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DOI
10.1109/TGCN.2017.2721818

Publication date
2017

Document Version
Final published version

Published in
IEEE Transactions on Green Communications and Networking

Decentralized Energy Demand Regulation in Smart Homes

S. N. Akshay Uttama Nambi, R. Venkatesha Prasad, *Senior Member, IEEE*, and Antonio R. Lua

***Abstract*—Smart grids offer better energy management for consumers as well as energy companies using bi-directional communication and control. With the advent of smart homes, energy companies can balance energy supply and demand to a large extent using many sensors/meters deployed. They can also nudge consumers to shift their demands to off-peak hours for load balancing and monetary benefits. We propose a decentralized demand scheduling algorithm that minimizes consumer discomfort and electricity cost of a household. Our algorithm utilizes *only* aggregated energy consumption of a household to derive optimal appliance level demand schedules. Furthermore, a low-complexity energy disaggregation algorithm is proposed to derive fine-grained appliance information and consumer preferences. We propose three important coefficients related to the energy usage of consumers. We utilize them to derive optimal day-ahead demand schedules. The decentralized algorithm is empirically evaluated using real-world energy usage data from open datasets, which include our own deployment. Our proposed scheduling algorithm saves up to 30% energy cost. This paper is one of the first to derive day-ahead schedules using real-world data from multiple households.**

***Index Terms*—Demand regulation, load shifting, scheduling, decentralized, energy disaggregation, smart grid.**

I. Introduction

SMART Grid (SG) takes advantage of communication and control technologies to integrate the power infrastructure with the information infrastructure [2], which comprises of information and communication technology (ICT) to measure and control power infrastructures. Thus a bidirectional communication is necessary between consumers and energy companies (or utilities) enabling immediate feedback on power usage, power quality, and pricing details [3]. This transformation enables both consumers and utilities to communicate with each other to balance energy supply and demand leading to reliable and robust operations of the SG.

With the advent of smart homes, numerous devices such as vacuum cleaners, smart washing machines, ovens, and refrigerators are becoming more intelligent and can be controlled remotely. In SG, utilities are allowed to dynamically adjust the electricity prices in order to control demand. The real-time pricing information communicated to the smart homes can be used to control and adjust the demands, at the customer premises. Demand regulation or demand-side management is a key technique that can control and influence energy demand at consumer-end to reduce the overall peak demand, reshaping demand profiles and increasing the robustness of SG [4]. Several demand-regulation techniques are proposed in the literature for load shifting [5], peak clipping and valley filling [6]. *Load shifting*, in particular, involves shifting loads from peak to off-peak hours, without significantly influencing the average load over time. Load shifting ensures the total energy consumed by the household does not overload the grid by altering the demand pattern of the household.

In this paper, demand regulation (DR) is defined as the change in energy consumption pattern in response to change in price of electricity. Specifically, we limit the DR to load shifting. Each household is assumed to be equipped with an *information system* that collects real-time demand measurements from smart meters and also controls energy consumption. Existing energy management systems (EMS)/information systems are mainly designed to improve energy efficiency and comfort, i.e., turning off appliances when not in use, changing HVAC/air-condition setpoints to minimize energy consumption [7], [8], etc. Recent EMS aim to reduce electricity cost by scheduling the demand of the household based on the electricity prices (real-time or day-ahead). These scheduling algorithms utilize either (i) fine-grained energy consumption information from the appliances or (ii) aggregate energy consumption of the household for load shifting. In the case of *fine-grained information*, energy consumption of each appliance in the household is analyzed for deriving schedules for appliances. These approaches require detailed user and appliance information to schedule loads effectively. In the case of *aggregate consumption*, the scheduler aims to determine the energy that needs to be shifted from the total consumption of the household at a given time period. This approach requires consumers to figure out which appliance needs to be turned-on/off to match the energy that needs to be shifted.

There still exists several challenges hindering the applicability of load shifting in residential households. We enlist some of the important ones here: (i) Most of the approaches presented [5], [9], [12] require detailed user and appliance level information to schedule loads effectively. This either

Manuscript received March 15, 2017; revised May 12, 2017 and June 16, 2017; accepted June 19, 2017. Date of publication June 29, 2017; date of current version August 17, 2017. This paper is an extended and revised version of a conference paper that was presented at IEEE Globecom, Washington, DC, USA, December 2016 [1]. The associate editor coordinating the review of this paper and approving it for publication was E. Ayanoglu. *(Corresponding author: R. Venkatesha Prasad.)*

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Digital Object Identifier 10.1109/TGCN.2017.2721818

requires the additional deployment of sensors or significant consumer involvement. (ii) Approaches based on aggregate energy consumption, either select a demand pattern based on historic data or require the consumer to shift energy. Quite often, consumers have no real knowledge of appliance level energy information. (iii) Most demand scheduling algorithms do not consider the heterogeneity of appliances in the household, flexibility in appliance usage, and appliance dependencies during scheduling. Hence the resultant schedule is either infeasible or the user comfort is severely hampered. (iv) Load scheduling or shifting is quite often performed in a centralized manner where energy consumption information is sent to the utilities or an aggregator to determine the optimal schedule. This raises several issues related to scalability and privacy. (v) Lastly, the scheduling algorithms are generally evaluated using simulation or numerical analysis, which may not reflect the ground truth very well [12]–[15]. Furthermore, the applicability of scheduling algorithms across different households is never considered in the prevalent research [20], [21].

