A new approach of optimal appliance scheduling for peak load reduction of an off-grid residential building

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Abstract

Demand for electricity, due to the fast growth in urbanization and industrialization, is on the rapid rise. Load shift is a basic method for demand side management (DSM) that can be used by the central controller in buildings and can lead to the maximum use of renewable energy sources, maximum economic benefits, and reduction of peak demand. This paper proposes an algorithm for shifting the flexible loads of four selected appliances with respect to boundary limits for each appliance. A standalone four-story building with different number of occupants is considered to evaluate this algorithm. The algorithm was trained on Richardson model to minimize two objectives including aggregated demand, and the scheduling discomfort. The proposed algorithm led to significant reduction in aggregated peak demand and thereby savings in standalone system investment. The results demonstrated a major reduction in peak demand from 37% to 44% for winter and summer seasons, respectively.

Keywords: *Demand side management, occupant behavior, load profile, appliance schedule*

Nomenclature	
TUD	*Time use data*
TUS	*Time use survey*
PV	*Photovoltaic*
DOE	*Department of energy*
DSM	*Demand side management*
OC	*Occupant comfort*
ZEB	*Zero energy building*
AWT	*Average waiting time*
WM	*Washing machine*
DW	*Dishwasher*
VC	*Vacuum cleaner*
TV	*Television*
BOS	*Balance of system*
ATUS	*American time use survey*

1 Introduction

High digitalization levels make new energy efficient buildings growingly sensitive to variations of occupancy behavior, which induce new challenges for the development of advanced control algorithms. In this regard, the main objectives of the developed control systems are to save energy, to reduce peak electricity demand, and to increase (Robillart, Schalbart, and Peuportier 2018). Indicators of comfort and wellbeing of residents, along with energy efficiency, are very important to consider for optimization operations (Li, Wang, and Hong 2021). To achieve such goals, control systems, based on the user's need, shall have focus on demand response. Besides, with processes such as shift demand, they shall provide a platform for reducing peak demand; however not creating a disruption in the residents' comfort. The intensity of energy consumption related to the residential load sector is such that it plays a significant role in the overall power balance, stability and efficient management. Several reports have investigated the need for the consideration of the control of this intensity of consumption. One of the proposed solutions to tackle current and future growth challenges is Demand Side Management (DSM) (Panda et al. 2022).

DSM involves all changes originating from the demand side of the market for achieving large-scale energy efficiency improvements by operating and using improved technologies and changes in consumers' behavior or energy practices (S Yilmaz, Rinaldi, and Patel 2020).

Generally, energy efficiency aims to reduce the overall energy consumption and thus focuses on the load immensity rather than on the peak load and time pattern. Actions taken under this strategy include increasing energy conservation and energy efficiency that aim to decrease the total load on the grid (S Yilmaz, Rinaldi, and Patel 2020). In the meantime, the issue of reducing the peak would be highly important, because this reduction can lead to a reduction in the marginal cost and as a result, a reduction in the cost of energy (Kobus et al. 2015). So, to reduce peak load, it is very important to address the issue of reducing the intensity of energy consumption in the building sector with the approach of changing the DSM. as the dominant part of this consumption is always related to the use of household appliances, which would be closely related to the occupation behavior, it is important to study the role of smart appliances (Kobus et al. 2015).

Occupant behavior modeling provides the possibility to forecast both energy performance and comfort in buildings to better support building operation and design (Gilani and O'Brien 2017). One of the issues and challenges encountered in the implementation policies of DSM systems is to reduce peak demand and the overall energy consumption charges with an acceptable level of comfort and convenience for the residential occupants (Panda et al. 2022). Following the results of IEA EBC Annex 66, which have properly addressed the simulation and definition of occupant behavior in buildings, Annex 79 is focused on "Occupant behavior-centric building design and operation" so as to place occupant needs as a priority; Hence, a fundamental change in the way occupancy role is required; that is, to consider occupants as a dynamic model input, which bi-directionally interacts with the building envelope and appliances rather than formerly presumed schedules in building energy simulations.

Recently, with the development of communication technologies and smart grids, numerous efforts have been made to reduce electricity peak demand. Some studies have focused on electrical load shifting to guarantee grid stability (Robillart, Schalbart, and Peuportier 2018).Dynamic programming has been used to study load shifting of heating systems in an energy efficient building (Robillart, Schalbart, and Peuportier 2018). Owing to the electricity demand response, the consumer demand for energy might be modified through various methods such as financial incentives or information. Advanced control systems might be used to reduce peak electricity

demand. Such control could be driven by electricity tariffs or due to limitations resulting from off-grid systems with the aim of reducing initial investment costs (Pineau and Hämäläinen 2000). The control could take advantage of the thermal mass of the building to shift electricity consumption from peak to off-peak hours (Kelly et al. 2011). The control can change the electricity consumption from peak hours to low hours by restricting the use of unnecessary high-consumption appliances; to do so the appliance behavior modeling is necessary (Selin Yilmaz, Firth, and Allinson 2017; Richardson, Thomson, and Infield 2008). Studies which model the occupants' interaction with buildings and control systems have included lighting (Reinhart, Mardaljevic, and Rogers 2006).
For instance, (Kobus et al. 2015) showed that it was possible for Households to shift demand for the washing machine to another time excluding the evening peak. They used the dynamic programming method to study the control of households receiving a dynamic electricity tariff, an energy management system and a smart washing machine. The results have shown that households shift their smart washing machine usage mostly to the days when the sun is shining and electricity is produced by their own solar panels. To meet such objectives and the growing demand for better control of energy efficient buildings, it would be necessary to develop new advanced control techniques accessible to building designers and operators. Different studies have suggested modeling and relationships between occupant behavior, appliance uses, and energy use; For example, (Palacios-Garcia et al. 2015) proposed stochastic modeling for lighting energy use. HVAC electric demand via the high-resolution stochastic bottom-up modeling was evaluated by (Palacios-García et al. 2018). The relationship between the occupant behavior and the electricity use is shown in (Palacios-García et al. 2018). Finally, for end-use energy simulation in residential buildings use of real data is recommended when sufficient data are available, but in cases with insufficient data, occupancy schedules can be generated synthetically as a helpful approach to be used in simulations (Richardson and Thomson 2013). (McKenna et al., 2015) improved Richardson model (Richardson et al., 2010) in which a two-state active-occupancy model was developed into four-state one where the states are separated as absent/present state and active/inactive state, so that an absent occupant is differed from one who is asleep at home. The model, using a first-order Markov chain, generates domestic electricity profiles and the generated profiles show a good coincidence with the UK time-use survey data. In addition, the proposed model is improved to eliminate the under-representation of 24h occupied houses. Further, (Richardson et al., 2010), using the profiles for appliance use and activity patterns, developed their

domestic lighting model to generate domestic electricity profiles for a single or a large number of dwellings. Daily activity patterns are constructed based on the active occupants' data (i.e., when occupants are at home and awake) and thereby daily electricity demand data is created synthetically. The model covers all the various types of household appliances (Richardson et al., 2010).

