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Appliance Scheduling Optimization in Smart Home Networks

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ABSTRACT In this paper, we propose a solution to the problem of scheduling of a smart home appliance operation in a given time range. In addition to power-consuming appliances, we adopt a photovoltaic (PV) panel as a power-producing appliance that acts as a micro-grid. An appliance operation is modeled in terms of uninterruptible sequence phases, given in a load demand profile with a goal of minimizing electricity cost fulfilling duration, energy requirement, and user preference constraints. An optimization algorithm, which can provide a schedule for smart home appliance usage, is proposed based on the mixed-integer programming technique. Simulation results demonstrate the utility of our proposed solution for appliance scheduling. We further show that adding a PV system in the home results in the reduction of electricity bills and the export of energy to the national grid in times when solar energy production is more than the demand of the home.

INDEX TERMS Appliance scheduling, optimization, branch-and-bound, smart home network, smart grid.

I. INTRODUCTION

The advent of smart grid has enabled the utilities to find ways for promoting small scale renewable energy generations and ways to keep the electricity demand in line with the supply during peak timings of usage. This ability to control usage is called demand-side management (DSM) and it could translate into as much as $59 billion in societal benefits by 2019 [1]. DSM plays a vital role in facilitating greater connection of intermittent renewable generation [2].

DSM manipulates residential electricity usage to reduce cost by altering the system load shape [3]. DSM programs comprise of two principal activities: 1) demand response (DR) programs and load shifting, and 2) energy efficiency and conservation programs. DR programs transfer customers' load during periods of high-demand to off-peak periods by offering them incentives [4] and can reduce critical peak demand or daily peak demand. Shifting daily peak demand flattens the load curve, allowing more electricity to be provided with less expensive base load generation. DR programs can also save the cost of building additional generation capacity to meet future critical peak demand.

Most of our high energy use is due to heating/cooling, cooking, lighting, washing and drying. The home appliances performing these functions are beginning to become smart with connectivity features. These features allow them to be automated to reap benefits that smart metering and variable tariffs bring. Such smart devices enable the consumers to take advantage of the DR program, where a utility can contact a consumer to reduce/shift his or her electricity consumption in return for certain monetary benefits. These devices can form part of a home area network (HAN), which consists of networking of devices inside or within close vicinity of a home.

The traditional grid has DR programs for large-scale consumers such as industrial plants or commercial buildings; however, a similar mechanism for the residential consumers does not exist mostly due to two reasons. First, it is hard to handle the large number of residential units without communication, sensors, and efficient automation tools. Second, the impact of DR programs is considered to be relatively small when compared with their implementation cost. The advent of smart grid, smart meters, low-cost sensors and smart appliances have led to novel residential energy management techniques that involve communications and interaction between consumers, devices and the grid [5]. Recent advances in smart metering technology enable bidirectional communication between the utility operator and the end-users and facilitate the option of dynamic load adaptation. In smart grid, real time pricing information updated by the utility provider is in fact directly related to the consumer.

A. LITERATURE REVIEW

In the study of dynamic DSM, different techniques and algorithms have been proposed, where the basic idea has been to reduce the energy bill corresponding to the time-of-use (TOU) tariffs incentives offered by the utility [6], [7].

TOU tariffs are varied throughout the day according to the supply and demand [8]. Consumers can also generate renewable energy, consume some portion of it locally, and sell the excess energy to the utility companies when permitted. For example, Ontario government's micro feed-in tariff (FIT) program in Canada allows home owners to sell locally generated energy [5], [22], [23].

In [5], a single objective optimization problem is presented to minimize the total cost of electricity usage at home. Four appliances were considered for comparing two optimization algorithms. Optimization based residential energy management was developed using external solver CPLEX. The authors assume average non-varying consumption value for complete operating cycle of an appliance.

Similarly authors in [6] discuss a model in which objective function encompasses three different criteria: cost minimization, maximization of scheduling preferences and maximization of climatic comfort. A mathematical programming problem is defined using a weighted objective function based upon the importance given by the user. Since the computational complexity of the problem is NP-hard, a heuristic algorithm has been proposed to derive suboptimal solutions within a limited computational time. The authors present results by randomly generating the load profile length and power consumed in the load profiles of devices.

In [24], optimization of appliances for a single home is done using convex programming framework. Since the on/off status of appliances can be gauged by the binary decision variables, by relaxing decision variables from integer to continuous values, the mixed integer linear problem can be formulated as a new convex programming problem. The authors consider minimization of cost and user dissatisfaction in the objective function.

In [25], the authors use particle swarm optimization to carry out scheduling according to the preference placed by user on benefit from different services. The authors calculate the schedule for hourly charging or discharging of the battery of a hybrid electric vehicle, hourly heating power of the heaters, hours for turning on the water heater and pool pump. In [26], the authors formulate an integer linear problem that minimizes cost, while at the same time ensuring that the heat and electricity demands are met. In [27], the authors consider the unit commitment problem that aims to find the minimum cost dispatch of available generation resources to meet the electrical load. The authors minimize overall cost considering the cost of energy production, spinning reserve and interruptible load using mixed integer programming. In [28], the authors consider the minimization of cost incurred by distribution network operators in case of variation of load. This strategy is based on varying the interruptible load and dispatchable generation to account for any load variation. In [29], the authors provide an optimization model that allows a consumer to adapt his or her cumulative hourly load level in response to varying hourly electricity prices. In [30], the authors present a solution for managing the use of energy supplies by minimizing the cost of using these supplies.

In [9], the authors reduce the peak-to-average ratio and cost using genetic algorithm. The authors do not use any threshold on peak power, instead, they consider that if the power is greater than a certain threshold, the price becomes high. The authors use delay time rate, which means that an application should finish the work as soon as possible. They consider a single constraint for meeting the length of operating time of the appliances. In the results section, the appliances with fixed power are used. In [10], the energy cost is minimized under the energy-price uncertainty, where the prices randomly vary around nominal values with a known underlying distribution. The authors consider energy-storage devices, and use simulated values of active level of appliances in a certain range. They do not consider any leveling and assume appliances to have a constant energy consumption. In [11], day-ahead prices and residential load schedule are obtained, then price is adjusted in real-time. The authors maximize the utility company's profit with respect to distribution grid constraints and minimize the consumer's electricity bill as well as disutility function.

In [12], the authors consider uniform distribution of power for each appliance and minimize cost using stochastic behavior of wind power. The authors present a protocol for home-area network design to permit load scheduling amongst flexible and controllable loads. The authors do not consider constraints for starting and ending of appliances. In [13], the authors minimize the energy cost to find the optimal energy consumption and operation time of the throttleable and shiftable appliances, respectively. Subsequently, a multi-objective optimization problem considering consumer preferences is formulated, with objectives to minimize the energy cost, operation delay and energy gap. The authors consider fixed energy consumption of devices with no PV panel and consider daily usage. In [14], the authors mainly discuss the architecture for PV system management in residential areas and PV monitoring system without considering any load scheduling problem. In [15], the authors consider flattening of load profile of the gird and providing uninterrupted power supply to homes. They present a design for controllers that consider the required power by home and based on available power from grid and other sources, manage the distribution. The appliance load scheduling problem is not considered in this reference.

In [16], the authors describe the design of a solar home system. In [17], the optimal scheduling of energy consumption in smart homes is presented using mixed-integer linear programming. In order to minimize a one-day forecasted energy consumption cost, operation and electricity consumption tasks are scheduled based on different electricity tariffs, electricity task time window and forecasted renewable energy output, and no leveling or reducing peak demand is considered. In [18], the authors deal with reducing cost and energy consumption, without considering any PV. The authors first provide a schedule that will achieve desired cost or energy savings, and include an objective to minimize deviation between historical activation use pattern and the proposed pattern, and do not consider any leveling. In the performance evaluation, they present the computation time of their presented approach.

