recommendation points. The pseudo-code is presented in Algorithm 4 and an example output is shown in Table 5.

E. CLASSIFY ENERGY CONSUMPTION

The merged recommendation points resulted from Algorithm 4 comprise the starting and ending time of all continuous recommendation points. The time interval specified by the start and endpoint of these recommendation points will be classified according to the price signals discussed thoroughly in Section III-A. For IESR experimental analysis we will use TOU-1, CPP, ToU-2, and ToU-3 price signals represented in Figs. 4b, 4c, 5a, and 5b respectively. As discussed earlier in Section III-A the price signal greatly affects the performance of IESR due to the distribution of peak hours. A price signal holding few peak hours reduces the cost-saving percentage as the probability of appliances working in peak hours reduces, whereas a price signal comprised of more peak hours increases the cost-saving percentage. We will perform the experimentation with multiple price signals to explain this

TABLE 2. 10 seconds interval energy.

Start	End	Power (W)
1	10	8
11	20	6
21	30	4
31	40	7
41	50	9
51	60	3
61	70	6
71	80	5
81	90	4
91	100	6
.	.	.
.	.	.
86,381	86,390	1
86,391	86,400	3

TABLE 3. Energy above on-power.

Start	End	Power (W)
1	10	8
11	20	6
21	30	4
31	40	7
41	50	9
61	70	6
71	80	5
81	90	4
91	100	6
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.

TABLE 4. Recommendation points.

Start	End	Power (W)
1	30	18
61	90	15
91	120	13
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.
.	.	.

Algorithm 3 Instant Recommendation Points

Input: *intEnergy*, *monitorUptoIntervals*, *maxUseLimit* ▷ Algorithm 2 interval energy
Output: *recommendationPoints*
Hint: The subscripts s, e, and p denote start, end, and power of an interval respectively

$n \leftarrow$ length *intEnergy*
$limit \leftarrow$ n / $monitorUptoIntervals$ ▷ finds maximum possible divisions of *intEnergy* data
$intStart \leftarrow 1$
$intEnd \leftarrow monitorUptoIntervals$
$c \leftarrow 1$
for $i \leftarrow 1, limit$ **do**
  $temp \leftarrow 0$
  for $x \leftarrow intStart, intEnd$ **do**
    if $intEnergy_s^{x+1} = intEnergy_e^x + 1$ **then** ▷ checks if next interval starts exactly after current interval ends to avoid intervals discontinuity
      $temp \leftarrow temp + intEnergy_p^x$
    end if
  end for
  if $temp > maxUseLimit$ **then** ▷ sum of intervals energy is greater than max use limit
      $recommendationPoints_s^c \leftarrow intEnergy_s^{intStart}$
      $recommendationPoints_e^c \leftarrow intEnergy_e^{intEnd}$
      $recommendationPoints_p^c \leftarrow temp/monitorUptoIntervals$
      $c \leftarrow c + 1$
  end if
   $intStart \leftarrow intStart + monitorUptoIntervals$
   $intEnd \leftarrow intEnd + monitorUptoIntervals$
end for

TABLE 5. Merge recommendation points.

Start	End
1	30
61	120

relationship. The pseudo-code for the classification of the time interval of recommendation point into peak,mid-peak, and off-peak is presented in Algorithm 5 and an example output is shown in Table 6.

F. CALCULATE CLASS-WISE ENERGY COST

After classifying time intervals into peak, mid-peak, and off-peak classes, the final step is the cost calculation of a recommendation point. We will only calculate the cost of peak and mid-peak time intervals as these are the only energy-saving intervals. The consumption in peak and mid-peak intervals can be scheduled to any off-peak hour to reduce electricity costs. The pseudo-code for the calculation of class-wise energy cost is presented in Algorithm 6 and the cost calculation from Table 5 is shown in Table 7. It can be noted from Table 7 that the Class-2 and Class-3 energy consumption can be scheduled to any off-peak hours resulting in cost savings.

The Algorithm 6 calculates the *total interval energy* in W using Algorithm 7 and converts it to kWh.

IV. EXPERIMENTAL STUDIES

To evaluate the energy cost-saving performance of the proposed IESR technique, we have performed a comprehensive set of experiments on two publicly available datasets discussed in the subsequent sections.

A. DATASETS

To simulate the energy cost-saving performance, IESR needs appliance energy consumption data of the smart home. IESR technique requires appliance energy consumption data measured at 1 Hz frequency and an appliance on-power threshold for experimentation. The datasets discussed in subsequent sections include appliances' energy consumption data and on-power threshold and contain all required attributes for our technique's testing. The purpose of using two datasets for experiments is to investigate the influence of different energy usage patterns of the appliances on the cost-saving performance of our technique.

1) ECO DATASET

The electricity consumption and occupancy (ECO[1]) dataset published by [35] is a multi-appliance dataset of 6 Swiss households recorded for 244 days. For our experimentation, this dataset is suitable as it contains different appliances with daily energy consumption data measured at a frequency of 1

[1]ECO Dataset

Algorithm 4 Merge Recommendation Points

Input: *recommendationPoints* ▷ recommendation points from Algorithm 3
Output: *recommendationMergedPoints*
Hint: The subscripts s and e denote start and end of an interval respectively

$n \leftarrow$ length *recommendationPoints*
$c \leftarrow 1$
$y \leftarrow 1$
for $i \leftarrow 1, n$ **do**
  if $c = 1$ **then**
    $recommendationMergedPoints_s^y \leftarrow recommendationPoints_s^c$
  end if
  $nextIntStart \leftarrow recommendationPoints_e^c + 1$
  if $c < n$ **then**
    if $nextIntStart \neq recommendationPoints_s^{c+1}$ **then**
    $recommendationMergedPoints_s^{y+1} \leftarrow recommendationPoints_s^{c+1}$
    $recommendationMergedPoints_e^y \leftarrow recommendationPoints_e^c$
    $y \leftarrow y + 1$
    end if
  else
    $recommendationPoints_e^y \leftarrow recommendationPoints_e^c$
  end if
    $c \leftarrow c + 1$
end for

TABLE 6. Example classification of an appliance energy consumption.