The rest of the paper is structured as follows. Section 2 describes the methodology for development of an optimized algorithm for appliance scheduling. Section 3 presents and discusses the results of the synthetically generated data for the whole building; and eventually, Section 4 summarizes the concluding remarks and puts forward future work steps.

2 Method for electric load prediction and peak load decrease

This study has proposed an operational schedule from a building operation manager perspective, for the selected appliances of a four-story building; In this regard, four electrical appliances, including washing machine (WM), dishwasher (DW), vacuum cleaner (VC), and microwave (MW) are selected so that their load shift impact on aggregated peak demand go under investigation. Based on (Andargie, Touchie, and O'Brien 2019) the level of control and experience is mentioned as one of the factors affecting occupant comfort (OC) in multi-unit residential buildings. In this article, OC is being assumed from this perspective; that is limited control over selected appliances results in lower comfort levels. Summer and winter seasons during weekday and weekend are chosen for analyzing occupancy behavior. In the following, all the working steps are defined precisely.

Demand and peak load reduction modelling

The latest Richardson model was used to generate stochastic electric demand data for a four-story building. The model was unified and improved based on the previously published modelling approaches in (Richardson et al. 2010; 2009).

in this study, the introduced model predicted the load demand for a whole day based on allocated random appliances in the house at the beginning of the simulation. In addition, the model takes the number of months and days of a year along with the number of occupants as input, so as to predict total appliance demand. Figure 1 shows a set of daily activities that residents might perform during a full day; these activities were the same for all the dwellings in the case of a four-story building.

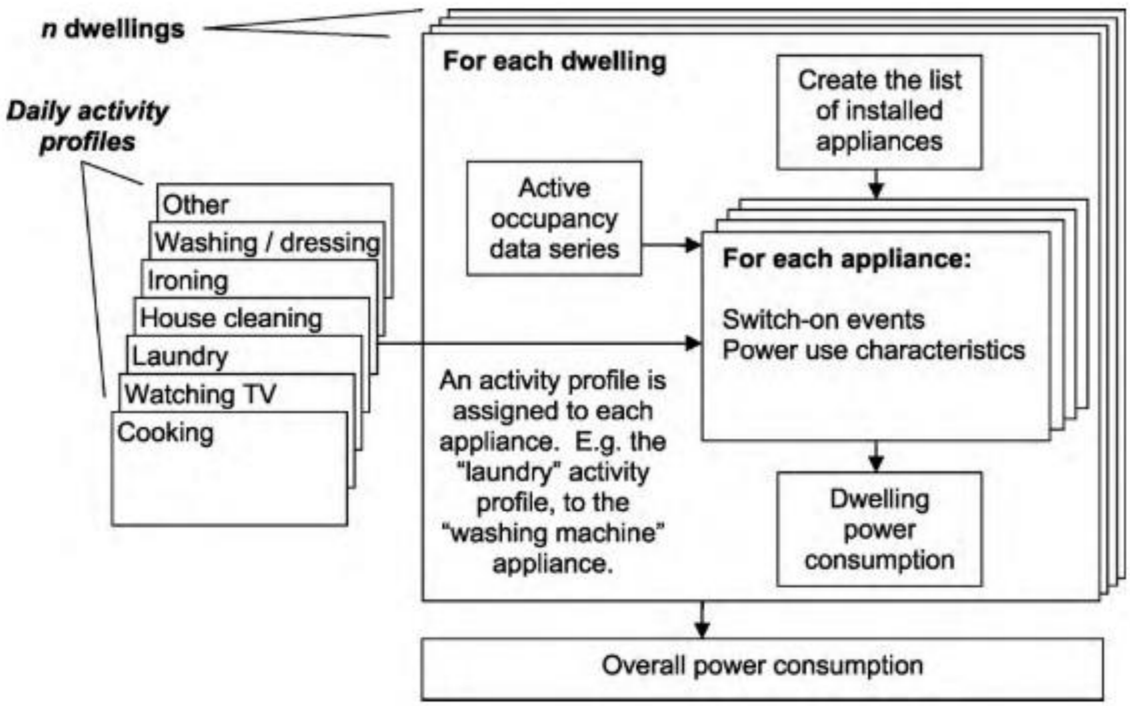

Figure 1. *Structure of electricity demand model* (Richardson et al. 2009)

In the right-hand side in Figure 1, the larger block shows the model for each dwelling. Inside the block, a series of active presence data was used for each electrical appliance, and each appliance was connected to a daily activity. When an appliance was turned on, based on its energy use characteristics the amount of energy consumed over a specified period was calculated. By summing the energy demand of all the appliances in the house, the total electricity demand of the house was determined, and likewise the aggregated demand of a four-story building was calculated as the algebraic sum of demand of each dwelling.

At the beginning of the simulation, the proposed unified model shown in Figure 1 equipped each house with a number of appliances; accordingly, the model has been developed in such a way that each house can have a number of appliances. So, a house might have several numbers of a specific appliance. For example, TV varies from zero to three, and this possibility has been already6 considered in the model. Each appliance has two modes that can be turned on or off.

When the appliance is not being used, it can be in standby mode and still consuming power with lower voltage. Many appliances such as TV have a constant demand for electricity when they are turned on; whereas, some other appliances mentioned in the model such as a washing machine that goes through different stages from start to finish, have a variable demand for electricity over time, the same is true for appliances including heating water, washing and spinning clothes.