In this paper, to overcome the above limitations, we propose a decentralized demand regulation scheme. The proposed demand scheduling algorithm utilize *only* the aggregated energy consumption of a household to derive optimal appliance level schedule. We derive fine-grained appliance information and user preferences from the aggregated energy information using a low-complexity energy disaggregation algorithm. This approach utilizes data from a single smart meter and eliminates the need for additional sensor deployment. Furthermore, the demand scheduling algorithm runs on an embedded system such as Raspberry Pi at the consumers premises, thus privacy-sensitive data is stored and processed locally at the household. This approach is highly scalable and avoids sharing of privacy-sensitive information to the utilities. The proposed demand scheduling algorithm is evaluated on our real-world deployment Dutch Residential Energy Dataset (DRED) in the Netherlands [10]. Furthermore, we show the applicability of the scheduler on another household in the USA using the open dataset REDD [11]. The scheduler implementation is made publicly available for the community to support additional analysis [10].

The primary objective of this work is to develop a decentralized demand regulation scheme that can, (i) determine appliance level information and user preferences for appliance usage, using only aggregated energy consumption from the smart meters and (ii) propose a demand scheduling algorithm that minimizes the user discomfort and electricity cost based on day-ahead hourly pricing. The main contributions of this paper are:

(i) We propose a novel decentralized demand scheduling algorithm that minimizes user discomfort and electricity cost of a household.

(ii) We describe three coefficients to analyze user preferences and appliance usage patterns using historic aggregated energy consumption.

(iii) We provide a detailed empirical evaluation of the proposed algorithm using real-world deployment and publicly open datasets.

TABLE I
COMPARISON OF STATE-OF-THE-ART APPROACHES

Work	Method	Consumer preference	Study type	Schedule level	implementation
[12]	Centralized	Partial	Numerical	Appliance	No
[13]	Decentralized	No	Simulation	Aggregate	No
[5]	Centralized	Partial	Simulation	Aggregate	No
[14]	Centralized	No	Simulation	Appliance	Partial
[15]	Centralized	Partial	Simulation	Appliance	No
Proposed	Decentralized	Yes	Data-driven	Appliance	Yes

II. RELATED WORK

Numerous DR programs [12]–[15], [20], [21] have been proposed to motivate changes in the consumers power consumption with the objective to either (i) minimize the electricity cost, (ii) maximize the social welfare, (iii) minimize the aggregated power consumption, or (iv) any combination of the above [20].

Table I provides a concise overview of state-of-the-art approaches against the proposed scheme. The columns indicate whether the scheduling algorithm is centralized or decentralized if consumer preferences are considered or not, whether the evaluation was based on simulation or data-driven if the scheduling algorithm is at the appliance level or aggregated, and if the scheduling algorithm can be implemented on an embedded system such as Raspberry Pi.

In [12] an optimized day-ahead pricing scheme is proposed by considering the flexibility of appliance scheduling. A cost minimization problem is formulated to reduce electricity cost. However, this approach does not consider consumer preferences and authors show only numerical analysis of the proposed scheduling algorithm. A genetic algorithm to derive optimal power schedule of a household is proposed in [13]. The genetic algorithm runs at the household to minimize electricity cost and to reduce the delay in the usage of appliances. Similar to [13], Chen *et al.* [5] propose a task scheduling algorithm that considers per-appliance delay and also long-term average delay to minimize the electricity cost. Contrary to the above approaches in this work, we not only consider a delay in appliance usage but we also consider the flexibility, appliance dependencies, and consumer preferences to schedule the appliance usage. In [14] an integer linear programming technique based online load scheduling algorithm is proposed to minimize energy cost in residential settings. In [15], a scheduling technique is proposed by modeling energy consumption and user preferences as a stochastic variable. Appliance-level schedules derived are evaluated using simulation results.

Recent efforts consider uncertainties in manually operated appliances [16], where robust optimization approaches for demand side scheduling is proposed. The proposed approach takes into account the worst case to reduce electricity payment of all home appliances. However, the worst case electricity needs are taken arbitrarily and only simulation results on how the proposed robust approach performs are described. In [17], a multi-residential load scheduling problem is considered. The authors propose a load scheduling algorithm by jointly considering multi-residence and multi-class appliance. While the authors consider multiple residences, they do not completely account for individual households household preferences. A sparse load shifting algorithm is presented in [18] to globally minimize the total energy consumption cost and the peak-to-average ratio. In [19] an optimal electric load scheduling problem is presented taking into account both energy and user dissatisfaction costs. User dissatisfaction is modeled as a convex function of time if the appliance either delayed or advanced from the preferred time of its operation. While these approaches try to minimize the time delay, the proposed algorithm in this paper also considers the time periods when an appliance is used, how long they are used and dependencies between other appliances. This information plays a crucial role in deriving schedules that maximize user preferences and comfort.