Start	End	Class-2 (mid-peak)	Class-3 (peak)
41,721	43,920		2200*s* (41,721 - 43,920)
68,841	81,440	2240*s* (79,201 - 81,440)	10,360*s* (68,841 to 79,200)

TABLE 7. Example calculation of class-wise energy cost.

Start	End	Class-2 mid-peak	Class-2 *kWh*	Class-3 peak	Class-3 *kWh*
41,721	43,920			2200*s* (41,721 - 43,920)	0.097
68,841	81,440	2240*s* (79,201 - 81,440)	0.099	10,360*s* (68,841 to 79,200)	0.46

TABLE 8. ECO: appliances.

Appliances	On-power (*W*)
Tablet	5
Dishwasher	500
Kettle	500
Lamp	15
Laptop	15
TV	15
Stereo	15

Hz recorded datewise in Matlab and CSV files. For every household, there is a significant portion of other consumption indicating energy consumption irrelevant to appliances under observation [35]. For household-2, the energy consumption related to appliances under observation is approximately 80% which indicates the good quality of household-2 data as compared to other households [35]. This is the reason we chose the household-2 data for our simulations.

2) UK-DALE DATASET

The UK domestic appliance-level electricity (UK-DALE[2]) dataset published by [36] is a well known publicly available data set used in many recent studies (i.e., [21]). It contains appliance energy consumption data at a frequency of 6 *Hz*, which we converted to 1 *Hz* by our preprocessing algorithm so that IESR technique performs experimentation without any modification on both ECO and UK-DALE datasets. The data measurement period of this dataset is more than 2 years, but we only perform experiments on 3 months of data (2013-11-01 to 2014-01-30) to simulate the results of our IESR technique. UK-DALE dataset comprises 1-54 appliances in different households, and we choose household-1 for experimentation that contains 52 active appliances.

[2]UK-DALE Dataset

3) APPLIANCES CLASSIFICATION ON UTILIZED DATASETS

There are many appliances in a household, so it is crucial to classify them before considering them for off-peak scheduling. In recent studies, smart home appliances are

Algorithm 5 Classify Energy Consumption Into Peak, Mid-Peak and Off-Peak

Input: *recommendationMergedPoints*, *priceSignal* ▷ recommendation merged points from Algorithm 4
Output: *recommendationMergedPoints* ▷ recommendation merged points with time interval classification
Hint: The subscripts s, e, h, and cl denote start, end, hour, and class respectively

$n \leftarrow$ length $recommendationMergedPoints$
$c \leftarrow 1$
for $a \leftarrow 1, n$ **do**
  $timeInt = recommendationMergedPoints^a_s$ to $recommendationMergedPoints^a_e$ ▷ time interval seconds, from start second to end
  $y \leftarrow$ length $timeInt$
  $cInt \leftarrow 1$
  for $b \leftarrow 1, y$ **do**
    for $h \leftarrow 1, 24$ **do**
      if $timeInt_{cInt} \geq priceSignal^h_s$ **AND** $timeInt_{cInt} \leq priceSignal^h_e$ **then**
        $class = priceSignal^h_{cl}$
      end if
    end for
    $tempClasses^{class}_{data_{cInt}} = timeInt_{cInt}$ ▷ storing time second at $cInt^{th}$ index of *data* present in $class^{th}$ index of *tempClasses*
    $cInt \leftarrow cInt + 1$
  end for
  if exists $tempClasses^1_{data}$ **then**
    $recommendationMergedPoints^a_{class1} \leftarrow tempClasses^1_{data}$
  end if
  if exists $tempClasses^2_{data}$ **then**
    $recommendationMergedPoints^a_{class2} \leftarrow tempClasses^2_{data}$
  end if
  if exists $tempClasses^3_{data}$ **then**
    $recommendationMergedPoints^a_{class3} \leftarrow tempClasses^3_{data}$
  end if
  $c \leftarrow c + 1$
end for

TABLE 9. UK-DALE: appliances.

Appliances	On-power (*W*)
Washing machine	20
Dishwasher	10
Soldering iron	5
Hoover	5
Iron	5
Straighteners	5
Hair dryer	5

categorized in various ways, i.e., [3], [26] categorize as shiftable, non-shiftable, and controllable appliances. [28] categorizes as base, interruptible, and non-interruptible appliances. [21] classifies as short-term, long-term, and no recommendation type. These categories resemble each other as the non-shiftable, base, and no recommendation types refer to appliances like fridges or ADSL routers. These appliances work 24 hours a day without interruption and are usually considered fixed energy loads for a household. The shiftable, interruptible, and long-term recommendation types refer to appliances that can be operated at any period of the day, and the user can schedule them for any off-peak hour. These appliances yield maximum energy cost conservation if scheduled wisely to an off-peak hour. Finally, the controllable, non-interruptible, and short-term recommendation types generally refer to appliances that need to be scheduled to the nearest off-peak hour, and their operation cannot be interrupted.