In [19], the authors consider scheduling of three kinds of appliances (1) heating-cooling system by using Dijkstra routing algorithm, where nodes are possible temperature points and the cost of each transition between nodes is a combination of energy cost and comfort (2) washing machine that is scheduled using exhaustive search by considering all possible starting moments as well as the respective cost of each of them, and (3) water heater whose total required duration is calculated and then most efficient time intervals to activate the device are presented. Each kind of scheduling is done independently, with no overall constraints. In [20], the authors present a power consumption management scheme based on maximizing comfort and meeting temperature and peak power constraints. This management is based on a protection layer that makes decision if some constraints such as maximum power are violated, and an anticipation layer that can schedule energy consumption in advance, based on predictions. The reference mainly deals with heating management in a household. In [21], the authors minimize the daily energy bill, constraints consist of activity scheduling and batteries constraints. They do not consider any leveling as well as constraints that restrict the running of each appliance to be uninterruptible and sequential. In the results section, the authors show that their proposed technique is able to reduce the electricity demand during peak hours.

Available DR optimization schemes are implemented through either incentive based rates or time based rates [24]. TOU pricing has been shown to have a significant influence on ensuring a stable and optimal operation of a power system. A residential customer's daily activities are characterized by a list of tasks to be scheduled at preferred time intervals. Some of these tasks are persistent, as they consume electricity throughout the day, e.g., the use of a refrigerator; others can be scheduled according to the user-specified constraints and the variable tariffs offered by the utility company to achieve cost savings and peak demand reduction [7].

Although the flexibility associated with appliances and time varying prices can achieve tangible benefits for customers, current residential load control activities are mainly operated manually, which pose great challenges to customers in optimally scheduling the operations of their appliances. Some customers may not have time to make such scheduling decisions and if prices vary fast and frequently, scheduling may be too complex. In order to let the users participate in the DR program and maneuver their consumption pattern through pricing signal, studies have suggested employing automated household energy management strategies. Hence, a centrally located automated intelligent device is necessary to optimize the appliances and load operation on behalf of customers. In [31], this device is called automated building energy management controller (BEMC). Energy box (eBox) referred in [6] does the computation while considering all the parameters, and demands consumers to strictly adhere to the suggested pattern. In [7], the implementation of the intelligent residential energy manager is done through a master energy controller (MEC). The personalized home energy management system manages all configurations at the customer-end to control various home appliances either remotely or locally through the MEC. At each residential unit in HAN, as outlined in [32], smart device controller (SDC) coordinates the energy demand and supply processes based on a communication infrastructure that can detect energy demand of the load associated within the HAN and check the availability of supply to address the demand.

B. CONTRIBUTIONS

Overall, the work carried out in existing reference do not consider some or all of the following scenarios: 1) Actual load profiles are replaced by average loads or maximum load of devices. As the load profiles of devices vary with respect to time, results of scheduling with average load may not always give a feasible solution, compared to using real load profiles. 2) Specific objective functions for leveling demands are not considered. Although an objective function that minimizes cost helps in leveling demand and avoiding peaks in the high-priced area, it may still lead to peak loads in low-priced region. 3) Most of the work in the literature does not provide a solution to the end-user where he or she may get an operating schedule of the devices, instead they concentrate on providing an overall optimum hourly demand level or consider cost reduction from the point of view of providers/dispatchers. 4) The constraints considered in some references ignore that appliances may have to run without interruption and sequentially. 5) The results mainly show the cost savings or reduction in demand during peak hours, no actual schedule of the devices is presented, which can in fact reveal further if the reduction in cost or demand has come at the expense of scheduling of appliances during inconvenient timings.

In this paper, we consider a scenario where automated energy consumption scheduling is done at a centralized controlling device (CCD) also referred to as a scheduler. Contrary to many references reviewed above, we present an approach that can be directly used by a consumer for appliance scheduling, according to input tariffs and peak load constraint. User preference for an appliance to start within a particular time interval is also taken into account. The considered scenario is more realistic as we consider constraints that allow the appliances to run sequentially and without interruption. All the home appliances are smart appliances, which immediately after being powered on and connecting to the HAN will exchange their handshake signals with the CCD. A smart meter can also serve the same purpose, where it is assumed to be equipped with an automated energy consumption scheduling function and all the appliance operating features in terms of operation cycle, power consumption and energy ID will get through the HAN to neighborhood area network and finally to the national grid. The CCD function is programmed based on the user's energy consumption needs, then it automatically

TABLE 1. Symbols used in problem formulation.

Symbol	Definition
i	Index of appliance to be scheduled
k	Time slot over a given period of a day
j	Index of number of load phases associated within each appliance
n_i	Set of number of un-interruptible load phases associated with each appliance i
N	Set of number of appliances for scheduling
m	Maximum number of time slots available in a day
P_{ij}^k	Load variable assigned to an appliance i, having load phase j during time slot k
C^k	Tariff in dollars in the time slot k
X_{ij}^k	A binary decision variable with value 1, if ith appliance with load phase j in the time slot k is processed; otherwise 0.

controls the operation of various appliances such as the batteries of electric vehicles, washer, dryer and dish washer.

We consider the limitations of existing methods and propose a solution to overcome these limitations. We formulate the problem of scheduling of smart appliances operations in a given time range as a problem consisting of two objective functions: one dealing with cost minimization, and the other dealing with leveling of demand. We propose a solution to the problem based on mixed integer programming technique. We further evaluate the performance of a residential energy model and optimize the performance of different types of loads associated within. In the results section, we take into consideration real load profiles of the appliances and generate starting and ending plan satisfying all the time and energy constraints given by the user. Our proposed solution can be directly used by a user to get a calculated schedule corresponding to variable tariffs and load profiles. Additionally it can be used for generating appliance scheduling plan in comparable time to be true as a real time process, thus, it is adaptable to any change in tariffs.

This paper is organized as follows: In Section II, we present the system model. In Section III we discuss the problem formulation and the proposed solution. In Section IV, we present results. Conclusions are given in Section V. A summary of symbol notations is shown in Table 1.

II. SYSTEM MODEL

A. TYPES OF LOADS

In a particular HAN, appliance load can be further subcategorized into manageable and non-manageable loads. Existing literature of energy management system focusses mainly on manageable loads because of its high energy consumption and predictability in its operation. In [6] and [31], manageable load has been further categorized as:

1) Shiftable load (flexible delay having certain consumption cycle with specified energy consumption profile), e.g., washing machine, dish washer, etc.
2) Interruptible load (e.g., water heater and refrigerator they are either ON with fixed energy consumption or OFF. However, their ON cycle duration depends upon user preference setting).
3) Weather based load (e.g., air conditioner and electric heaters which depend upon weather and power absorption of premises).

Non-manageable loads include TV, laptops, lights, etc. There are appliances that are in home use such as TV, lights, clock, phones, computers etc. Their loads compared to the major load discussed above are insignificant and not power consuming. Moreover, these appliances are interactive and have little scheduling flexibilities.

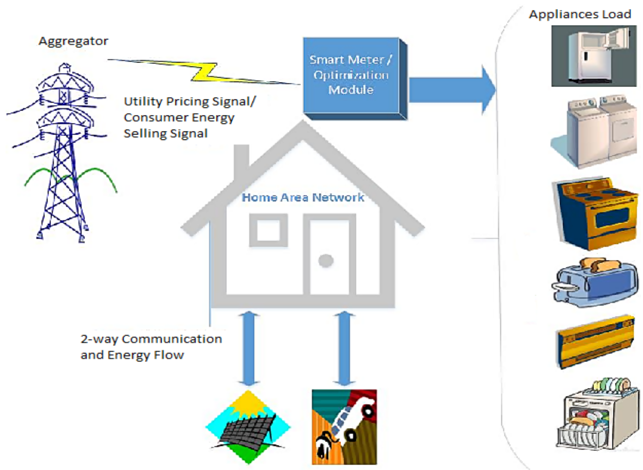

FIGURE 1. HAN model for appliance scheduling.