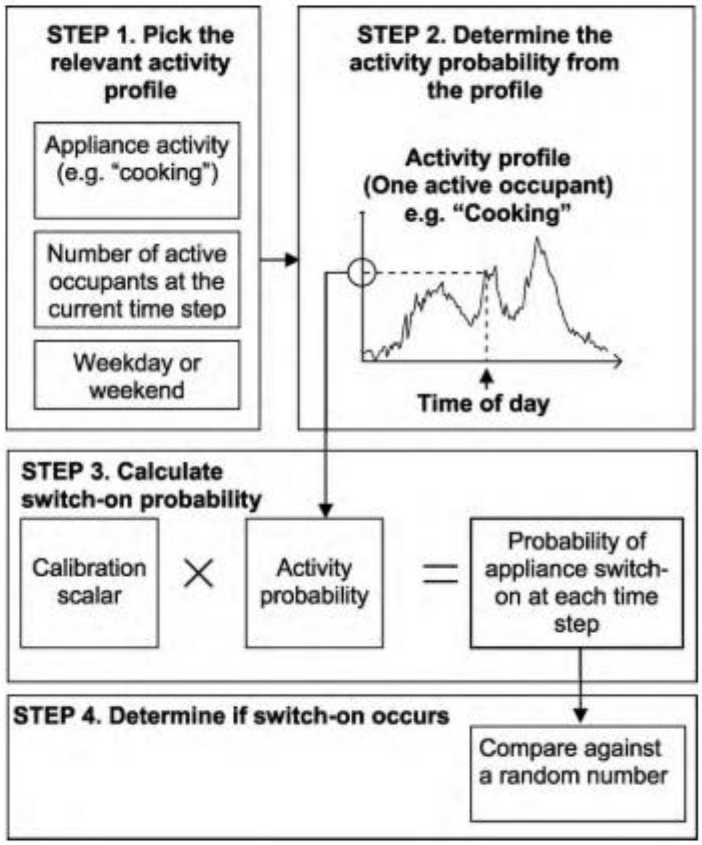

Figure 2. *Switch-on events* (Richardson et al. 2009)

The process indicating Whether the appliance turns on or not is shown in Figure 2. In the first step, the activity profile being related to the desired electrical appliance, was selected; then the number of active occupants in the house was determined. Besides, whether the desired day was a weekend or a working day was determined. In the second stage, the probability that each person being active in the house would be engaged in that activity at that specific time or not was obtained from the activity profile. According to Figure 2, in the third step, the probability of the activity was multiplied by the calibration measurement scalar to calibrate the model outputs based on Richardson model. Each appliance has a "calibration scalar" which is factored into the probability of switch-on as shown in Figure 2, and thus determines the average number of times that the appliance is used in a year. In the case of automatic appliances such as fridges, this corresponds to the number of times that the thermostat starts the compressor. A calibration scalar is adjusted in a way that over a very large number of stochastic simulations runs, the mean annual consumption of the appliance would be correct (Richardson et al. 2009).

Finally, in the fourth step, the results of the previous steps are compared with a random number between zero and one. If the obtained probability number is greater than the random number, the event of turning on that electrical appliance would occur.

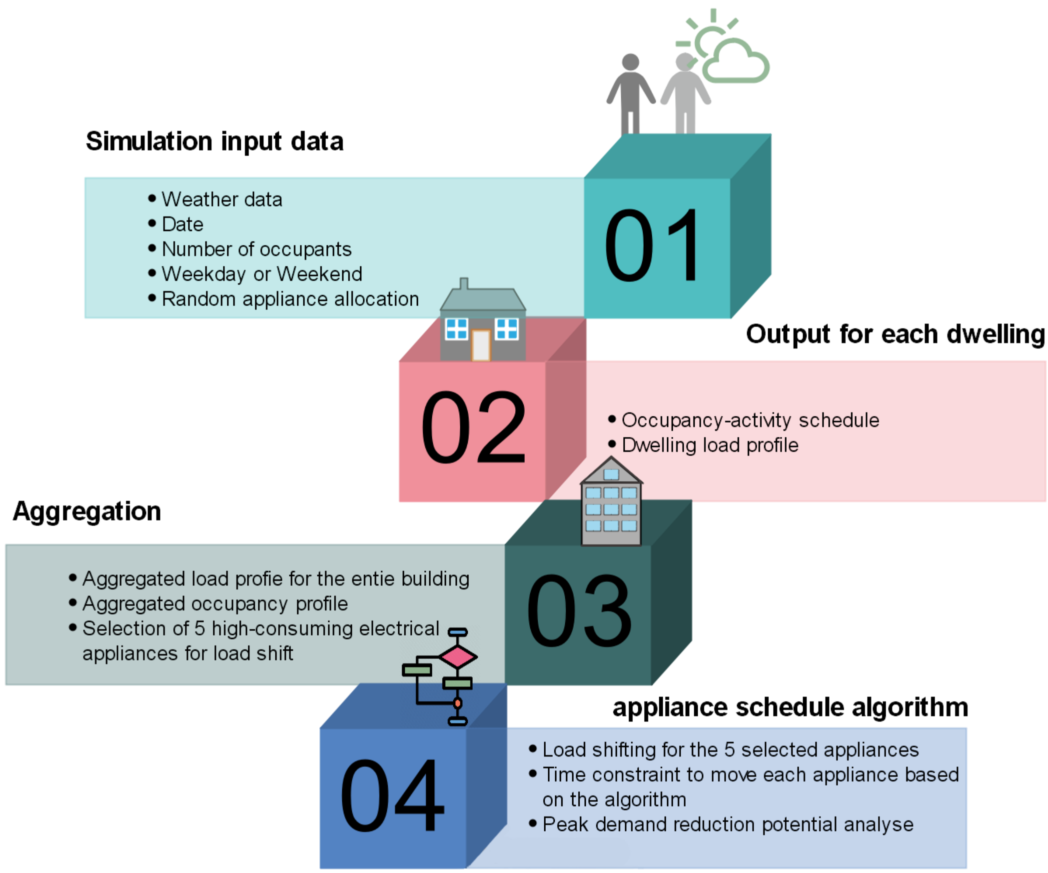

Figure 3. *Main components of the proposed method*

To conduct this study, the working steps and the overall framework of the model are shown in Figure 3. In Step 1, the proposed model, using input data including occupancy probabilities, appliance use probabilities, number of occupants, and weather data, a load demand profile is synthetically generated for each dwelling. based on Richardson model, in each simulation run, the model randomly allocated 19 appliances out of 33 based on their probabilities to the dwelling (Richardson et al. 2010).