For IESR experimentation, we consider ECO and UK-DALE datasets and the appliance categorization presented by [21]. For off-peak scheduling recommendations, appliance classification is necessary as all appliances are not suitable for off-peak scheduling hours. According to [21] classification, short-term recommendation type appliances (mobile/laptop chargers, toaster, microwave) need to be scheduled to the closest off-peak hour in the price signal. In contrast, long-term recommendation type (dishwasher, iron, washing machine) appliances can be scheduled to any off-peak hour. For IESR experimentation, we include both short-term and long-term recommendation type appliances from the ECO dataset as the number of long-term appliances is low in ECO compared to UK-DALE whereas we only include long-term recommendation type appliances for the UK-DALE dataset. The list

Algorithm 6 Calculate Class-Wise Energy Cost

Input: $recommendationMergedPoints$, $priceSignalAvg$, P^A

▷ recommendation merged points from Algorithm 5

Output: $recommendationMergedPoints$

Hint: The subscripts $cons$ denotes consumption, $priceSignalAvg^3$, $priceSignalAvg^2$, and $priceSignalAvg^1$ denote peak, mid-peak, and off-peak hour price respectively

1: $n \leftarrow$ length $recommendationMergedPoints$
2: **for** $c \leftarrow 1, n$ **do**
3: **if** exists $recommendationMergedPoints^c_{class2}$ **then**
$energy_{class2} \leftarrow calculateIntervalEnergy(P^A, recommendationMergedPoints^c_{class2})$
$recommendationMergedPoints^c_{class2^{cons}} \leftarrow energy_{class2}$
$totalSeconds_{class2} \leftarrow$ length $recommendationMergedPoints^c_{class2}$
$kwh_{class2} \leftarrow calculateKwh(energy_{class2}, totalSeconds_{class2})$
$recommendationMergedPoints^c_{class2^{kwh}} \leftarrow kwh_{class2}$
$costClass2 \leftarrow kwh_{class2} \times priceSignalAvg^2$
$costAsClass1 \leftarrow kwh_{class2} \times priceSignalAvg^1$
$recommendationMergedPoints^c_{class2^{cost2}} \leftarrow costClass2$
$recommendationMergedPoints^c_{class2^{cost1}} \leftarrow costAsClass1$
$recommendationMergedPoints^c_{class2^{costSaving}} \leftarrow costClass2 - costAsClass1$
4: **end if**
Repeat process from line 3 to 4 for class-3 cost calculation
$c \leftarrow c + 1$
5: **end for**

of appliances (with on-power threshold) used in experiments from ECO household-2 and UK-Dale household-1 is given in Table 8 and 9 respectively. The on-power threshold of ECO and UK-DALE appliances is given at NILM-EVAL[3] and UK-DALE-Metadata[4] respectively.

B. 24-HOUR ENERGY CONSUMPTION

It is essential to calculate smart home appliances' 24-hour energy consumption (kWh) to compute the real energy cost. According to the price signals ToU-1 (Fig. 4b), CPP (Fig. 4c), ToU-2[5] (Fig. 5a), ToU-3[6] (Fig. 5b) which are summarised in Table 10, we calculate 24-hours energy consumption and the cost for peak, mid-peak, and off-peak hours individually for the appliances mentioned in Table 8 for ECO household-2 and Table 9 for UK-DALE household-1 during the experimentation period. Similarly, we also provide the off-peak, mid-peak, and peak distribution for Unscheduled hourly energy consumption distribution presented in [28]. Table 11 presents the distribution of energy consumption in peak, mid-peak, and off-peak hours, their respective costs, and the maximum margin of cost saving that can be accomplished if we schedule all peak and mid-peak loads to an off-peak hour. The cost-saving margin exclusively depends on the price signal as the distribution of peak, mid-peak, and off-peak hours is strictly based on the price signal.

[3]NILM-EVAL
[4]UK-DALE Metadata
[5]ToU-2
[6]ToU-3

Algorithm 7 Calculate Interval Energy

Input: P^A, $intervalSecondsData$
Output: $energy_W$

1: $n \leftarrow$ length $intervalSecondsData$
2: $tempTotal \leftarrow 0$
3: **for** $a \leftarrow 1, n$ **do**
$second \leftarrow intervalSecondsData_a$
▷ appliance energy second at index a
$tempTotal \leftarrow tempTotal + P^A_{second}$
4: **end for**
5: $energy_{watts} \leftarrow tempTotal/n$

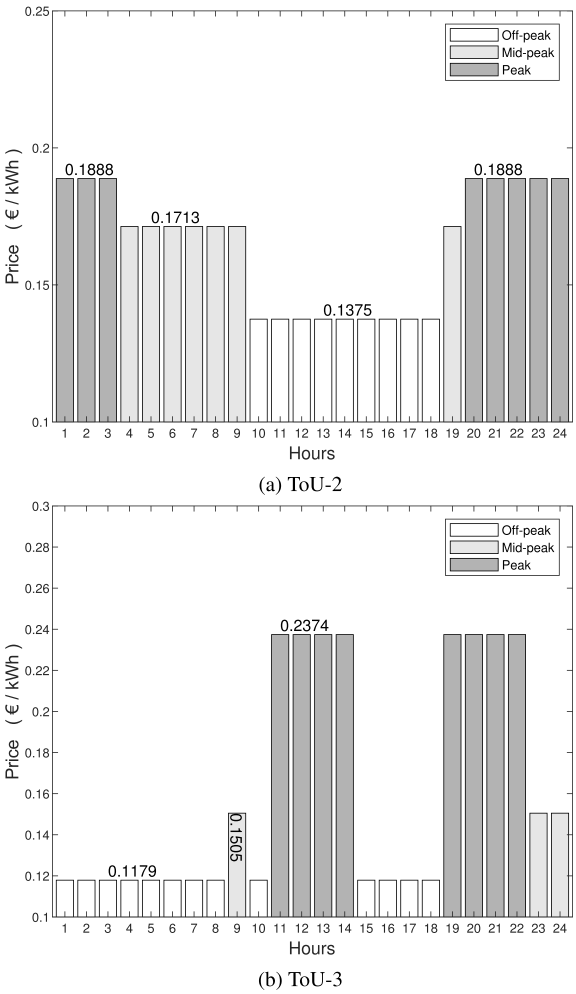
TABLE 10. Summary of price signals.