B. DESCRIPTION OF MAJOR HOME APPLIANCES

Fig. 1 summarizes the system model. We consider a mid-size home with the following major electricity consuming appliances: dishwasher, clothes washer and dryer, refrigerator, air-conditioner (AC), oven-1, oven-2 and electric vehicle (EV). The home also has on-grid photo voltaic (PV) panels for electricity generation. It is known that different appliances have definite timing of completion of their cycles and thus have definite power consumption vector, which can be ascertained either from the appliance specifications or measuring demand experimentally at equal time intervals till the completion of cycles. The load vector for EV used in this paper is taken from the data used in [33]. We have adopted the power vectors of the appliances from a study done at Virginia Tech. Advance Research Institute [34]. The time-dependant power vectors are called load profiles in the rest of the paper. The TOU tariffs used in this paper are 13.5 cents/kWh, 11.2 cents/kWh and 7.5 cents/kWh for on peak, mid peak and off peak, respectively [35]. In the following, we describe each of the appliances along with its load vector.

1) DISHWASHER

The dishwasher has three main operating cycles: wash, rinse and dry and it takes approximately 105 minutes to complete all the cycles. During the running of the dish washer, load varies from maximum 1.2 kW to minimum 0.6 kW as shown in Fig. 2. The energy consumption is about 1.44 kWh for

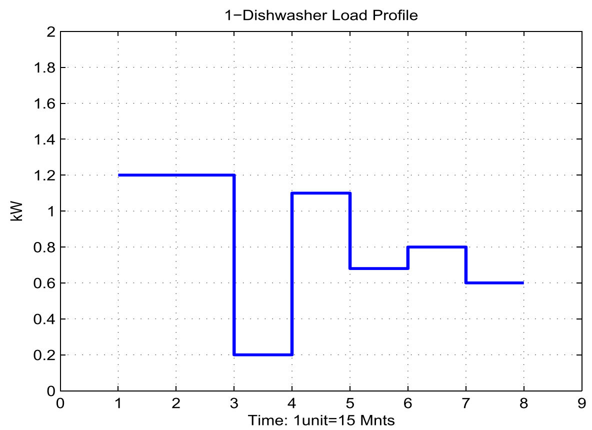

FIGURE 2. Load profile of dishwasher [34].

FIGURE 4. Load profile of refrigerator [34].

one complete cycle of dishwasher. Dishwasher is classified in category of shiftable load.

2) CLOTH WASHER AND DRYER WORKING IN TANDEM

This is a case of two appliances working in sequence. Cloth washing machine precedes the dryer and has three cycles of operation: wash, rinse and spin, which take 45 minutes to complete. The power load varies between 0.52 kW to 0.65 kW. Then after lapse of 15 minutes, dryer starts, which takes 60 minutes to complete. The load of dryer varies from 2.97 kW to 0.19 kW. The load profile of such a device is shown in Fig. 3. The energy consumption of the combined appliances is 2.68 kWh per operation. Cloth washing machine and dryer are classified in the category of shiftable load.

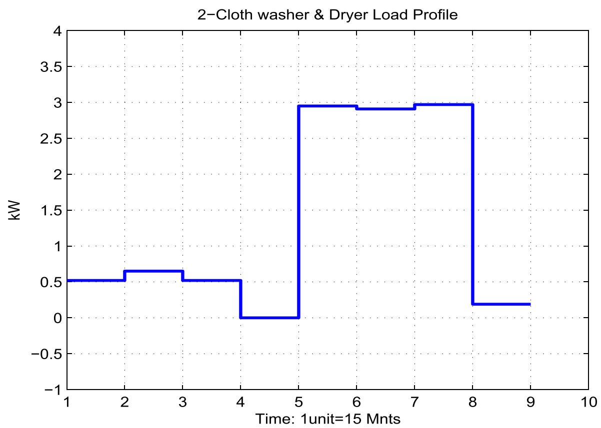

FIGURE 3. Load profile of cloth washer & dryer [34].

3) REFRIGERATOR (15.6-cuft) WITH TOP FREEZER

Refrigerator falls in the category of appliances which works 24 hours a day. The only time compressor rests is when the inside temperature is lower or equal to the set temperature of the refrigerator. The compressor also rests when defrost heating starts. The load profile of the refrigerator is shown in Fig. 4, which is marked by spikes at regular intervals reaching 0.37 kW, due to defrosting of the refrigerator. The maximum and minimum load during the operation of the refrigerator is 0.37 kW and 0 kW respectively. The electricity energy consumption is 3.43 kWh/day. Refrigerator is classified as continuous non-shiftable load.

4) CENTRAL AIR-CONDITIONER

The load profile of the central air-conditioner (AC) is shown in Fig. 5 which resembles like a series of square wave train showing peak load of 2.75 kW when compressor of AC is working, and 0.25 kW when the compressor is switched off. This occurs when inside room temperature is equal or below the set room temperature. However, air fan continues to work for circulation of air. The energy consumption of 2.5-ton AC is around 31.15 kWh per day. AC is classified as continuous non-shiftable load with sub-classification as weather based load.

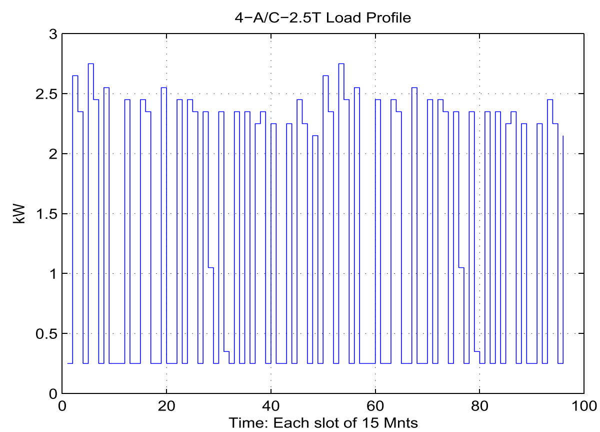

FIGURE 5. Load profile for air-conditioner [34].

5) OVEN FOR MORNING

The use of cooking ovens falls into the category of appliances that are used more than once in a day. For instance, an oven used in the morning and in the evening can be treated as two separate appliances. The use of oven in the morning is of short duration and usually lasts 30 minutes. The load varies from 1.28 kW to 0.83 kW as shown in Fig. 6. The electricity consumption is estimated to be 0.53 kWh. Oven is considered as shiftable load to user specified time preferences.

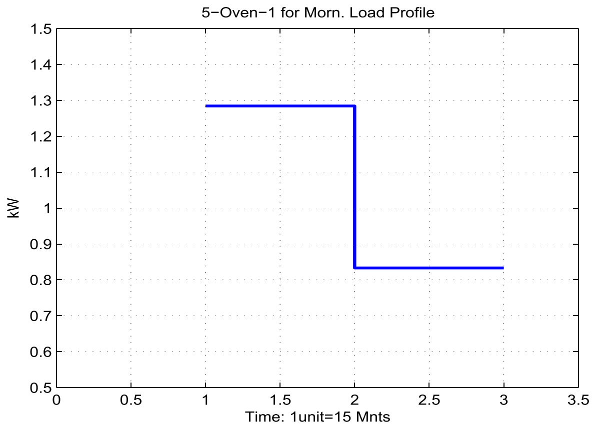

FIGURE 6. Load profile for oven used in morning hours [34].