The state-of-the-art techniques do not completely capture consumer preferences and appliance usage patterns. Furthermore, these techniques cannot be readily applied to multiple households or datasets. In this work, we extend the state-of-the-art methods by considering smart meter data from multiple households across different locations to validate the scheduling decisions. We utilize only aggregated data of the household to derive appliance level day-ahead schedule with the help of a low-complexity energy disaggregation algorithm and demand schedule. A Modified Combinatorial Optimization (ModCO) algorithm is proposed to derive fine-grained appliance information from the aggregated data. Finally, a decentralized demand scheduler is proposed to derive day-ahead appliance schedule that minimizes electricity cost and associated consumer discomfort. This work is one of the first to derive day-ahead schedules using real world data from multiple households.

III. System Model

Each household is assumed to have an information system (i.e., Raspberry Pi or Arduino) connected with the smart meter to balance energy demand by applying demand regulation techniques. Fig. 1 shows the system model of the proposed decentralized demand scheduling system in smart homes.

The energy utilities send the day-ahead hourly pricing to all its consumer base. The information system at the household then derives day-ahead schedules to minimize electricity cost. To derive day-ahead schedules, the aggregated energy demand data from the smart meter is given to the energy disaggregation block. Energy disaggregation block employs a Modified Combinatorial Optimization (ModCO) algorithm to infer per-appliance energy consumption information. This information is also used to derive consumer preferences such as, appliances that are currently used and its duration, usage patterns in weekdays and weekends, etc. The appliance level energy information along with consumer preferences are used by the demand scheduler to derive day-ahead schedules. The demand scheduler utilizes several coefficients to minimize the electricity cost and consumer discomfort. The proposed day-ahead schedule is then communicated to the household/occupants via the information system. This we call *local feedback*, which can be used to understand the effectiveness of the proposed schedule or how the occupants are adapting. Furthermore, the information system communicates the proposed schedule to the energy utilities, we call this *global feedback*. The global feedback allows the utility to plan the energy purchase and also to balance energy at a larger scale like neighborhood and township.

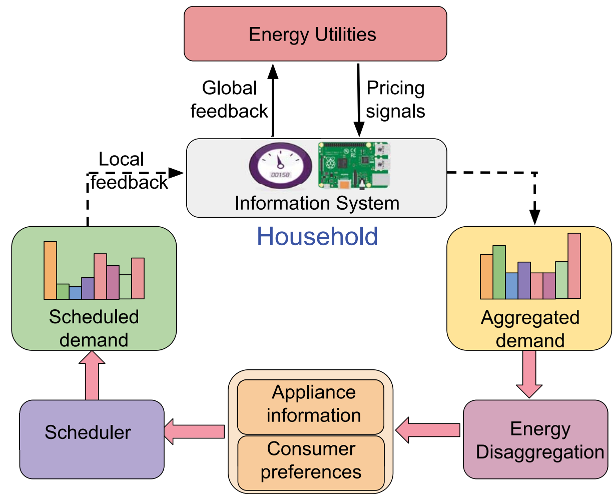

Fig. 1. System model of decentralized demand scheduling.

In this work, we distinguish the appliances in smart homes as *non-schedulable* and *schedulable*. The former represents appliances that require fixed energy requirement and are not subjected to scheduling decisions. These appliances include television, refrigerators, modems, etc. Schedulable appliances allow appliance usage to be shifted in time and has a direct relation to consumer preferences and behavior. These appliances include dishwashers, washing machines and clothes dryers. The distinction between the loads can be automatically done by analyzing the appliance usage patterns.

Energy disaggregation: Hitherto, several energy disaggregation algorithms such as Combinatorial Optimization (CO) and Factorial Hidden Markov Model (FHMM) [22]–[24] have been proposed to derive appliance level information. We first describe the traditional CO algorithm and then propose our Modified Combinatorial Optimization (ModCO) algorithm.

Combinatorial Optimization (CO): The goal of an energy disaggregation algorithm is to provide estimates of actual energy consumed by each appliance from the aggregate energy consumption data. Let $\hat{y}_t^{(n)}$ be the estimated energy consumed and $y_t^{(n)}$ be the actual energy demand of each appliance n at time t. $\bar{y}_t$ represent the aggregate energy reading of the household. The ground truth state of an appliance is represented by $x_t^{(n)} \in Z \geq 0$ and $\hat{x}_t^{(n)}$ represents the appliance state estimated by the disaggregation algorithm. CO finds the optimal combination of appliance states, which minimizes the difference between the sum of predicted appliance power and the observed aggregate power. It is given by,

$$\hat{x}_t^{(n)} = \arg\min_{\hat{x}_t^{(n)}} \left| \bar{y}_t - \sum_{n=1}^{N} \hat{y}_t^{(n)} \right| \tag{1}$$

where N is the set of all appliances in the household and t is the current time period. The predicted energy consumption of an appliance $\hat{y}_t^{(n)}$ is then mapped to the closest appliance state $x_t^{(n)}$. This approach requires an appliance model, which includes power consumption details for each state of the appliance. This is further used during inference to predict the current state of the appliance. The computational complexity of disaggregation for T time periods is $O(TS^N)$, where S is the number of appliance states and N is the set of all appliances.

CO algorithm has several drawbacks. Firstly, this optimization problem resembles subset sum problem and is NP-complete. Furthermore, the computation complexity in CO increases exponentially with the number of appliances. Secondly, this algorithm does not differentiate between appliances with similar power consumption and appliances with similar states. Third, this algorithm assumes all the appliances in the household are being monitored and assigns some portion of energy to appliances even if they are not currently used, resulting in low disaggregation accuracy.