In Step 2, the occupancy-activity schedule was analyzed along with the load profile. In Step 3, the aggregated load and occupancy profiles were calculated for the entire building with four story. The four high consuming electrical appliances were selected to include DW, WM, MW, and VC; their load profile was extracted from the total daily demand schedule to investigate load shifting strategy. In Step 4, the developed algorithm in the current study was applied to the entire building demand profile. The assumed values for load shift time constraints in the following were considered to move the selected loads during the day in a way that OC would not be interrupted. Due to the appliance schedule, the peak demand reduction potential was studied in Step 4. It should be noted that in this step electric kettle was neglected because of two reasons; firstly, this appliance showed less impact on the total peak demand reduction. secondly, it could interrupt OC more than the other four appliances. Figure 4 shows the proposed peak shaving algorithm in this study which is programmed in Excel environment using VBA code. Firstly, the algorithm takes some input data including the number of dwellings, number of their occupants, weather data, number of appliances, and allowable boundary limit for appliance load shifting. Secondly, the aggregated peak demand is calculated for the dwelling(s). Among the appliances allocated to the dwellings, the first appliance is selected for load shift. Each appliance activity has a predefined cycle length which is considered as a block of demand. This block might happen from 0 to a number of times over one day. The algorithm shifts the block(s) with respect to boundary limits and also calculates the new aggregated peak demand each time to obtain the best location for blocks where the minimum peak demand is reached. Eventually, the algorithm goes to the next appliance(s) and shifts the block loads with respect to their boundary limits.

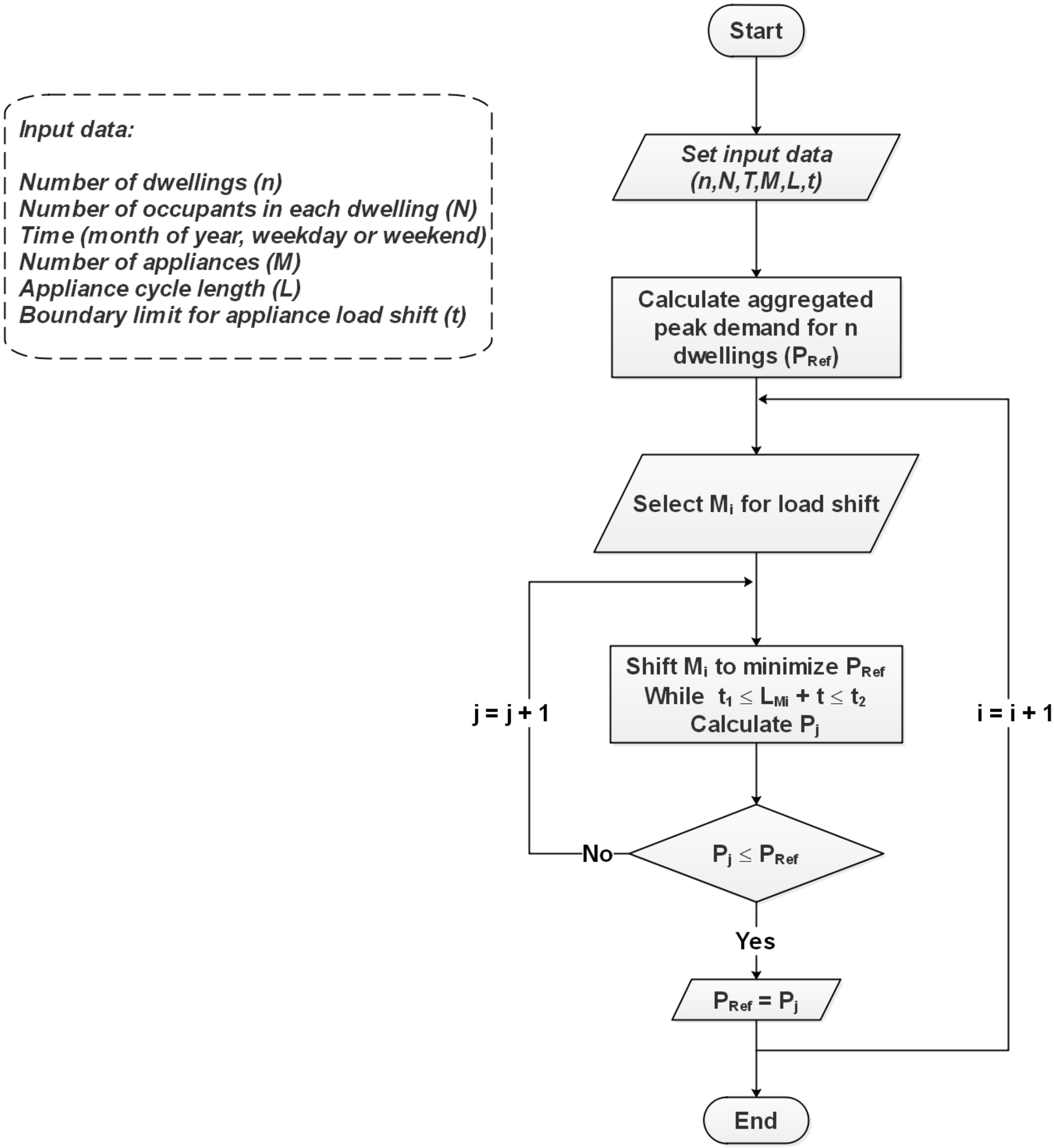

Figure 4. *Algorithm to minimize a building peak demand via appliance load shifting*

After each simulation run, the Richardson model generates load data for each dwelling, and it lists them with 1-min resolution in an Excel spreadsheet; consequently, 1440 cells are produced for a whole day beginning from 00:00 ending in 23:59. In order to study how load shifting of high consuming energy appliances have affected the total peak demand of residential buildings, the scenario shown in Figure 5 is considered.

In this scenario, an off-grid four-story building residing four families each with different number of occupants is assumed. Due to the fact that the limited control on appliance use results in lower OC, here a new index is defined as average waiting time (AWT) to evaluate peak demand reduction versus the OC level. In the following, AWT index is precisely defined.