6) OVEN FOR EVENING

The use of oven in evening is extended and usually two burners are used. The evening oven runs for 1.5 hours, during which time the load varies between 2.35 kW and 0.75 kW as shown in Fig. 7. The electricity consumption is 1.72 kWh.

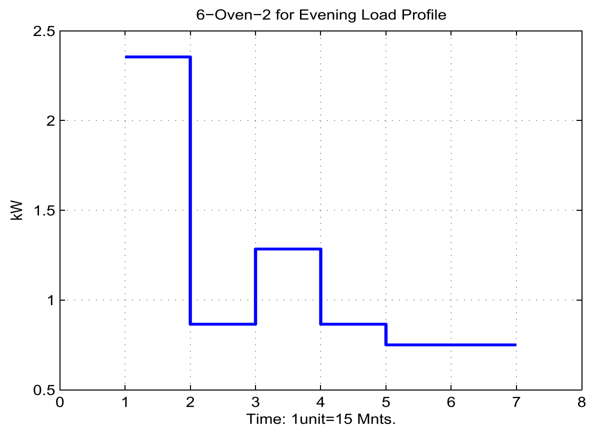

FIGURE 7. Load profile for oven used in evening hours [34].

7) ELECTRICAL VEHICLE

Electrical vehicles (EVs) are slowly gaining popularity and automobile manufacturers are producing hybrid vehicles that work both on gas and electric batteries. The batteries are charged through home electricity. The EV takes 2.5 hours to charge fully at a constant 3 kW load and immediately tapers off to zero. The consumption of EV is estimated to be 7.50 kWh. EV is considered as shiftable load to user preference time when TOU tariff is the lowest like between 7 PM to 7 AM. The load vector for EV used in this thesis model is taken from the data used in the publication [33] and shown in Fig. 8.

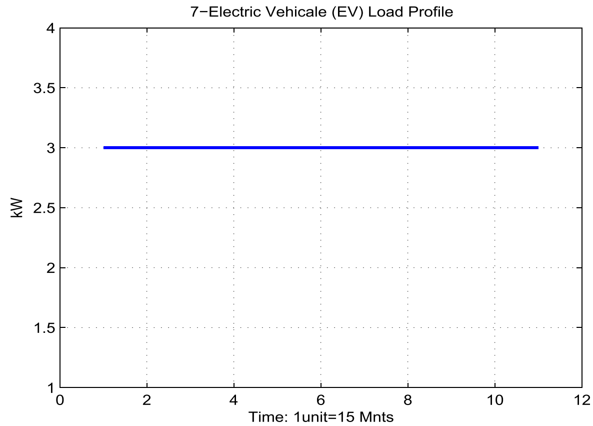

FIGURE 8. Load profile for electric vehicle [33].

8) MICRO-GRID

A typical micro-grid for buildings integrates the operation of electrical and thermal energy supply and demand. The supply may include energy sources from distribution grid, fuel cells, renewable energy sources such as PV solar panels and wind power, etc. [36]. We consider a micro-grid of 3kW PV panel system with on-grid connection and having a profile given in [37]. Electricity generated by the PV system will be consumed in home. On-grid connection means that PV panels are connected to the national grid. If during any instance of time, PV produced electricity is more than the demand of home, the surplus electricity will be exported to the national grid. When the electricity produced by PV is less than the demand in the home, the surplus electricity will be imported from the national grid. The PV panel energy selling rate is considered as 39.617 cents/kWh [23]. Power profile of a typical 3kW solar panel is shown in Fig. 9, according to which power varies from 2.9 kW to 0 and energy production on a sunny day is 23.11 kWh.

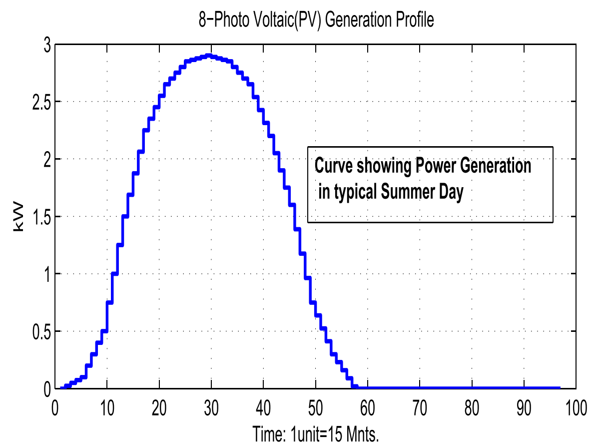

FIGURE 9. Locally generated PV panel profile [37].

9) OTHER APPLIANCES

There are appliances that are in home use such as TV, lights, clock, phones, computers etc. Their loads compared to the major load discussed above are insignificant and not power consuming. Moreover, these appliances have little scheduling flexibilities.

C. DURATION OF OPERATION

A day of 24 hours is divided into 96 time slots. All the time slots are represented by their starting times. The starting slot and ending slot times over the whole day are 6:00 AM and 5:45 AM, respectively. Thus each time slot represents an interval of 15 minutes, giving a total of 96 time slots in a day. The end time of an individual slot is obtained by adding 15 minutes to the starting time. For example, for time slot 2, the starting time is 06:15AM and ending time is 06:30AM.

D. EXECUTION WINDOW OF EACH OPERATION

For each appliance, there is a minimal starting time and a maximal ending time. For instance, if a user comes home at 05:00PM and wants to end dinner not later than 08:30PM, then the oven may be scheduled on any time after 05:15PM and has to finish by 07:45PM. We limit the case where each appliance is executed exactly once during the day. However, we can take into account multiple usage of the same appliance by considering the appliance and multiple appliances of the same type. The scheduler is free to switch on the appliances on any time as long as it respects the starting and ending time constraints within the range.

E. EXAMPLE LOAD PROFILE OF APPLIANCE

An appliance operation process follows a load profile, comprising a set of sequential load phases, e.g., the load profile of a dishwasher in kW is [1.2, 1.2, 0.2, 1.1, 0.68, 0.8, 0.6] spaced at 15 minutes apart and has seven load phases. The whole cycle of dishwashing takes 105 minutes. The dishwasher has three sub-cycles: wash, rinse and dry, which are carried sequentially in that order. The first 45 minutes associated with wash cycle, next 30 minutes for rinse and the remaining 30 minutes are spent in washing. A load phase is un-interruptible and sequential.

There can be additional inter-appliance operational constraints. A certain appliance cannot start before some other appliance finishes, e.g., dryer cannot start before completion of washing. More importantly, due to safety reasons, the sum total of loads of all the appliances at any point of time cannot exceed a pre-defined peak load. To put the appliance load phases in operation with operational constraints, the appliance's scheduler determines the load assignments, as a function of time in a day with the objective to find the least energy cost of the appliances and/or a flat demand curve (minimizing peak load).

III. APPLIANCE SCHEDULING OPTIMIZATION PROBLEM FORMULATION AND SOLUTION

In this section, appliance scheduling is formulated using a mixed integer programming (MIP) technique for which use of decision variables and auxiliary binary decision variables are defined and applied. We further describe the proposed solution.

A. PROBLEM DEFINITION

The set of number of appliances for scheduling are denoted by N and their corresponding number of set of un-interruptible load profile for each appliance is denoted by n_i for $i = 1, 2, 3, \ldots, N$. P_{ij}^k represents load variable assigned to an appliance i having load phase j during time slot k.