	ToU-1 (*cents*)	CPP (*cents*)	ToU-2 (€)	ToU-3 (€)
Reference	Fig. 4b	Fig. 4c	Fig. 5a	Fig. 5b
Peak hours	2	6	9	8
Peak price	27.08	123.4	0.2374	0.1888
Mid-peak hours	5	-	3	7
Mid-peak price	17.41	-	0.1505	0.1713
Off-peak hours	17	18	12	9
Off-peak price	9.35	11.4	0.1179	0.1375

For this reason, we performed IESR experimentation on four different price signals to show the effect of price signals on energy cost saving. In addition to this, we also present graphically 24-hour original energy consumption distribution of Unscheduled [28], ECO, and UK-DALE datasets in Fig. 6, and this distribution helps in identifying off-peak, mid-peak

TABLE 11. Total energy consumption of ECO and UK-DALE classified as peak, mid-peak and off-peak.

Dataset	Duration (start to end date)	Price signal	Peak		Mid-peak		Off-peak		Total	Cost saving
			kWh	cost	*kWh*	cost	*kWh*	cost	cost	margin
ECO 557.25 *kWh*	01-Jun-2012 *to* 31-Jan-2013	ToU-1 ($)	25.27	6.84	69.55	12.11	462.43	43.24	62.19	10.09
		CPP ($)	117.19	144.61	-	-	440.07	50.17	194.78	131.25
		ToU-2 (€)	304.69	72.33	91.64	13.79	160.92	18.97	105.09	39.4
		ToU-3 (€)	274.12	51.75	77.67	13.30	205.46	28.25	93.3	16.68
UK-Dale 397.16 *kWh*	01-Nov-2013 *to* 30-Jan-2014	ToU-1 ($)	36.38	9.85	97.04	16.89	263.74	24.66	51.4	14.27
		CPP ($)	119.40	147.34	-	-	277.76	31.66	179	133.73
		ToU-2 (€)	124.93	29.66	41.39	6.23	230.83	27.21	63.1	16.28
		ToU-3 (€)	108.17	20.42	117.65	20.15	171.34	23.56	64.13	9.52
Unscheduled 50.51 *kWh*	24-hours	ToU-1 ($)	6.7	1.81	10.96	1.91	32.85	3.07	6.79	2.07
		CPP ($)	18.4	22.71	-	-	32.1	3.66	26.37	20.61



(a) ToU-2

(b) ToU-3

FIGURE 5. ToU-2 and ToU-3: energy price models.

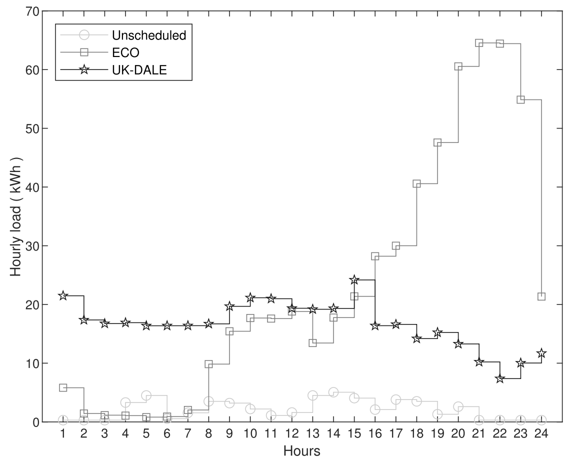


FIGURE 6. 24-hours original energy consumption distribution.

and peak hour energy distribution. The Unscheduled [28] 24-hours energy consumption distribution will be used for comparative analysis in Section IV-D.

C. EXPERIMENTAL RESULTS

We performed extensive experimentation using many combinations of IESR parameters (i.e., *interval* and *monitorUptoIntervals*) with four price signals ToU-1, CPP, ToU-2, and ToU-3. For the experiments, we created an array with values between 5 to 60 with the step size of 5 for both of these parameters. Then we find all combinations of *interval* and *monitorUptoIntervals* that are 144 in total. With simulations performed on both ECO and UK-DALE datasets using these many combinations of *interval* and *monitorUptoIntervals* with four price signals, we ensure that IESR performs well with diverse parameters and also guarantees flexibility for a smart home user to meet the off-peak scheduling requirements for heterogeneous appliances. We present summarized results of energy cost-saving percentage and the performance of IESR in Table 12 for ECO and Table 13 for UK-DALE dataset.

In Table 12 and Table 13, the cost-saving percentage is calculated by dividing the cost-saving by the total cost. The performance percentage is calculated by dividing the cost-saving by the cost-saving margin. The total cost and cost-saving margin are already presented in Table 11. The cost-saving margin is calculated to analyze the cost-saving performance of IESR. The cost-saving margin indicates the total energy cost-saving achievable if IESR schedules all mid-peak and peak energy consumption to an off-peak hour. The results in Table 12 and Table 13 indicate that with large values of IESR parameters (i.e., *interval* and *monitorUptoIntervals*), the cost-saving percentage and the performance of IESR decreases. This finding is because with large values of *interval* and *monitorUptoIntervals*, the number of recommendations identified per appliance decreases because of increased monitoring time. Since the smart home user chooses appliance monitoring parameters, we believe that the user achieves maximum comfort by assigning parameters that sustain a balance between cost-saving performance and the number of recommendations per appliance.