Modified CO (ModCO) algorithm: This improves the traditional CO in four aspects, (i) ensures the effect of small fluctuations in aggregate power is minimal; (ii) preserves consistency in consecutive state estimations – using *priority combinations*; (iii) eliminates the need for appliance level modeling by employing a crowd-sourced power consumption database, and (iv) reduces the computational complexity associated with determining the state combinations. We employ a crowd-sourced generic appliance model from the power consumption database. For example, the power consumption database [25] provides crowd-sourced information on maximum and idle power for a wide range of loads indexed by type, manufacturer, and model number. This information can be obtained a priori using the datasheets of appliances or crowd-sourced data, thus eliminating appliance energy modeling.

In the traditional CO, at each time interval, the algorithm tries to find the set of appliances, which are closest to the current aggregated energy consumption. This may result in a different set of appliances being used in each consecutive interval. Hence, it is necessary to preserve the consistency in selecting appliances during consecutive state estimations. We define *priority combination* – that is the set of appliances which are assumed to be currently running. This information can be retrieved from the last iteration of the algorithm. In each interval, ModCO first evaluates the priority combination to check whether the sum of all appliances in the priority combination matches the current aggregated value. If the difference between the sum of priority combination and the aggregated energy is within a threshold δ, then the current priority combination is retained as the predicted set.

Our algorithm evaluates the following expression to determine whether the current priority combination of appliances is still valid or not, $[|\bar{y}_t - \sum_{n=1}^{K} \hat{y}_t^{(n)}| \leq \delta]$, where $\bar{y}_t$ represent the aggregate energy data of the household, $\hat{y}_t$ is the estimated energy consumed by each appliance, K is the set of appliances present in the priority combination and δ is the variation threshold. The variation threshold parameter minimizes the effect of small fluctuations in aggregate power. However, when the difference between current priority combination and aggregate consumption is greater than δ, we find the new state combination of appliances that match the aggregated energy consumption [23].

IV. Day-Ahead Demand Scheduling Algorithm

We now describe an algorithm that generates day-ahead demand schedule for a household, which minimizes electricity cost and consumer discomfort. Discomfort refers to the inconvenience experienced by the consumers during load shifting. The derived schedule is communicated to the occupants via information system to execute it the next day. Our algorithm is agnostic to time granularity, i.e., it can be applied for an entire day, during peak time periods, hourly, etc.

We formulate a cost minimization problem at the consumer-end by effectively scheduling loads based on day-ahead hourly pricing. Appliance usage patterns and consumer preferences are derived from the disaggregated energy data. The hypothesis considered here is that the proposed day-ahead schedule should resemble the historic energy consumption pattern of the consumer and it has minimal discomfort since the consumers have executed them previously. However, consumer preferences may change over time. Hence, our algorithm creates schedule not only based on historical demand patterns of consumers, but also by determining several coefficients that define consumer preferences and appliance usage patterns.

Fig. 2 shows an overview of the schedule generation algorithm. Our algorithm has five modules *viz.,* schedule creation, pattern abstraction, schedule filtering, schedule selection and schedule enhancement.

A. Schedule Creation

The first step is to find all possible demand schedules of consumers from their historic demand data. These schedules represent the energy usage behavior of consumers in the past. We then group these schedules at different granularities, i.e., either weekdays or weekends, the day of the week, etc. The past schedules generated are feasible and have minimal impact on the daily routines of the consumers since they have already executed them at some point in the past.

A feasible schedule could be chosen from the past schedules that coincides with the type of day in consideration. For example, a schedule for Saturday may choose only schedules of past Saturdays or weekends. In such a way, the final proposed schedule retains a greater resemblance to what the consumer typically does on that day. It may be possible that some of these schedules do not match user preferences either due to the huge variation in demand profile on that day or due to the arrival of guests in the household, etc. Hence it is necessary to determine representative schedules that accurately depict consumer preferences from the past schedules.

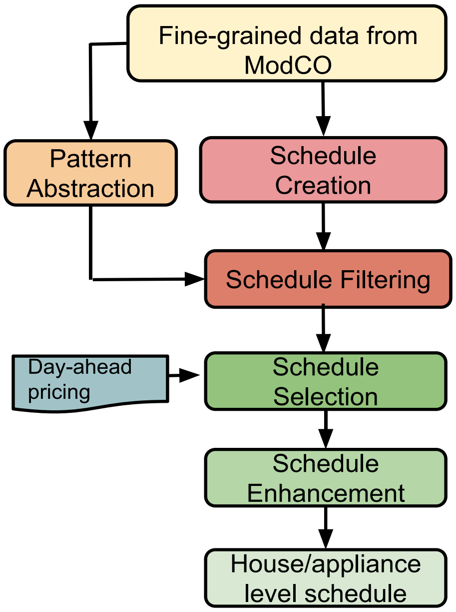

Fig. 2. Overview of schedule generation algorithm.

B. Pattern Abstraction

We propose three energy usage coefficients to analyze appliance usage patterns and consumer preferences.