B. DECISION VARIABLES

The typical unit for P_{ij}^k is kW, but when this is multiplied by a factor of $(15/60 = 0.25)$, its unit will be changed into kWh. The load profiles P_{ij}^k are real and continuous decision variables. In addition to P_{ij}^k, we need auxiliary binary decision variables to indicate whether a particular load profile is being processed or not. Binary decision variables are denoted by $X_{ij}^k \in \{0, 1\}$. $X_{ij}^k = 1$, if an appliance i and its load phase j is being processed during the time slot k, otherwise $X_{ij}^k = 0$. Similarly, we can introduce other auxiliary binary variables $S_{ij}^k = 1$ indicating an appliance i, load phase j is already finished by time slot k. It means X_{ij}^k and S_{ij}^k are complementary and either binary variables $X_{ij}^k = 1$ or $S_{ij}^k = 1$, i.e.,

$$X_{ij}^k + S_{ij}^k = 1, \quad \forall i, j, k. \tag{1}$$

C. OBJECTIVE FUNCTION

The first objective of the load scheduler is to minimize the total electricity cost for operating the appliances based on 24-hours ahead TOU electricity tariff. Let C^k denote electricity TOU tariff for time slot k. Then the total cost of electricity consumption function f_C is given by the following equation:

$$P1A: f_C = \min_{\boldsymbol{X}} \sum_{k=1}^{m} C^k \left(\sum_{i=1}^{N} \sum_{j=1}^{n_i} P_{ij}^k X_{ij}^k \right), \tag{2}$$

where $\boldsymbol{X}$ is a vector whose entries are X_{ij}^k. Once first load phase starts, it will sequentially complete all the phases without interruption. The corresponding auxiliary binary variable $X_{ij}^k \in \{0, 1\}$ is used with P_{ij}^k as on/off switch to estimate the time slot k, when the appliance first phase starts till all of its load phases end. Therefore, optimization will be on binary variable X_{ij}^k for all values of $\{i, j, k\}$ of which appliance i and its load profile j are known and only k is unknown. This will provide optimal layout of appliances with their respective start and end slot time with the objective to minimize energy cost according to the TOU tariff and minimize and level peak demand of the appliances by using (2), and (3) and (4) given in the following.

Eqn. (2) has a different variant if a micro-grid (G) is added:

$$P1B: f_C = \min_{X} \sum_{k=1}^{m} \sum_{i=1}^{N} \sum_{j=1}^{n_i} \left(C^k P_{ij}^k X_{ij}^k - g^k G_{ij}^k X_{ij}^k \right) \quad (3)$$

where g represents feed-in tariff. G_{ij}^k is the power produced by PV panel consisting of different phases j at time k. Micro-grid component in the objective function is constant as it has fixed possible starting and ending time. The optimization will be achieved through appliance scheduling only.

The second objective is to minimize the maximum peak load function f_L of the home:

$$P2: f_L = \min_{X} \sum_{k=1}^{m} \sum_{i=1}^{N} \sum_{j=1}^{n_i} \left(P_{ij}^k X_{ij}^k - q \right)^2, \quad (4)$$

where q is the average load of all the appliances considered and is given by (5).

$$q = \frac{\frac{1}{4}\left(\sum_{i=1}^{N} \sum_{j=1}^{n_i} P_{ij} \right)}{24} \quad (5)$$

Here, P_{ij} is the variable to indicate assigned load of appliance i having phase j. This in fact translates to minimizing the sum of squared of deviation (SSOD) from the average value of the appliances load. SSOD is a measure of leveling effect in the load demand curve. When the peaks in the demand pattern decrease and the gaps are filled, SSOD of the load curve will reduce.

D. CONSTRAINTS

The constraints are grouped into energy constraints and timing constraints:

1) ENERGY CONSTRAINTS

To make sure that load phases of appliances fulfill their energy requirements, the following constraint is imposed:

$$0.25\left(\sum_{k=1}^{m} P_{ij}^k \right) = E_{ij} \quad \forall\{i, j\}, \quad (6)$$

where E_{ij} is the energy requirement for appliance i with load phase j and m is the available time slots in a day.

The load safety constraint puts upper limit to the peak coincident load demand of all appliances not exceeding a certain pre-defined limit β.

$$\sum_{i=1}^{N} \sum_{j=1}^{n_i} P_{ij}^k \leq \beta \quad \forall\{k\} \quad (7)$$

The peak signal β is provided by the grid operator, which is a demand response signal.

2) TIMING CONSTRAINTS

a: UN-INTERRUPTIBLE OPERATION

This situation can be modeled by the constraint that, for all i and j, $X_{ij}^k = 0$. This can also be explained by the following auxiliary constraint equations:

$$X_{ij}^k + S_{ij}^k \leq 1 \quad \forall\{i, j, k\}. \quad (8)$$

If $S_{ij}^k = 1$, then at time $= k$, load phase j in appliance i is already finished. Hence, the corresponding $X_{ij}^k = 0$. The condition triggering $S_{ij}^k = 1$ is that X_{ij}^k switches from 1 to 0, i.e., the load profile just finished. This situation is shown as:

$$X_{ij}^{k-1} - X_{ij}^k \leq S_{ij}^k \quad \forall\{i, j\}, \quad \forall\{k = 2, 3, 4, \ldots m\}, \quad (9)$$

Another constraint is as follows:

$$S_{ij}^{k-1} \leq S_{ij}^k \quad \forall\{i, j\}, \quad \forall\{k = 2, 3, 4, \ldots m\} \quad (10)$$

where m is the number of available time slots in a day. This means that S_{ij}^k should remain unity.

b: SEQUENTIAL PROCESSING

Sequential processing of load phases in a load profile of an appliance means that a load phase cannot start unless its preceding phases have finished. This requirement can be described using the auxiliary decision variable S_{ij}^k as follows:

$$X_{ij}^k \leq S_{i(j-1)}^k \quad \forall\{i, j\}, \quad \forall\{k = 2, 3, 4, \ldots m\} \quad (11)$$

c: USER TIME PREFERENCES

The appliance user can setup the time preference constraints specifying the time interval an appliance must be finished within. It means that appliance cannot be run outside of the time preference interval.

$$t_{st} - t_{end} \geq \alpha, \quad (12)$$

where t_{st} is the starting time of the range selected by the user, t_{end} is the ending time of the range selected by the user and α is the length of the load profile of an appliance.

The number of cycles or positions that can be available for starting an appliance is given by:

$$cyc = t_{end} - t_{st} - \alpha + 2. \quad (13)$$

As an example consider an appliance load profile of the dishwasher:

$$P_{i,j} = \begin{bmatrix} 1.2 & 1.2 & 0.2 & 1.1 & 0.68 & 0.8 & 0.6 \end{bmatrix},$$

where $i = 1$ refers to the dishwasher. Also $\alpha = 7$ is the length of the load profile consisting of number of load phases in an appliance load. Also user time range constraints for starting and ending of appliance is given as $t_{st} = 2$ (06:15AM) and $t_{end} = 14$ (09:15AM). Since we are working on the time slots given with respect to the hour of the day, we consider time slot number for all our calculations of available time positions for allocating an appliance. Using (13) we get the result as $cyc = 7$, which is the available number of time slots in a day in which an appliance can be operated.

E. PROPOSED SOLUTION

The objective function given in (2) can be solved using mixed-integer programming (MIP) technique. We divide the time scale into 96 time slots. This is determined in MIP through binary decision variable X_{ij}^{k}, when its value is 1 at one particular slot and 0 for all the remaining slots. In this work, there is a need for 8×96 binary variables for describing the scheduling of appliances as there are seven appliances and one PV panel.