Moreover, the results in Table 12 and Table 13 also indicate that the smart home user can choose different combinations of the parameters for heterogeneous appliances. For targeting appliances with high energy usage for a long period of time, the smart home user may choose large values of *interval*, *monitorUptoIntervals* and $thresh_{max}$. Likewise, to monitor appliances with a short period of time and low energy consumption, the user may choose small values of *interval*, *monitorUptoIntervals* and $thresh_{max}$. In this way, IESR ensures flexibility for appliance monitoring and provides user comfort during off-peak scheduling management, as well.

It can be noted from the results in Table 12 and Table 13 that the cost-saving percentage varies with price signals. IESR achieves maximum cost-saving percentages with CPP, ToU-2, ToU-3, and ToU-1 for the ECO dataset. For the UK-DALE dataset, the maximum cost-saving percentage is achieved with CPP, ToU-1, ToU-2, and ToU-3, respectively. These findings signify that the price signals influence the performance of IESR as the energy consumption data is constant for all price signals during simulations. The cost-saving percentage is higher with CPP price signals as the cost difference of off-peak and peak hours is very high, causing a high margin for cost-saving. The results also determine that off-peak scheduling reduces energy load on smart grids during peak hours, consequently reducing energy production costs. Therefore, off-peak scheduling directly benefits smart grids in low energy production costs. The peak demands are fulfilled by additional production plants usually operated with fossil fuels causing high energy costs during peak hours [37].

In the subsequent sections, we explain the cost-saving results for both the ECO and UK-DALE datasets thoroughly.

1) ECO RESULTS

The simulation results on the ECO dataset are presented in Table 12 and the results show that the best performance is achieved keeping both *interval* and *monitorUptoIntervals* at 5*s* and 5, respectively. The maximum energy-saving percentage obtained for ToU-1, CPP, ToU-2 and ToU-3 is 11.98%, 52.32%, 28.63%, and 13.33% respectively. Likewise, the performance of IESR according to energy-saving margin for ToU-1, CPP, ToU-2, and ToU-3 are 73.84%, 77.64%, 76.37%, and 74.58% respectively. The cost-saving percentage and energy-saving margin performances decrease gradually as the length of *interval* and *monitorUptoIntervals* increase due to a decrease in the number of recommendations identified with a long monitoring period.

2) UK-DALE RESULTS

The simulation results on the UK-DALE dataset are presented in Table 13. The results indicate that the best performance according to the ToU-1 price signal is achieved keeping both *interval* and *monitorUptoIntervals* at 30*s* and 30 respectively. The cost-saving percentage for ToU-1 is 23.35%, and IESR performance is 84.09%. On the other hand, for CPP, ToU-2, and ToU-3 price signals, keeping both *interval* and *monitorUptoIntervals* at 5*s* and 5, the maximum energy-saving percentage achieved is 59.58%, 20.70%, and 12.38% and IESR performance according to energy-saving margin is 79.74%, 80.22%, and 83.40% respectively.

3) WAITING TIME AND PAR RESULTS BASED ON PRICE SIGNALS

The users' comfort is directly related to the waiting time for appliances. There is always a trade-off between reducing energy costs and appliances' waiting times or reducing PAR and electricity costs. As a result, when users prefer to schedule an appliance for an off-peak hour, they must always bear a slight discomfort in terms of appliance waiting time. However, if appliances are turned on depending on the user's desire, there is no waiting time for this unscheduled case.

We calculate cost savings based on the fact that if we shift all peak load to off-peak hours. However, still, we cannot be sure what the user's choice will be on the recommendation point. The user may choose to schedule the load to the next nearest off-peak hour or any other peak hour listed in the price signal. Suppose the user decides the nearest off-peak hour, then the waiting time will be minimum. However, if the user chooses any other option, the waiting time will increase. We suggest future work to simulate the user response against recommendation points to calculate waiting time and peak-to-average ratio. Whereas in existing optimization algorithms, there is no user involvement while scheduling. Therefore, the waiting time and peak-to-average ratio can be calculated since the algorithm decides which next off-peak hour to select for scheduling.

Nevertheless, we calculated an average waiting time and PAR value by simply scheduling all peak loads to the nearest off-peak hour according to a price signal peak to off-peak distribution. The obtained results are given in Table 14.

The estimated average waiting time in Table 14 is the same for all price signals concerning ECO and UK-DALE as we shift the load to the nearest off-peak hour. Consider the ToU-1 price signal in Fig. 4b; for the calculation of waiting time, we have to shift the load from hours 7 to 13 toward hour 14 or

TABLE 12. ECO: cost saving and performance analysis.