(i) *Flexibility coefficient:* represents the average usage duration of an appliance in each hour of the day. This indicates the time periods when an appliance was used previously and how much time it was used. Fig. 3 shows flexibility coefficients heatmap of appliances during weekdays and weekends of a household from REDD dataset [11]. It can be seen that, appliance usage is high in mornings (7-10AM) and evenings (6-8PM) on weekdays. However, during the weekends the appliance usage is spread across the day. Flexibility coefficient indicates a preferable time period of appliance usage by the users.

(ii) *Sensitivity coefficient:* indicates the preferred time delay in the usage of an appliance by consumers. Some appliances can tolerate longer delays compared to others. For example, the coffee machine might allow shorter delays than the washing machine as the user always prepares coffee within a specific (and shorter) time period.

(iii) *Dependency coefficient:* indicates the appliance dependencies, associations and usage sequence. In general, the occupants have a daily routine making it possible to use an appliance in a sequence. For example, TV is always associated with a home theater.

C. Schedule Filtering

Schedule filtering employs the energy usage coefficients described previously to filter and select schedules that most accurately represent consumer preferences. We select the subset of schedules that adhere to the derived usage patterns and discard schedules that occurred only a few times or that are not representative of a typical day. Fig. 4 shows the difference between a representative and non-representative schedule based on per-appliance usage time. It can be seen that, a representative schedule has most of the appliances adhering to the appliance usage time periods (flexibility) of a typical day. Moreover, in a non-representative schedule, only a few appliances adhere to the average usage duration. In this paper, the filtering of schedules is done in combination with all the three energy usage coefficients.

The schedule filtering is based on individual appliances and to derive a representative schedule for a household, a minimum number of appliances need to adhere to the requirements derived. This setting is adjustable by the consumer or the utility or after negotiation. It represents the harshness in schedule filtering and can be used to identify the discomfort. For example, a requirement of low number of appliances to adhere to the coefficients may result in the selection of a schedule not matching the user preferences, leading to high consumer discomfort. The bounds on the coefficient values are derived based on consumer preferences. Finally, the filtered schedules are the representative schedules for that household.

D. Schedule Selection

From the set of representative schedules derived, we find the schedule that minimizes the electricity cost. Day-ahead hourly pricing information from the utilities[1] is obtained to identify the schedule that results in minimal electricity cost.

The scheduler selects the schedule with least electricity cost by solving the following cost minimization problem,

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^{N} \sum_{t=1}^{24} C_t \; D_t^{(i)}, \\ \text{subject to} \quad & 0 \le D_t \le D_{max}, \forall t, \end{aligned} \tag{2}$$

where N is the total number of representative schedules, C_t is the hourly electricity cost and D_t is the hourly energy demand of a representative schedule i. D_{max} represents the maximum hourly energy demand of the household.

E. Schedule Enhancement

Finally, we try to enhance the cost-optimal schedule derived previously. Enhancements are typically appliance load shifting based on the flexibility and sensitivity coefficients, to further reduce the cost and discomfort associated. Hence the optimization problem in (2) can be re-written as,

$$\begin{aligned} \text{minimize} \quad & \sum_{t=1}^{24} C_t \; D_t \\ \text{subject to} \quad & 0 \le D_t \le D_{max}, \forall t, \\ & l_f^a \le f\left(d_t^a\right) \le u_f^a, \quad s\left(d_t^a\right) \in \left(l_s^a, u_s^a\right), \forall a \in A, \end{aligned} \tag{3}$$

where C_t is the hourly cost, D_t is the cost-optimal energy demand, d_t^a is the appliance energy demand, f^a and s^a are the flexibility and sensitivity coefficients for each appliance, $a \in A$ the set of appliances, and l_f^a, u_f^a, l_s^a, u_s^a are the corresponding lower and upper bounds of flexibility and sensitivity coefficients.

[1]Day-ahead hourly prices: http://www.powersmartpricing.org/pricing-table/.

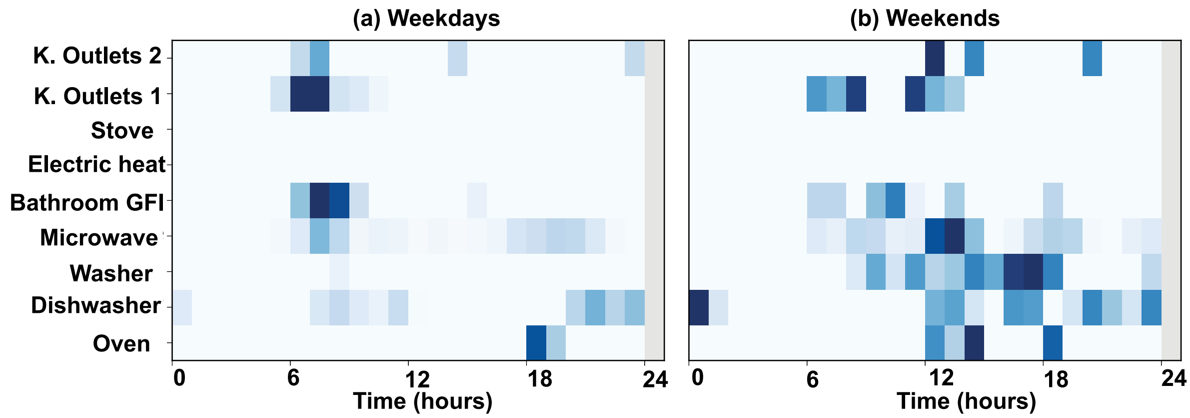

Fig. 3. Usage patterns of appliances in REDD.