Solving NP-hard discrete optimization problems optimally is often an immense job requiring very efficient algorithms. We use a branch and bound (B&B) algorithm, which is useful for solving such a problem. The B&B algorithm is the basic technique for solving MIP programming problems [39], [40]. The B&B algorithm searches the complete space of solutions to a given problem for the best solution. The algorithm is based on the observation that the enumeration of integer solutions has a tree structure. Now the main idea in B&B is to avoid growing the whole tree as much as possible, because the entire tree is just too big in any real problem. Instead, B&B grows the tree in stages, and grows only the most promising nodes at any stage. It determines which node is the most promising by estimating a bound on the best value of the objective function that can be obtained by growing that node to later stages. Branching occurs when a node is selected for further growth and the next generation of children of that node is created. The bounding comes in when the bound on the best value attained by growing a node is estimated. We use YALMIP toolbox [38] in Matlab that has an interface for Gurobi solver [41], which is used to implement our B&B based solution.

IV. OPTIMIZATION OF ENERGY COST AND PEAK LOAD RESULTS

We run our MILP program code to schedule appliances for minimizing the energy cost and minimizing the peak load based on (2) and (4) for the following four cases:

- A: Appliances assigned to the full time range.
- B: Appliances assigned to fixed range equal to the length of the load profiles.
- C: Appliances with mixed time range equal to or greater than the load profiles.
- D: Case A above with PV panels.
- E: Case B above with PV panels.

In TOU pricing, the electricity price per kWh varies for different times of the day to fill the valleys and reduce the peak load for more horizontal load distribution. However, the maximum peak load in home is controlled through an additional constraint that the sum of loads at any time be always equal to or less than 5.5 kW in our case. The maximum peak is always assigned by the electricity provider. Reducing the cost of electricity bill is important and relevant in this work. Therefore, the effect on cost energy will be studied for the five different appliances scheduling scenario shown above.

For each case, we present a scenario, followed by optimization results. These results consist of load patterns, assigned starting and ending times, and other parameters such as total energy consumption (TEC), energy cost (EC), energy exported (EE), maximum peak load and its associated time (MPLAT), and SSOD with $q = 2$ kW. The results are obtained in most cases in less than five seconds, using a computer with Intel i3 processor, which shows that results can be obtained in near real-time. If a computer with higher computational capability is used, the processing will be faster.

A. APPLIANCES ASSIGNED TO THE FULL TIME RANGE

In this case, appliances can be assigned to any time slot. Running the optimization algorithm for minimizing peak load and minimizing cost of energy, separately, i.e, P1A and P2, with appliances range available from time slot 1 (06:00 AM) to time slot 96 (06:00AM), it is found that the scheduler assigns some appliances to inconvenient starting time slots. We consider two cases separately as follows:

1) MINIMIZATION OF PEAK LOAD

In case of peak load minimization, the emphasis is on allocating the appliance operation over time scale where there will be leveling of peak loads over the given range of time. For this scenario, we are optimizing (4) over a given full time range of 24 hours divided in to 96 slots. Therefore, load graph of all the appliances run over the day would tend to be leveled irrespective of the utility pricing signal (TOU) as shown in Fig. 10. The starting and ending time of appliances in this case is shown in Table 2.

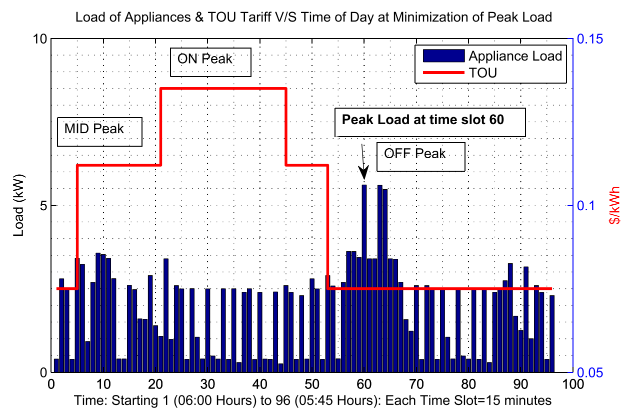

FIGURE 10. Load pattern of appliances while minimizing peak load over full time range of slots from 1 - 96.

As shown in Table 2, scheduled time of dishwasher to start operating from 10:00 AM and ending at 11:45 AM is not preferable. Dishwasher should be scheduled to operate after dinner time. Similarly, the timing of oven-1 (Morning) starting at 10:45 AM is too late and oven-2 (Evening) starting at 3:30 AM is too early. Appliance scheduling as a result of peak load minimizing under full time range (1-96) is, therefore, inconvenient and not adoptable. Other parameters are shown in Table 8 and will be compared next.

TABLE 2. Appliances starting and ending times for minimizing peak load over a full time range.

Sr. No	Appliance	Start Time	End Time
1	Dishwasher	17(10:00 AM)	23(11:30 AM)
2	Clothes Washer Dryer	5(7:00 AM)	12(8:45 AM)
3	Refrigerator	1(6:00 AM)	96(05:45 AM)
4	A/C	1(6:00 AM)	96(05:45 AM)
5	Oven-1 (Morning)	68(10:45 PM)	69(11:00 AM)
6	Oven-2 (Evening)	87(3:30 AM)	92(05:45 AM)
7	Electrical Vehicle	57(8:00 PM)	66(10:15 PM)

2) MINIMIZATION OF ENERGY COST

In this scenario, using objective function (2), we want to consider the appliances in HAN to operate while minimizing the cost of energy used based on time range starting from slot 1 to time slot 96. Appliance dynamic responses are maneuvered by utility TOU signal as shown in Figure 11. Table 3 shows the starting and ending time of appliances when minimizing the energy bill.

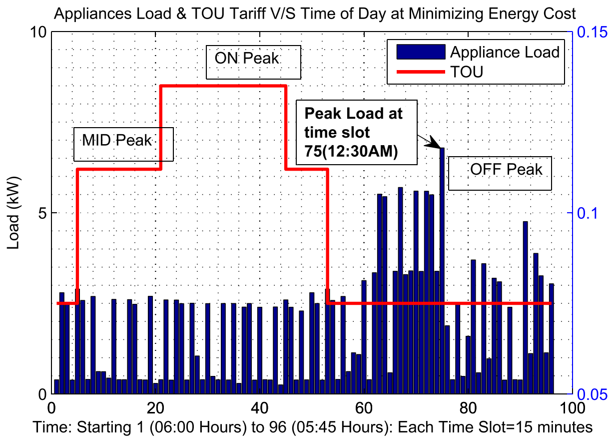

FIGURE 11. Load pattern of appliances while minimizing cost of energy over full time range of 1 - 96 slots.

Figure 11 shows that while minimizing cost of energy, the scheduling of appliances have moved in time range where TOU tariff is low. The maximum peak load is 6.79kW, which occurs at time slot 75 (12:30 AM).

As expected, the cost of electricity in case of minimization of energy cost is indeed lower than the case of minimization of peak load. The cost of electricity when minimizing peak load is $4.63 as shown earlier. The cost of energy when minimizing energy cost is $4.46 showing energy cost reduction of 3.6%. The reduction of energy cost came with an increase in peak load level distortion, i.e., SSOD. The SSOD increased from 156.98 to 238.80 (increase of 52.7%) in minimizing peak load and minimizing energy cost, respectively.

TABLE 3. Appliances starting and ending times for minimizing cost of energy over a full time range.

Sr. No	Appliance	Start Time	End Time
1	Dishwasher	80(1:45 AM)	86(3:15 AM)
2	Clothes washer Dryer	58(8:15 PM)	65(10:00 PM)
3	Refrigerator	1(6:00 AM)	96(05:45 AM)
4	A/C	1(6:00 AM)	96(05:45 AM)
5	Oven-1 (morning)	75(12:30 AM)	76(12:45 AM))
6	Oven-2 (Evening)	91(4:30 AM)	96(05:45 AM)
7	Electrical Vehicle	66(10:15 PM)	75(12:30 AM)

Time allocations for dishwasher, oven-1 (Morning) at time slot 75 (12:30 AM) and oven-2 (Evening) to time slot 91 (4:30 AM) to operate are still inconvenient timings. Therefore, there is a need to review the constraints of time slot range assignment of the appliances for its operations keeping its time of suitability and convenience. It is also to be noted that the peak load has increased significantly and has to be restricted to a limit.