	ToU-1 ($)		CPP ($)		ToU-2 (€)		ToU-3 (€)	
total cost	62.19		194.78		105.09		93.3	
cost saving margin	10.09		131.25		39.4		16.68	
interval-monitor-up-interval: 5-5								
	peak	mid-peak	peak	mid-peak	peak	mid-peak	peak	mid-peak
kWh	18.34	52.06	90.98	-	233.52	66.91	205.20	56.2
cost-peak	4.97	9.07	112.27	-	55.43	10.07	38.74	9.63
cost-off-peak	1.71	4.87	10.37	-	27.53	7.89	28.21	7.73
cost-reduction	3.25	4.2	101.90	-	27.9	2.18	10.53	1.9
cost saving	7.45		101.90		30.09		12.44	
cost saving (%)	**11.98**		**52.32**		**28.63**		**13.33**	
performance (%)	**73.84**		**77.64**		**76.37**		**74.58**	
interval-monitor-up-interval: 10-10								
kWh	16.79	49.59	88.96	-	229.74	65.78	202.11	54.34
cost-peak	4.55	8.63	109.77	-	54.53	9.9	38.16	9.31
cost-off-peak	1.57	4.63	10.14	-	27.08	7.75	27.78	7.47
cost-reduction	2.98	4	99.63	-	27.45	2.15	10.37	1.84
cost saving	6.98		99.63		29.6		12.21	
cost saving (%)	11.22		51.15		28.17		13.09	
performance (%)	69.18		75.91		75.13		73.20	
interval-monitor-up-interval: 20-20								
kWh	10.37	41.11	76.82	-	206.17	53.86	180.84	43.9
cost-peak	2.81	7.16	94.79	-	48.94	8.11	34.14	7.52
cost-off-peak	0.97	3.84	8.76	-	24.3	6.35	24.86	6.03
cost-reduction	1.84	3.32	86.03	-	24.64	1.76	9.28	1.49
cost saving	5.16		86.03		26.39		10.77	
cost saving (%)	8.30		44.17		25.11		11.54	
performance (%)	51.14		65.55		66.98		64.57	
interval-monitor-up-interval: 30-30								
kWh	5.77	31.54	64.25	-	186.22	41.79	162	36.96
cost-peak	1.56	5.49	79.29	-	44.20	6.29	30.58	6.33
cost-off-peak	0.54	2.95	7.32	-	21.95	4.93	22.27	5.08
cost-reduction	1.02	2.54	71.96	-	22.25	1.36	8.32	1.25
cost saving	3.57		71.96		23.62		9.57	
cost saving (%)	5.74		36.94		22.48		10.26	
performance (%)	35.38		54.83		59.95		57.37	
interval-monitor-up-interval: 40-40								
kWh	5.49	28.33	58.57	-	177.67	36.97	153.06	35.49
cost-peak	1.49	4.93	72.28	-	42.17	5.56	28.9	6.08
cost-off-peak	0.51	2.65	6.68	-	20.94	4.36	21.04	4.88
cost-reduction	0.97	2.28	65.6	-	21.23	1.21	7.86	1.2
cost saving	3.26		65.6		22.44		9.06	
cost saving (%)	5.24		33.68		21.35		9.71	
performance (%)	32.31		49.98		56.95		54.32	
interval-monitor-up-interval: 50-50								
kWh	5	26.19	54.27	-	168.54	30.93	142.05	33.25
cost-peak	1.36	4.56	66.97	-	40.01	4.66	26.82	5.7
cost-off-peak	0.47	2.45	6.19	-	19.87	3.65	19.53	4.57
cost-reduction	0.89	2.11	60.78	-	20.14	1.01	7.29	1.13
cost saving	3		60.78		21.15		8.42	
cost saving (%)	4.82		31.20		20.13		9.02	
performance (%)	29.73		46.31		53.68		50.48	
interval-monitor-up-interval: 60-60								
kWh	4.74	23.93	48.96	-	157.78	26.71	131.06	30.71
cost-peak	1.28	4.17	60.42	-	37.45	4.02	24.74	5.26
cost-off-peak	0.44	2.24	5.58	-	18.6	3.15	18.02	4.22
cost-reduction	0.84	1.93	54.84	-	18.85	0.87	6.73	1.04
cost saving	2.77		54.84		19.73		7.77	
cost saving (%)	4.45		28.15		18.77		8.33	
performance (%)	27.45		41.78		50.08		46.58	

the following hours, which are off-peak hours. In this case, we do not have any user response to the recommendation points; therefore, we cannot precisely calculate the waiting time. However, to provide a clear picture of the situation, we calculated average waiting time and PAR values by shifting all loads from hours 7 to 13 toward hour 14.

TABLE 13. UK-DALE: cost saving and performance analysis.

	ToU-1 ($)		**CPP ($)**		**ToU-2 (€)**		**ToU-3 (€)**	
total cost	51.4		179		63.1		64.13	
cost saving margin	14.27		133.73		16.28		9.52	
interval-monitor-up-interval: 5-5								
	peak	mid-peak	peak	mid-peak	peak	mid-peak	peak	mid-peak
kWh	30.94	79.47	95.22	-	99.96	34.24	88.47	100.40
cost-peak	8.38	13.84	117.5	-	23.73	5.15	16.70	17.2
cost-off-peak	2.89	7.43	10.85	-	11.78	4.04	12.16	13.8
cost-reduction	5.49	6.41	106.64	-	11.95	1.12	4.54	3.4
cost saving	11.9		106.64		13.06		7.94	
cost saving (%)	23.15		**59.58**		**20.70**		**12.38**	
performance (%)	83.39		**79.74**		**80.22**		**83.40**	
interval-monitor-up-interval: 10-10								
kWh	30.78	78.94	94.36	-	98.54	33.65	86.85	100.24
cost-peak	8.34	13.74	116.44	-	23.39	5.06	16.4	17.17
cost-off-peak	2.88	7.38	10.76	-	11.62	3.97	11.94	13.78
cost-reduction	5.46	6.37	105.69	-	11.78	1.1	4.46	3.39
cost saving	11.83		105.69		12.87		7.85	
cost saving (%)	23.02		59.04		20.40		12.24	
performance (%)	82.90		79.03		79.05		82.46	
interval-monitor-up-interval: 20-20								
kWh	30.2	75.51	87.12	-	89.93	28.83	71.59	86.52
cost-peak	8.18	13.15	107.51	-	21.35	4.34	13.51	14.28
cost-off-peak	2.82	7.06	9.93	-	10.60	3.4	9.84	11.89
cost-reduction	5.36	6.09	97.58	-	10.75	0.94	3.67	2.93
cost saving	11.45		97.58		11.69		6.6	
cost saving (%)	22.28		54.51		18.53		10.29	
performance (%)	80.24		72.97		71.81		69.33	
interval-monitor-up-interval: 30-30								
kWh	32.2	76.88	85.7	-	86.76	22.40	61.97	92.44
cost-peak	8.86	13.38	105.75	-	20.59	3.37	11.7	15.84
cost-off-peak	3.06	7.19	9.77	-	10.23	2.64	8.52	12.71
cost-reduction	5.8	6.2	95.98	-	10.37	0.73	3.18	3.13
cost saving	12		95.98		11.1		6.31	
cost saving (%)	**23.35**		53.61		17.59		9.84	
performance (%)	**84.09**		71.77		68.18		66.28	
interval-monitor-up-interval: 40-40								
kWh	28.5	66.71	84.3	-	84.44	23.89	61.2	91.55
cost-peak	7.72	11.61	104.11	-	20.04	3.6	11.55	15.68
cost-off-peak	2.66	6.24	9.62	-	9.95	2.82	8.41	12.59
cost-reduction	5.06	5.38	94.5	-	10.09	0.78	3.14	3.1
cost saving	10.43		94.5		10.87		6.24	
cost saving (%)	20.29		52.79		17.23		9.73	
performance (%)	73.09		70.66		66.77		65.55	
interval-monitor-up-interval: 50-50								
kWh	28.68	67.56	84.78	-	76.69	21.68	61.23	91.85
cost-peak	7.77	11.76	104.62	-	18.2	3.26	11.56	15.75
cost-off-peak	2.68	6.31	9.6	-	9.04	2.56	8.42	12.63
cost-reduction	5.09	5.45	94.95	-	9.16	0.71	3.14	3.11
cost saving	10.53		94.95		9.87		6.25	
cost saving (%)	20.49		53.04		15.64		9.75	
performance (%)	73.79		71		60.63		65.65	
interval-monitor-up-interval: 60-60								
kWh	26.82	61.62	62.66	-	66.16	20.69	59.76	88.88
cost-peak	7.26	10.73	77.32	-	15.7	3.11	11.28	15.23
cost-off-peak	2.51	5.76	7.18	-	7.8	2.44	8.22	12.22
cost-reduction	4.76	4.97	70.18	-	7.91	0.68	3.07	3.01
cost saving	9.73		70.18		8.58		6.08	
cost saving (%)	18.93		39.21		13.60		9.48	
performance (%)	68.19		52.48		52.70		63.87	