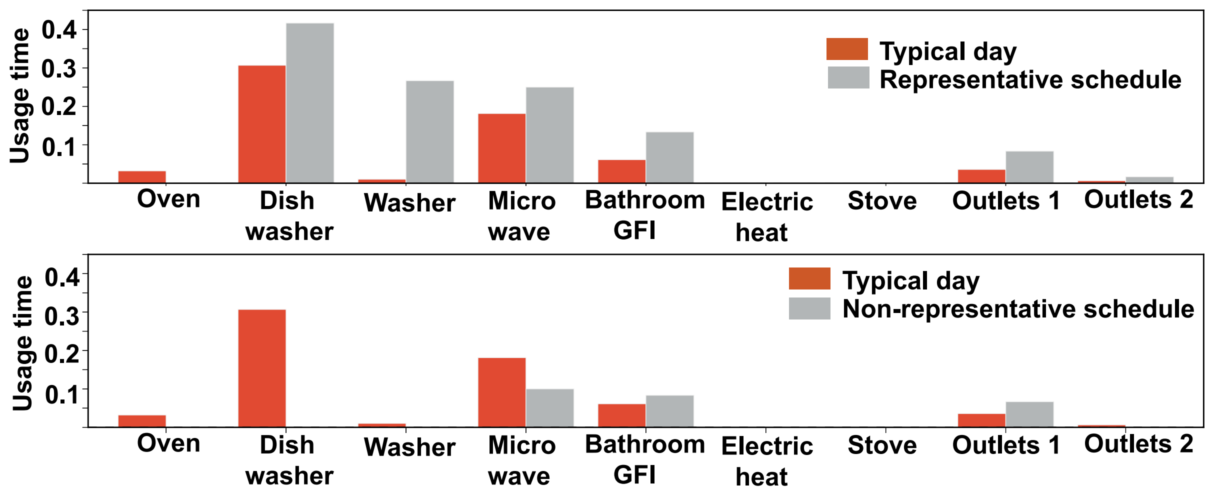

Fig. 4. Appliance time usage duration in REDD.

We propose an iterative method to solve (3) where each appliance usage is either retained at the same time period (if cost is lower) or shifted within the flexibility and sensitivity range derived using energy data. As mentioned previously, the former indicates the average usage time period of an appliance in an hour and the latter indicates the time delay the appliance can tolerate. The iterative method generates a sequence of improving approximate solutions that adhere to these coefficients. Furthermore, the scheduler needs to ensure, (i) an appliance usage event should not be subdivided into smaller events to avoid expensive hours and (ii) an appliance event duration should not be altered, i.e., neither stretching nor shrinking of an event is allowed. Our algorithm ensures the above conditions are met and shifts the appliance usage accordingly.

Since the iterative method is applied only on the cost-optimal schedule, the computational complexity associated in load shifting is minimal. Fig. 5 shows the demand shifting of schedulable loads for cost-optimal and enhanced schedule. It can be seen that from the cost-optimal schedule appliance usage are shifted to obtain the enhanced schedule. The shifting of appliance usage is based on the electricity price and consumer preferences derived using the energy usage coefficients. The comparison of cost-optimal and the enhanced schedule with day-ahead electricity price is shown in Fig. 6. The proposed scheduler can also be used with other pricing schemes such as hourly or real-time pricing. The first four steps of the proposed algorithm (schedule creation, pattern abstraction, schedule filtering and schedule selection) remain the same. However, the schedule enhancements (described in Eq. (3)) needs to be modified, specifically, the number of time slot and cost per time slot will be changed.

Furthermore, the proposed scheduler can incorporate renewable energy sources such as solar and the wind to balance the energy demand and supply. In this case, D_t in (2) and (3) can be replaced with $\hat{D}_t$, where $\hat{D}_t$=D_t - D_{RES}. Here, D_t is the demand required by the household, D_{RES} is the demand generated from renewables such as solar and the wind, and $\hat{D}_t$ is the energy demand borrowed/requested from the grid.

V. Experimental Evaluation

We provide a performance evaluation of the proposed scheduler across multiple datasets to support wide adoption and also to validate our work. We first describe the datasets employed for empirical evaluation. We then provide detailed results on energy disaggregation and efficacy of the scheduler.