B. APPLIANCES WITH FIXED TIME RANGE

Consider a scenario where an unconcerned consumer may likely use appliances without giving due considerations to TOU tariffs and limit to peak load. Such a situation is described as a worst case. In this connection, consider a home where appliances operate on the fixed time range equal to the length of load profile as per schedule given in Table 4. The starting time of the appliances given by the consumer is fixed and there is no room for operating the appliances other than the time given by the user irrespective of the TOU. Based on the input range given in Table 4, Table 5 gives starting and ending time of the appliances, obtained using the proposed optimization algorithm. These times are the same as the given input ranges and show the effectiveness of the

TABLE 4. Range of time constraints given for appliances in fixed range.

Sr. No	Appliance	Load Profile Length	Range	No. of slots allocation
1	Dishwasher	7	61-67	1
2	Clothes Washer Dryer	8	21-28	1
3	Refrigerator	96	1-96	1
4	AC	96	1-96	1
5	Oven-1 (Morning)	2	5-6	1
6	Oven-2 (Evening)	6	49-54	1
7	Electrical Vehicle	10	45-54	1

TABLE 5. Appliance with fixed schedule (time range = length of a load profile).

Sr. No	Appliance	Start Time	End Time
1	Dishwasher	61(09:00 PM)	67(10:30 PM)
2	Clothes Washer Dryer	21(11:00 AM)	28(12:45 PM)
3	Refrigerator	1(6:00 AM)	96(05:45 AM)
4	AC	1(6:00 AM)	96 (05:45 AM)
5	Oven-1 (Morning)	5(7:00 AM)	6(7:15 AM)
6	Oven-2 (Evening)	49(6:00 PM)	54(7:15 PM)
7	Electrical Vehicle	45(5:00 PM)	54(7:15 PM)

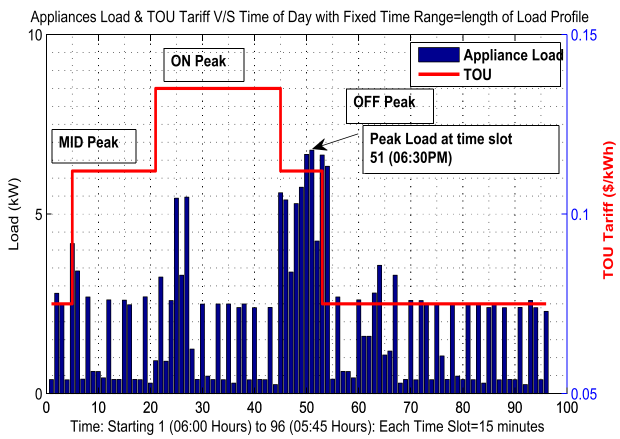

FIGURE 12. Load pattern of appliances operating on fixed time range equal to the load profile.

TABLE 6. Range of time constraints given for appliances in mixed range.

Sr. No	Appliance	Profile Length	Time Range	Available Time slots
1	Dishwasher	7	67-96	24
2	Clothes Washer Dryer	8	17-96	73
3	Refrigerator	96	1-96	1
4	AC	96	1-96	1
5	Oven-1 (Morning)	2	3-7	4
6	Oven-2 (Evening)	6	53-61	4
7	Electrical Vehicle	10	73-96	15

proposed solution in dealing with given constraints. Demand curve of the above situation is shown in Fig. 12, along with TOU tariff curve. It shows that most of the appliances are scheduled in the region of peak and mid peak of TOU tariff, as the scheduling is not done with respect to TOU tariffs. The peak load of 6.78 kW occurs at time slot 51 (6:30 PM), which is in mid-peak TOU tariff. Other parameters are given in Table 8.

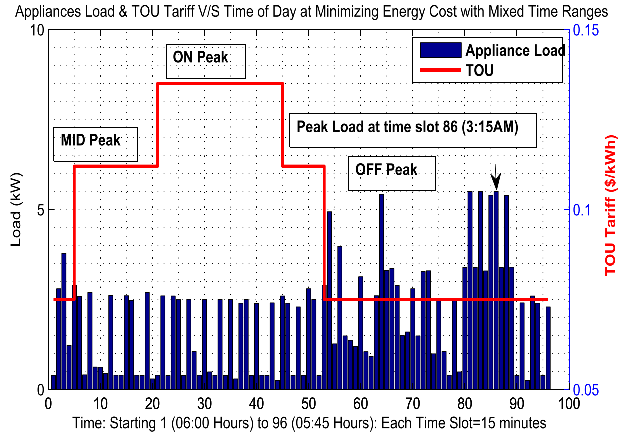

FIGURE 13. Load pattern of appliances operating on mixed time range.

TABLE 7. Appliances starting and ending times for mixed time range schedule.

Sr.No	Appliance	Start Time (Slot no. and Time)	End Time (Slot no. and Time)	Allowed Time Range
1	Dishwasher	68(10:45 PM)	74(12:15 AM)	[67-96]10:30 PM-05:45 AM
2	Clothes Washer Dryer	60(8:45 PM)	68(10:45 PM)	[17-96]10:00 AM-05:45 AM
3	Refrigerator	1(6:00 AM)	96(05:45 AM)	[1-96]6:00 AM-05:45 AM
4	AC	1(6:00 AM)	96(05:45 AM)	[1-96]6:00 AM-05:45 AM
5	Oven-1 (Morning)	3(6:30 AM)	4(06:45 AM)	[3-7]6:30 AM-07:30 AM
6	Oven-2 (Evening)	54(7:15 PM)	59(8:30 PM)	[53-61]7:00 PM-9:00 PM
7	Electrical Vehicle	80(1:45 AM)	90(4:15 AM)	[73-96]12:00 AM-6:00 AM

C. APPLIANCES WITH MIXED TIME RANGE

In this case, time range space is provided in Table 6 for optimizing the scheduling of appliances as per convenience of its operations. The time range provided is either equal or greater than the length of the load profiles to give flexibility for appliance scheduling and more time slots options for allocating appliances. Only refrigerator and AC have fixed range equal to their respective load profiles. It is noted that energy demand of appliances being constant, reduction of peak demand and electricity cost could occur by appropriately shifting loads away from the peak TOU tariff timings. We also seek optimization scheduler to determine the minimum energy cost with additional constraint that peak load be less than or equal to 5.5 kW at any instant of the time range. The combined appliance load distribution is shown in Fig. 13 and the recommended starting and ending times of the appliances is given in Table 7, obtained using the proposed algorithm. The electricity consumption is 48.45kWh, which remains constant and its cost is reduced from $4.92 in case A to $4.46 based on TOU Tariff and peak load is reduced from 6.78kW to 5.5kW, a reduction of 18.9%. The load curve shows that shiftable loads under flexible time range move

TABLE 8. Comparison of results.