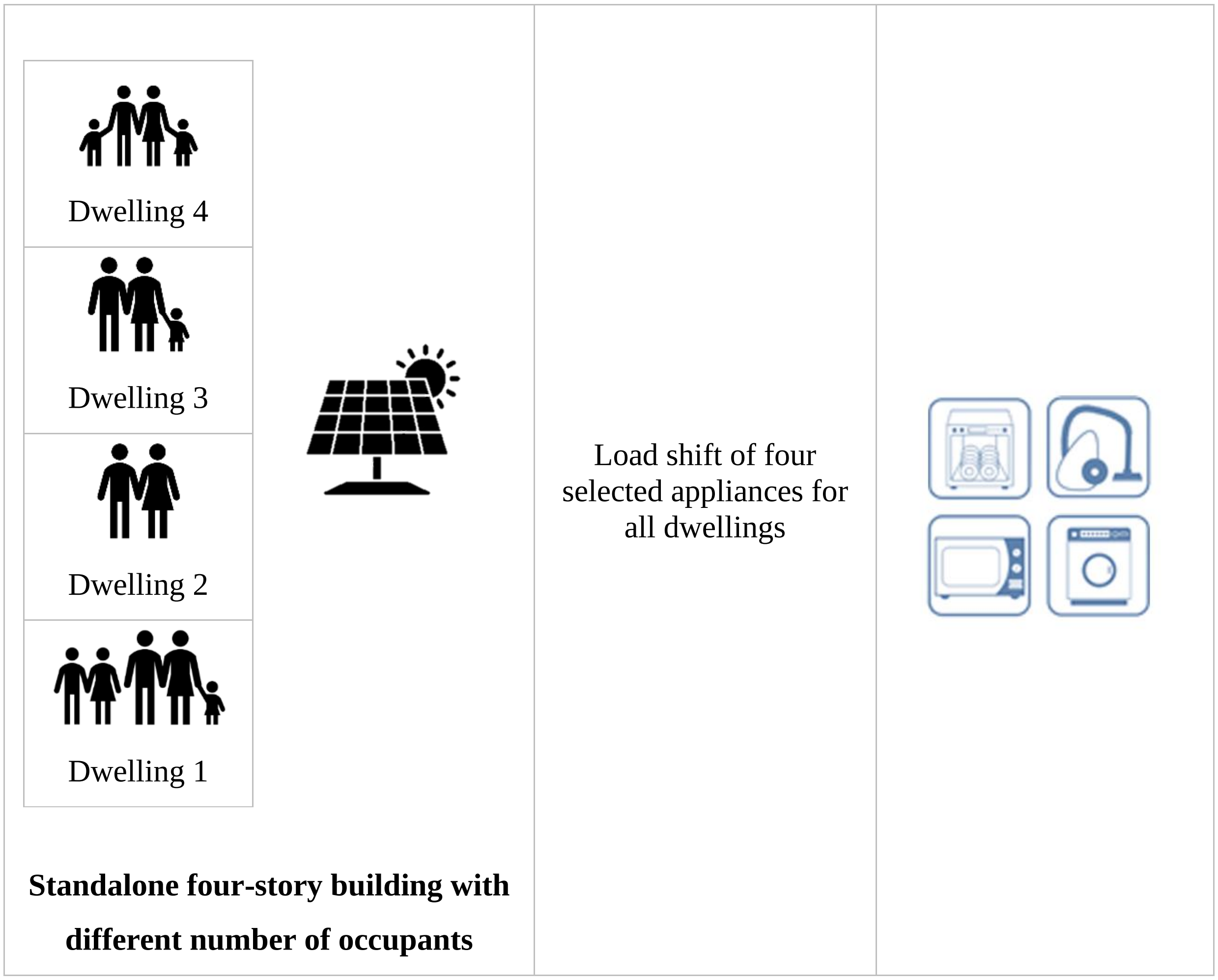

Figure 5. *Schematic diagram of a multi-family building scenario for peak demand reduction*

Average waiting time index for Appliance load shifting

Considering the fact that a load shift strategy interrupts OC by rescheduling each appliance load, this study defined an index called AWT to evaluate and quantify how each step of load shifting in the scenario affects OC. This index shows how long the occupants averagely are to be waiting for running their considered appliance. A graphical presentation of this issue is given in Figure 6. The AWT index was obtained by dividing the total waiting time for one or more appliances (W_i) by the number of cycles (N_{cycle}) that the appliance(s) are used.

$$AWT_{tot} = \frac{\sum_{i=1}^{n} W_i}{N_{cycle}} \qquad (1)$$

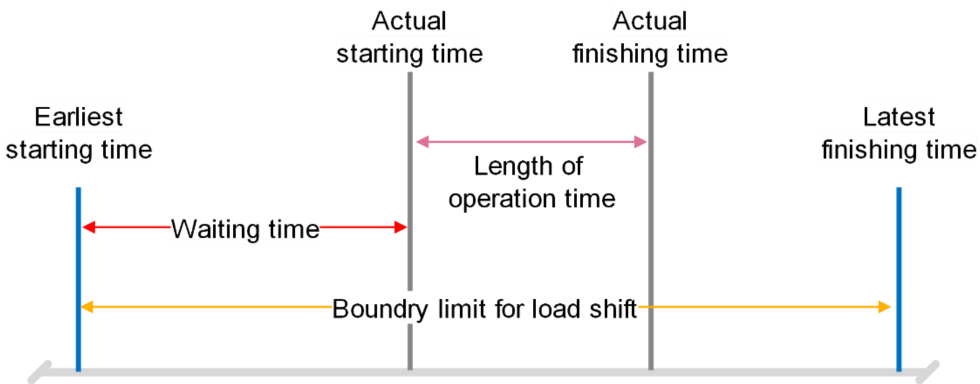

Figure 6. *Graphical representation of estimated waiting time for an appliance due to load shift*

Scenario: Description of Standalone Four-Story Building with Different Number of Occupants

To analyze how the peak demand was affected with the load shifting strategy, a four-story building with different number of occupants was considered. The Richardson model, based on a random set of appliances, generated the output data for each dwelling. Each appliance had its energy related characteristics comprising of cycle length, energy use per cycle, standby energy use, etc. Table 1 shows 19 random appliances allocated to each dwelling with the related characteristics.