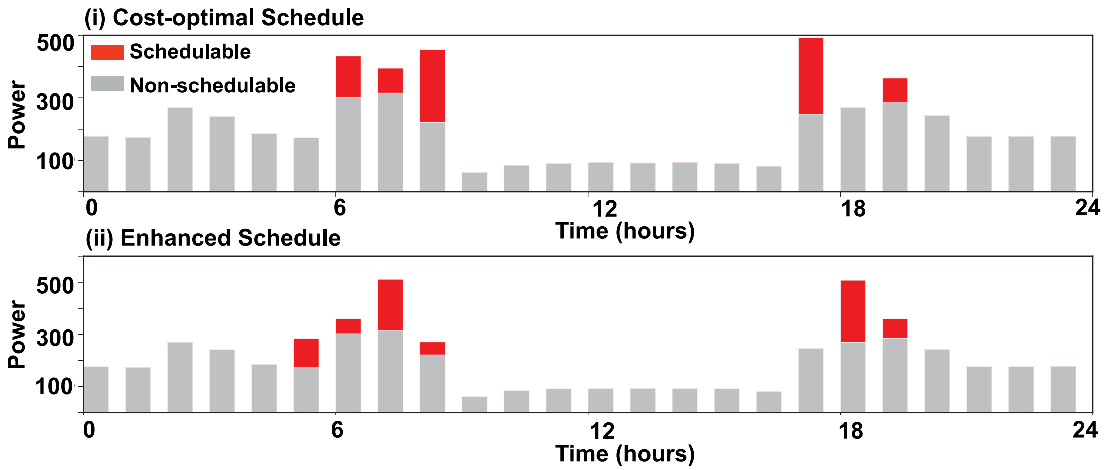

Fig. 5. Cost-optimal and enhanced schedule in REDD.

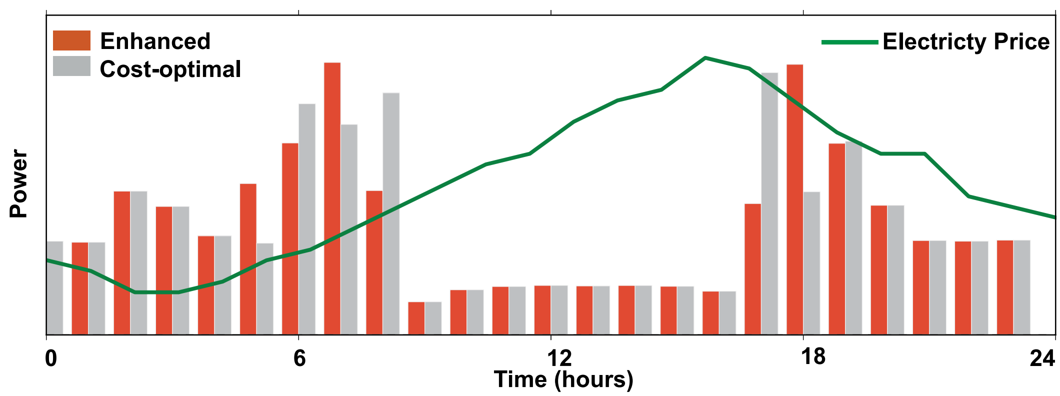

Fig. 6. Comparison of cost-optimal and enhanced schedule in REDD.

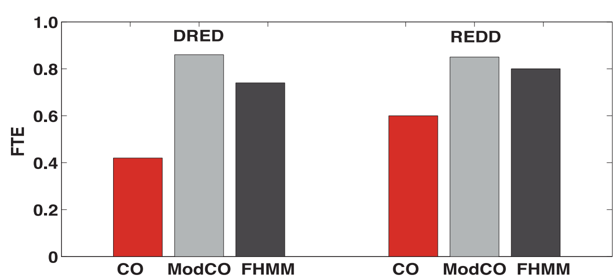

Fig. 7. Comparison of CO, ModCO and FHMM algorithms.

A. Datasets

The energy disaggregation and demand scheduler were evaluated using our deployment Dutch Residential Energy Dataset (DRED) in the Netherlands [10]. Furthermore, the proposed models were also evaluated with a publicly available energy dataset called REDD (Reference Energy Disaggregation Dataset) [11].

(i) DRED: Our deployment consists of several sensors measuring power, occupancy and activities of occupants. The sensors were carefully installed to avoid any inconvenience to the occupants. We collected data at both aggregated and appliance level using smart meters such as plugwise sensors[2] at 1 Hz sampling frequency for over 6 months. The dataset is made public and more details about the deployment can be found in [10].

(ii) REDD: It is one of the first publicly available dataset with both appliance and aggregated energy consumption data. The dataset includes data from 6 households in the USA. Each household has more than 15 appliances and the data was collected at 1 Hz sampling frequency. In our evaluation, we use House-1 data and more details can be found in [11].

[2]Plugwise energy monitoring: https://www.plugwise.com/smile-p1.

B. Results

Modified CO: We now compare the results of ModCO with traditional CO and FHMM. We employ *Fraction of total energy assigned correctly (FTE)* metric to evaluate the disaggregation accuracy. It measures the fraction of energy correctly assigned to an appliance and is one of the common accuracy metrics for disaggregation algorithms [11], [24]. FTE is the overlap between the actual fraction of energy consumed by each appliance (y_t) and the fraction of energy assigned to each appliance ($\hat{y}_t$). It is defined as,

$$FTE = \sum_a min\left(\frac{\sum_a y_t^{(a)}}{\sum_{a,t} y_t^{(a)}}, \frac{\sum_a \hat{y}_t^{(a)}}{\sum_{a,t} \hat{y}_t^{(a)}}\right) \tag{4}$$