Parameters	Case A1	Case A2	Case B	Case C	Case D	Case E
TEC (kWh)	48.45	48.45	48.45	48.45	48.45	48.45
EC ($)	4.63	4.46	4.92	4.46	4.92	4.46
EE (kWh)	0	0	0	0	8.77	10.20
MPLAT (kW@slot)	5.61@60 (8:45 PM)	6.79@75 (12:30 AM)	6.78@51 (6:30 PM)	5.50@86 (3:15 AM)	6.34@53 (7:00 PM)	5.50@86 (3:15 AM)
SSOD	156.98	238.80	291.31	201.53	499.68	524.77

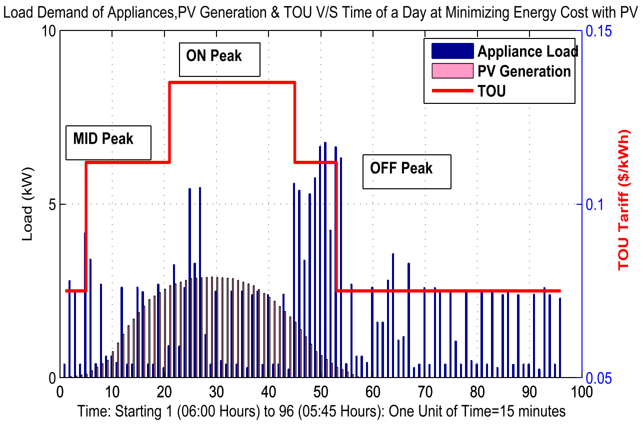

FIGURE 14. Load pattern of appliances and PV generation operating on fixed time range.

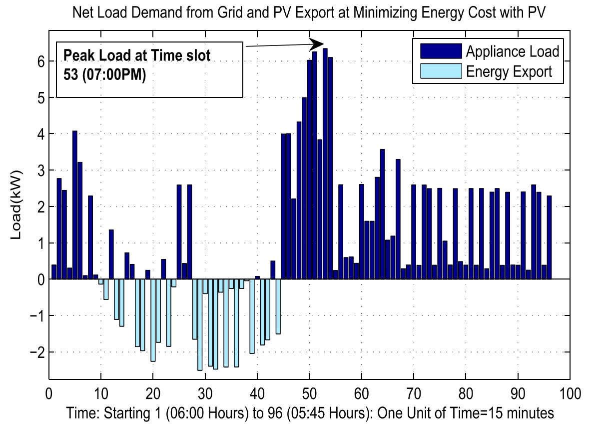

FIGURE 15. Net load demand from the grid and PV export for minimizing energy cost in fixed time range.

to region where tariff is low as evident from Fig. 13, which shows the effectiveness of our approach.

D. APPLIANCES WITH FIXED TIME RANGE WITH PV PANEL

Next, we study the effect of local electricity generation through installation of 3 kW PV panels. PV panels will generate power as co-power supplier in addition to supply from the national grid. Consider the same appliance configuration shown in Table 5 with 3 kW PV panels. The load patterns of appliances along with power generated by PV panel are overlapped on time-wise basis as shown in Fig. 14. The net demand of load from the national grid and export of power to the utility grid are shown in Fig. 15. Other parameters calculated from the solution obtained by the proposed optimization algorithm with the objective function P1B (with micro-grid) are shown in Table 8. The results show that amount of energy and total electricity cost is the same as in case A. But if we take the effect of PV panel generation shown by the parameter EE, the net import from national grid decreased from 48.45kWh to 34.11kWh. Therefore, the cost of energy decreased from $4.92 to $3.11 based on TOU tariff. The home simultaneously exported 8.77kWh to national grid. The expected sales proceed from the export of energy is $3.47 based on FIT is $0.396/kWh as of 2014 [23]. Instead of payment, the net amount receivables from the electricity supplier is $0.36. Peak demand is reduced from 6.78kW to 6.34kW showing a reduction of 6.4%. The reduction in peak demand is due to the reason that peak is occurring at the tail end of solar generation time.

E. APPLIANCES WITH MIXED TIME RANGE WITH PV PANEL

Next, we optimize the scheduling of appliances on the basis of minimizing energy cost subject to the same constraints given in Table 6 and including additional constraint that the load at any time be always less than or equal to 5.5 kW with 3 kW PV panels. The scheduling of appliances comes to be the same as the scenario discussed in case B, but final demand curves are totally different because of the effect power supply by PV panels. There is a mix of import and export of electric power from and to national grid. Fig. 16 shows the demand of appliances and supply of power from PV panels. The flexible loads have shifted to the low tariff portion of TOU curve. Fig. 17 shows the net flow of load. The upper portion of the graph shows import from the national grid and lower part of the graph shows export to the national grid. Other parameters are shown in Table 8. The results show that the amount of energy and total electricity cost are the same as in case B. But if we take the effect of PV panel generation, the net import from national grid decreased from 48.45kWh to 35.54kWh. Therefore, the cost of energy decreased from $4.46 to $2.84 based on TOU tariff. The HAN simultaneously exported −10.20kWh to national grid. The expected sales proceed from the export of energy is $4.04 based on FIT $0.396/kWh. Instead of payment, the net amount receivable from the electricity supplier is $1.20. The net cost of energy is −$1.20 as against $4.46, showing energy cost reduction of 126.9%. Peak demand remained the same at 5.5kW due to the constraint that peak load at any time

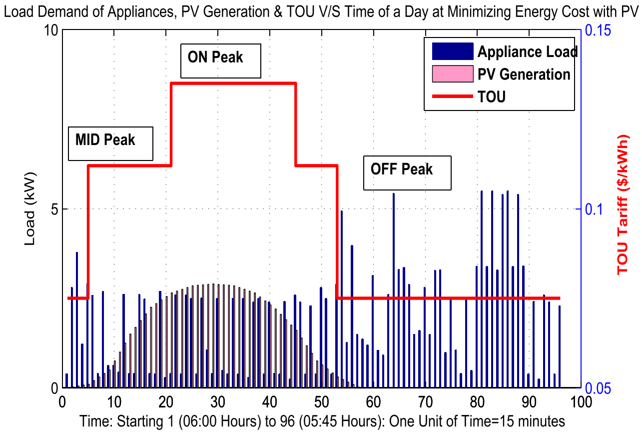

FIGURE 16. Load pattern of appliances and PV generation for minimizing cost in mixed time range.

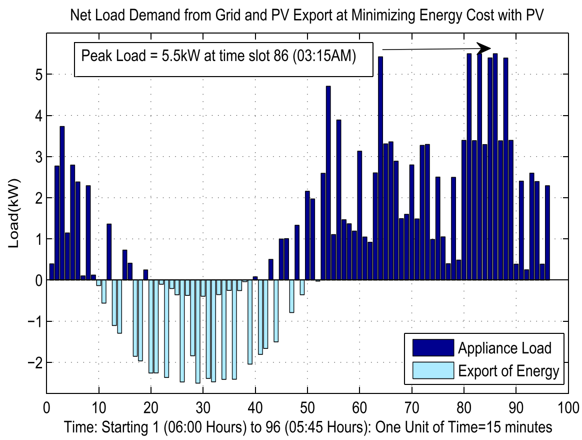

FIGURE 17. The net load demand from the grid and PV export for minimizing energy cost in mixed time range.

must not go above 5.5kW. The SSOD in case two has the lowest value as the optimization allows to level the demand curve. In cases C and D, it is higher as the effect of PV panel causes the demand to decrease between slots 10 and 45 in case C and between slots 10 and 50 in case D. As this demand is reduced over a larger range in case D, the SSOD is larger.

V. CONCLUSION

In this paper, we formulated the appliance scheduling problem in home area networks as a problem consisting of two objectives along with constraints. The first objective deals with the lowering of electricity cost and the second objective deals with the minimizing of maximum peak load. The problem for appliance scheduling was shown to be a mixed integer programming with a binary decision variable for switching an appliance ON and OFF, thus making our optimization problem type a non-convex. We used seven appliances of different shiftable types of load and one micro-grid i.e., PV panel. We utilized branch-and-bound algorithm to solve our problem. Simulation results showed the effectiveness of our proposed solution in lowering the electricity cost and peak load. We further showed that the addition of PV panel enabled lowering of cost and export of electricity to the main grid.

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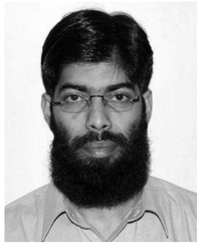

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