Also, it can be noted in Table 14 that the estimated PAR values are relatively higher in our scenario compared to optimization-based techniques [28] since our study focuses on the identification of appliances based on user requirements. Minimizing the average waiting time, PAR, and energy cost simultaneously, on the other hand, becomes

TABLE 14. The estimated average waiting time and PAR.

	ECO & UK-DALE	ECO	UK-DALE
	AWT	PAR	
ToU-1	3	4.85	9.23
CPP	2.5	6.34	8.22
ToU-2	6.6	15.91	14.92
ToU-3	11.18	13.74	6.23

an optimization problem that is not the focus of this study.

D. COMPARATIVE ANALYSIS OF ENERGY COST SAVING

There are many off-peak scheduling algorithms discussed in the state-of-the-art literature and it is essential to compare IESR cost-saving results with other techniques to demonstrate the improved performance of IESR, among other techniques. For comparative analysis, we formulated a novel evaluation metric that helps investigate the performance of IESR and other techniques on the same criteria. We first find the peak and off-peak energy consumption ratio with (3) from the 24-hour energy consumption distribution given in Table 11 and drawn in Fig. 6. This ratio is different for different datasets as it is based on the price signal peak and off-peak hour distribution discussed in detail in Section IV-B. After the calculation of peak and off-peak ratio, the second step is to find the performance of various techniques using (4). For comparative analysis, we find comparative performance from the energy cost-saving results discussed in [28]. It is important to note that we calculate peak and off-peak distribution for only ToU-1 and CPP for Unscheduled [28] energy consumption as they calculated the cost-saving percentage only for these two signals. Consequently, we compare our IESR cost-saving percentage with four meta-heuristic methods, MFO, WOA, HHO, and AEO presented in [28] according to ToU-1 and CPP price signals only.

It is evident from the results given in Table 15, that the performance of IESR is better when compared to MFO, WOA, HHO, and AEO techniques according to the proposed novel evaluation metric. IESR technique achieves the comparative performance of 46.23% and 138.82% according to ToU-1 and CPP price signals, respectively, for the UK-DALE dataset. In addition to this, IESR reaches the maximum comparative performance of 58.34% and 196.2% according to ToU-1 and CPP price signals respectively for the ECO dataset.

$$Ratio_{peak}^{offPeak} = \frac{offPeak_{kWh}}{midPeak_{kWh} + peak_{kWh}} \tag{3}$$

where $offPeak_{kWh}$, $midPeak_{kWh}$, and $peak_{kWh}$ represents the total energy consumption in off-peak, mid-peak, and peak hours respectively.

$$Performance_{Comp} = Ratio_{peak}^{offPeak} \times CSP \tag{4}$$

where $Performance_{Comp}$ represents the comparative performance and CSP denotes cost saving percentage.

V. INSIGHTS AND DISCUSSIONS

Our main objective in this study is to develop an energy cost-saving recommendation technique that monitors smart home appliances in real-time. Real-time appliance monitoring identifies the energy usage pattern of appliances, leading to the recognition of peak-hour energy consumption. Energy consumption during peak hours can be reported to the smart home user with a suggestion of shifting this peak hour energy load to an off-peak hour to reduce the energy cost. Although peak hours vary depending on the price signal under consideration, we thoroughly study the relationship between price signal and the performance of an off-peak scheduling technique. From the experimental results, we notice that the energy-saving performance of IESR with the CPP price signal is higher than ToU price signals. This is because the price difference among peak and off-peak hours in CPP is too high, whereas it is relatively lower in ToU.