Table 1. *Appliances allocated to each dwelling with energy related characteristics based on the Richardson model* (Richardson and Thomson 2010)

Appliance category	Appliance type	Mean cycle length (min)	Mean cycle power (W)	Standby power (W)
Cold	Fridge freezer	22	190	0
	Refrigerator	18	110	0
Consumer	Answer machine	0	0	1
Electronics + ICT	Cassette / CD Player	60	15	2
	Clock	0	0	2
	Cordless telephone	0	0	1
	Hi-Fi	60	100	9
	Iron	30	1000	0

	Vacuum	20	2000	0
	Personal computer	300	140.7	5
	TV 1`	73	124	3
	VCR / DVD	73	33.6	2
	TV Receiver box	73	26.8	15
Cooking	Oven	27	2125	3
	Microwave	30	1250	2
	Kettle	3	2000	1
	Small cooking (group)	3	1000	2
Wet	Dishwasher	60	1130.6	0
	Washing machine	60	2500	1

The proposed algorithm in Figure 4 shifts the load demand of the four selected appliances so as to minimize the building peak demand. The selected appliances were rescheduled with different limit boundaries; the sensitivity analysis for each appliance was reported in the results.

The time constraints to shift the loads for each of these four appliances are assumed as described in Table 2.

Table 2. *Load shift time constraints in the demand management algorithm for three selected electrical appliances*

Appliance	Mean cycle length	Boundary limit for load shift
VC	20 min	180 min (90 min before and after)
DW	60 min	240 min (120 min before and after)
WM	60 min	720 min (360 min before and after)
MW	30 min	90 min (45 min before and after)

3 Results

In this section, the simulation results are described before and after applying the proposed algorithm on the assumed standalone building. Figure 7 shows the electricity use over one day in summer, for the entire building having lodged four families, which is simulated based on the Richardson model.

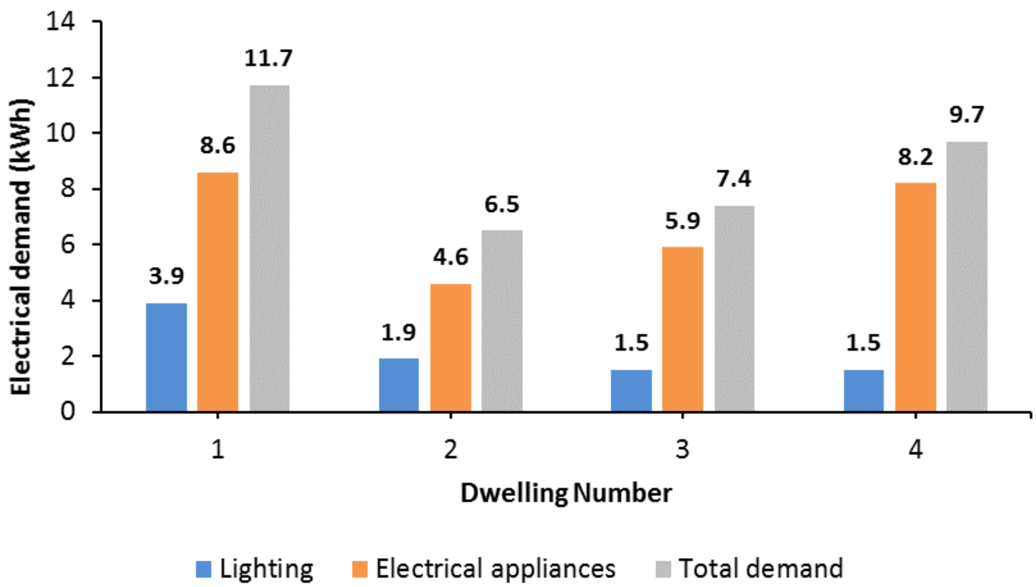

Figure 7. *Household electrical demand for the four dwellings separately for lighting and appliances*

Peak shaving algorithm for appliance scheduling

Here it shall be noted that prior to running each simulation for each dwelling, 19 electrical appliances out of 33 were randomly assigned to the dwellings, but four high energy consuming appliances were selected for load shift study. Weekdays and weekends during summer and winter seasons were chosen for analyzing occupancy behavior.

Figure 8 shows the electricity demand of four appliances in the summer working day prior to the application of the algorithm. According to Figure 8, the peak demand is happened around 1 PM and corresponds to the value of 9 kW. The key factor to this incident might be due to WM, DW, and microwave respectively. Figure 9illustrates how the peak shaving algorithm is aimed to flatten the demand curve and has consequently resulted in 34.5% peak demand reduction to a value of 5.9 kW.

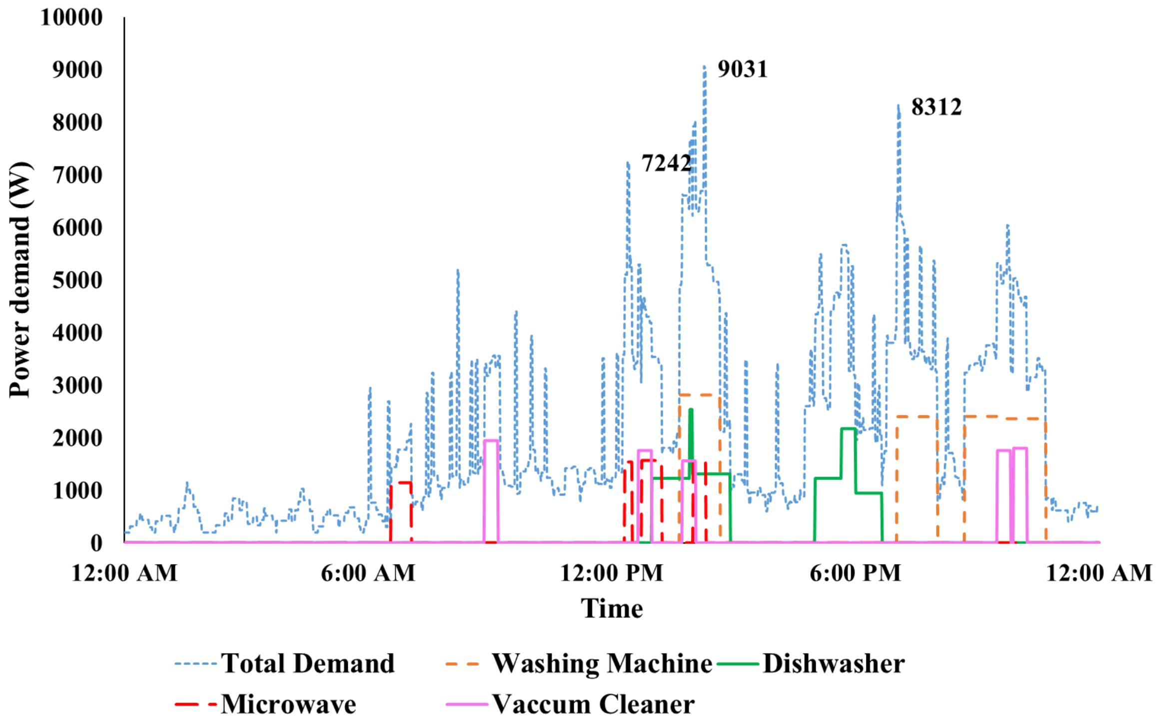

Figure 8. *Load profile for four appliances in the summer working day before applying algorithm*