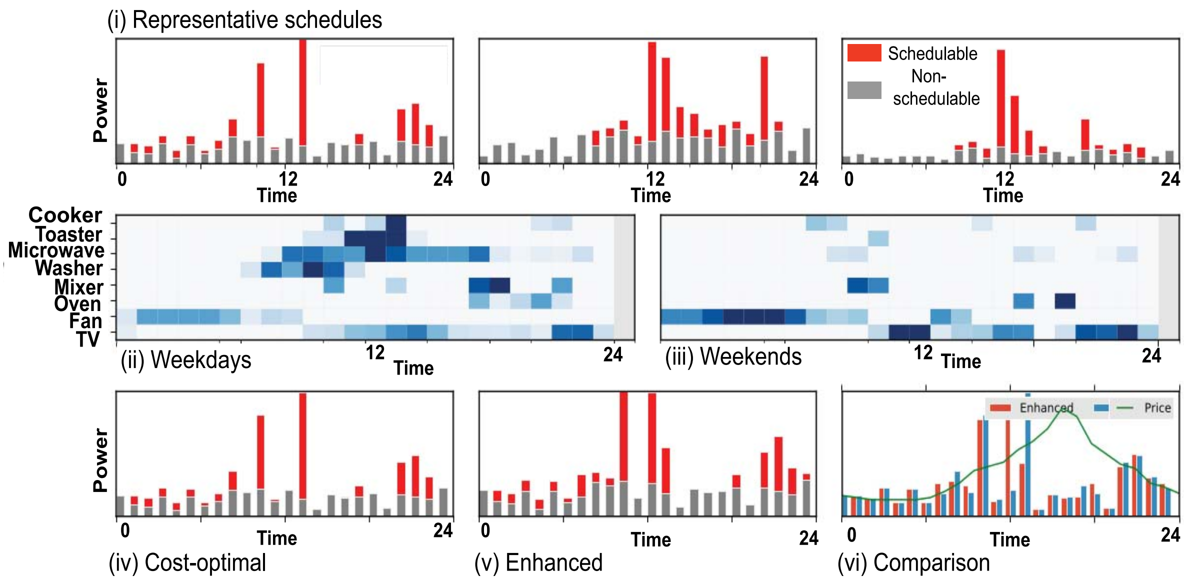

Fig. 8. Optimal schedule for a day in our DRED dataset.

where $a \in A = \{1, \ldots, |A|\}$ and $|A|$ is the total number of appliances. Also $t \in \{1, \ldots, T\}$ and T is the total time period considered.

Fig. 7 show the FTE values for all appliances in DRED and REDD datasets. It can be seen that, the proposed ModCO performs significantly better than CO for both the datasets. Furthermore, it performs better than FHMM in DRED and has similar performance in REDD. Note that, unlike CO and FHMM, ModCO does not have any training phase and has significantly lesser computational complexity. For both the datasets, ModCO has energy disaggregation accuracy of over 85%. In general, only a few appliances constitute the majority of power consumed in a household. Hence, it is necessary to derive accurate information of these top energy consuming appliances. When only top-k appliances are considered for energy disaggregation, the disaggregation accuracy increases to 92% and 89% for DRED and REDD datasets respectively.

Demand scheduling: We implemented our algorithm described in Section IV on a Raspberry Pi to determine day-ahead appliance schedule. Fig. 8 shows the results from each step of the scheduler in DRED dataset. From all possible schedules, Fig. 8(i) shows the filtered representative schedules with schedulable and non-schedulable loads. The grey color indicates the non-schedulable loads such as refrigerator, modem, etc., and the red color shows the schedulable loads washing machine, dishwasher, etc. Fig. 8(ii), (iii) shows the appliance usage pattern in weekdays and weekends derived from disaggregated data.

Fig. 8(iv) shows the cost effective schedule obtained based on the day-ahead pricing using (2). The cost-effective schedule shows the schedule executed previously by the household. The scheduler algorithm adapts the cost-effective schedule iteratively to further minimize user discomfort based on the energy usage coefficients proposed. Fig. 8(v) shows the derived enhanced schedule using flexibility and sensitivity coefficients. Finally, Fig. 8(vi) shows the enhanced and cost-optimal schedule along with the day-ahead price. On this particular day in DRED, around 70% of the schedulable load was shifted to achieve minimum cost and discomfort. Fig. 6 shows the comparison of enhanced and cost-optimal schedules for a household in REDD dataset. On the average monthly electricity cost reduction of 25% and 30% can be seen in DRED and REDD households using the proposed scheduler. The proposed scheduler can be adapted to incorporate renewable energy sources and battery storage. Furthermore, since all the data is stored and processed locally the proposed decentralized demand scheduler is highly scalable. Moreover, the information system at each household can negotiate in a distributed fashion to further minimize the total aggregate load on the grid.

VI. Conclusion

In this paper, we presented a decentralized algorithm to derive optimal day-ahead schedules using consumer preferences and appliance usage patterns. The derived day-ahead schedules minimize the electricity cost and also associated consumer discomfort at the same time based on day-ahead hourly electricity price. The proposed algorithm was empirically evaluated across multiple datasets such as DRED and REDD. Cost savings of up to 25% and 30% can be achieved in DRED and REDD for monthly electricity consumption. Indeed this is the first time actual energy consumption datasets are used to evaluate load shifting at the consumer premises. Furthermore, we implemented our algorithm on a low-cost embedded system, i.e., Raspberry Pi at the household. This approach is highly scalable and avoids sharing of privacy-sensitive information with the utilities. The proposed algorithm can also be applied to other variations of electricity pricing such as real-time pricing, critical-peak pricing and time-of-use pricing. We can extend this easily to incorporate renewable energy sources, such as solar and the wind, balancing the energy demand, generation and supply.

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