We introduce flexible parameters to identify peak-hour energy load using IESR. The peak hour load identification starts based on the user-specified parameters ensuring the user's wishes in the appliances monitoring process. In order to establish an energy-saving recommendation, IESR first verifies the user appliance monitoring specifications, and secondly, it checks if an appliance consumes energy during peak hours. Until these two conditions are not verified, IESR keeps on monitoring the appliances' energy consumption patterns. IESR ensures maximum user comfort by scheduling the appliances to the nearest off-peak hour yielding minimum waiting time in contrast to other state-of-the-art off-peak scheduling techniques [21], [26], [28].

Also, the appliances' energy consumption patterns affect the performance of the off-peak scheduling techniques. To illustrate, if appliances consume energy mostly during peak hours, the performance of off-peak scheduling techniques increases, whereas if appliances continue to operate mainly in off-peak hours, the performance of the off-peak scheduling techniques diminishes. To investigate this correlation, we calculate the 24-hour energy consumption distribution of three different datasets (i.e., ECO, UK-DALE, and Unscheduled) given in Fig. 6. We compute off-peak, mid-peak, and peak-hour energy distribution according to the price signals to calculate the maximum cost-saving margin. The cost-saving margin refers to the difference in total energy cost when all mid-peak and peak energy consumptions are scheduled to an off-peak hour. The performance of IESR concerning cost-saving margin proves the effectiveness of the proposed technique. We calculate the off-peak to peak ratio to perform comparative analysis among different techniques. However, existing studies [3], [21], [26], [28] do not examine the relationship of appliances' energy consumption patterns and the performance of the off-peak scheduling techniques.

The performance of an off-peak scheduling technique is determined by energy cost-saving percentage. As various studies use different datasets for experimentations, it becomes difficult to examine which technique outperforms others with respect to energy cost-saving. To address this problem,

TABLE 15. Comparative performance analysis of different techniques.

Techniques	Price signals	Peak (kWH)	Mid-peak (kWh)	Off-peak (kWh)	$Ratio^{offPeak}_{peak}$	Cost Saving (%)	$Performance_{Comp}$
WOA	ToU-1	6.7	10.96	32.85	1.86	2.67	4.97
	CPP	18.4	-	32.1	1.74	29.34	51.05
HHO	ToU-1	6.7	10.96	32.85	1.86	2.88	5.36
	CPP	18.4	-	32.1	1.74	28	48.72
MFO	ToU-1	6.7	10.96	32.85	1.86	3.43	6.38
	CPP	18.4	-	32.1	1.74	26.86	46.73
AEO	ToU-1	6.7	10.96	32.85	1.86	10.95	20.37
	CPP	18.4	-	32.1	1.74	37.05	64.47
IESR - UK-DALE	ToU-1	36.38	97.04	263.74	1.98	23.35	**46.23**
	CPP	119.40	-	277.76	2.33	59.58	**138.82**
IESR - ECO	ToU-1	25.27	69.55	462.43	4.87	11.98	**58.34**
	CPP	117.19	-	440.07	3.75	52.32	**196.2**

we devise a novel evaluation metric that examines the performance of the scheduling techniques based on the off-peak to peak ratio. For the new evaluation metric, we consider both mid-peak and peak hours as peak hours. The experimental results in Table 15 indicate that IESR intensely outperforms existing techniques. The new evaluation metric helps to perform comparative analysis among various off-peak scheduling techniques.

Moreover, the results of experiments conducted on two datasets indicate that IESR reaches the highest performance when the monitoring time of an appliance is short (i.e., *interval* and *monitorUptoIntervals* at 5s and 5). With a short monitoring time, IESR detects maximum instant recommendation points achieving maximum energy cost-saving percentage. On the other hand, the experimental results of the UK-DALE dataset with ToU-1 price signal present that the highest cost-saving percentage is achieved with *interval* and *monitorUptoIntervals* at 30s and 30, respectively. Our findings indicate that the cost-saving performance may vary for IESR parameters on different datasets due to different distributions of off-peak and peak energy consumption. Overall, it can be concluded with an experimental evaluation that IESR accomplishes the highest energy cost-saving in a smart home.

VI. CONCLUSION AND FUTURE WORK

This paper presents an off-peak scheduling technique to reduce energy costs by monitoring smart home appliances. The proposed technique, IESR, identifies instant recommendation points for scheduling appliances to an off-peak hour. It monitors appliances in real-time in contrast to other existing techniques and targets appliances with high energy usage during mid-peak and peak hours for scheduling. As a result, shifting peak hour load to off-peak hours diminishes the load on smart grids.

Also, we investigated the influence of energy price signals on the performance of off-peak scheduling techniques. IESR performance is relatively better with the CPP price signal as the cost difference of peak and off-peak hours is very high in CPP. IESR attains a cost-saving performance of 77.64% and 84.09% for the ECO and UK-DALE datasets, respectively. Furthermore, we devise a novel evaluation metric to compare the performance of various off-peak scheduling techniques and accordingly IESR considerably outperforms state-of-the-art techniques by achieving significant improvements for ToU-1 and CPP price signals.

Due to a lack of recommendation responses, i.e., user responses to instant recommendations, the calculation of exact waiting time and the peak-to-average ratio are not achievable. These can only be estimated by relying on the distribution of price signals' peak to off-peak hours. Therefore, in future research, a dataset with recommendation responses can be simulated or collected in a real-time smart home to investigate the waiting time and peak-to-average-ratio response of IESR. Moreover, off-peak scheduling may create a new peak that needs to be addressed in future research work. To avoid new off-peaks, we will attempt to develop a scheduling predictor algorithm that monitors the load distribution in upcoming peak hours.

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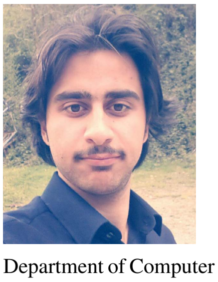

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