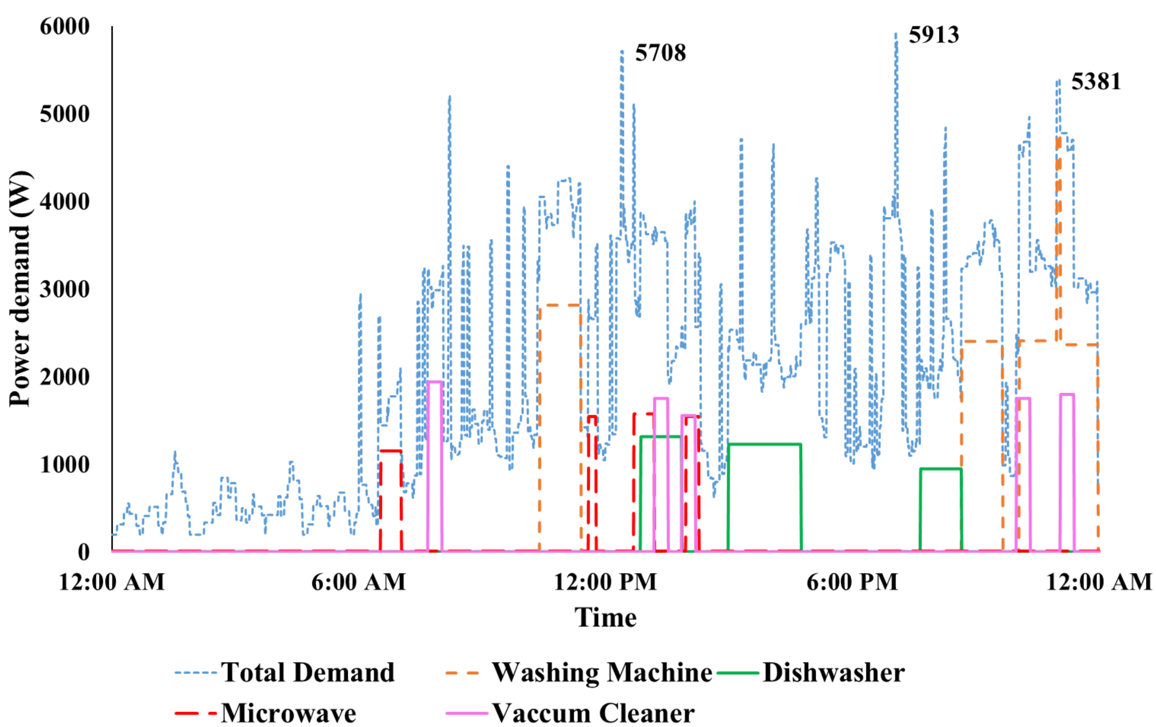

Figure 9. *Load profile for four appliances in the summer working day with the optimized algorithm*

Figure 10 shows the overall demand of the building in a random summer weekend which compared to a working day, reasonably illustrates more demand. Peak demand is raised to a value of about 10.6 kW around 9 PM where the simultaneous use of WM in each house along with VC, DW, and microwave might be seen as the main factor.

Figure 11 illustrates that where the new peak is moved to around 5 PM with a value of 5.8 kW, the peak demand is reduced to half via applying the algorithm.

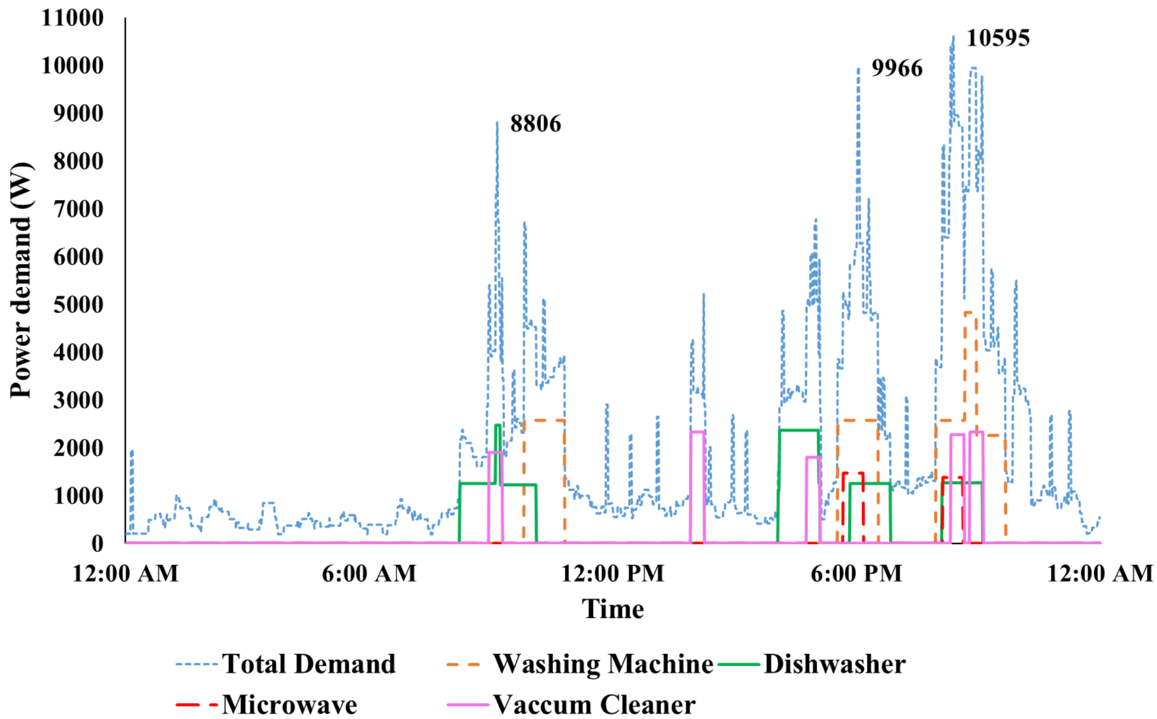

Figure 10. *Load profile for four appliances in the summer weekend without the peak shaving algorithm*

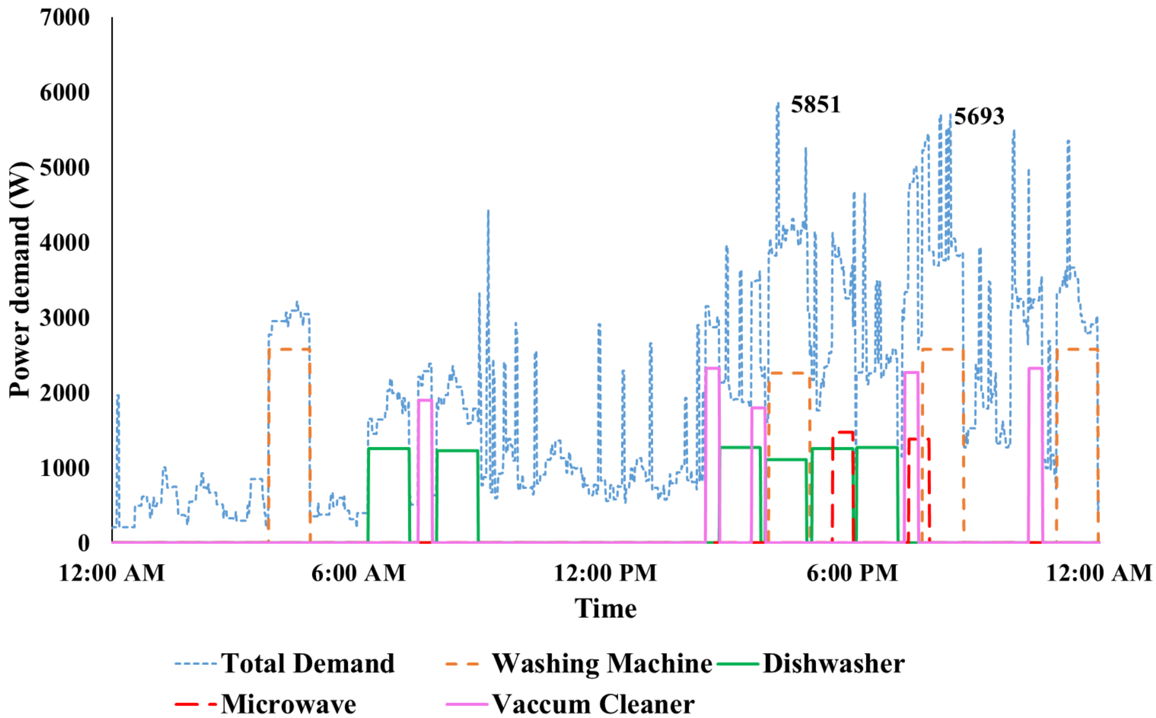

Figure 11. *Load profile for four appliances in the summer weekend with the peak sharing algorithm*

Figure 12 depicts that in a winter working day, because of using VC, WM and DW at the same time, 7.6 kW peak demand is happened around 9 PM. After applying the peak shaving algorithm to the appliances, Figure 13 shows a reduction of about 37% in peak demand through the load shift.

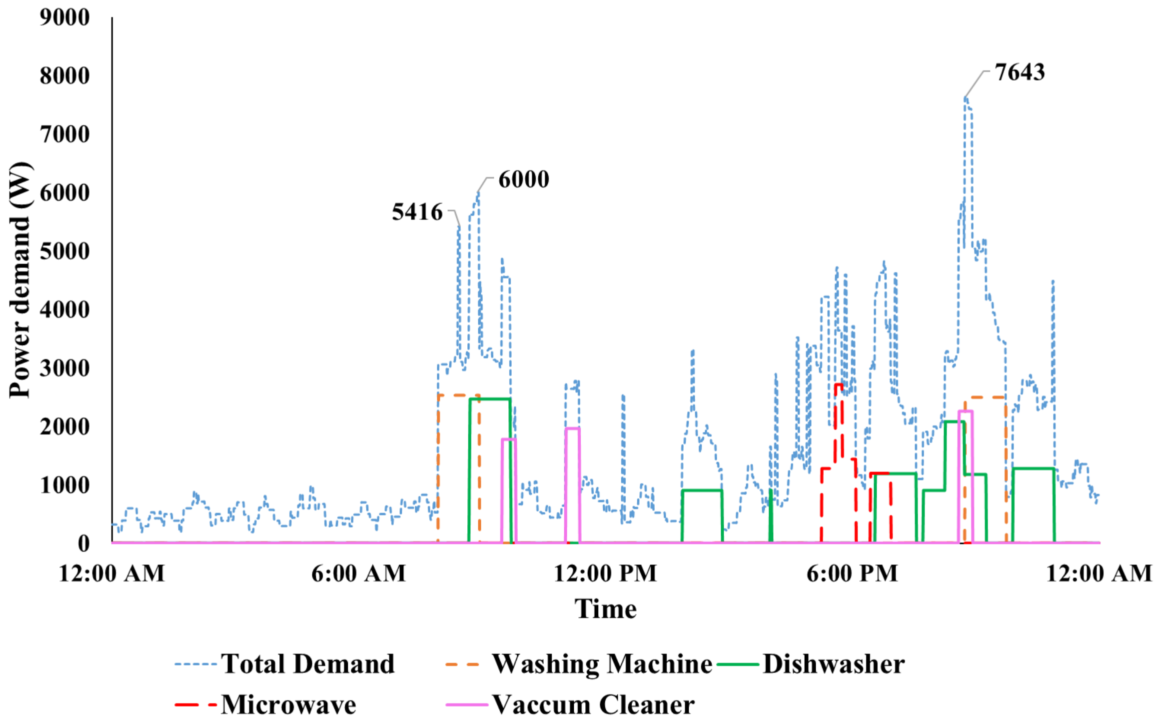

Figure 12. *Load profile for four appliances in the winter working day without peak shaving algorithm*

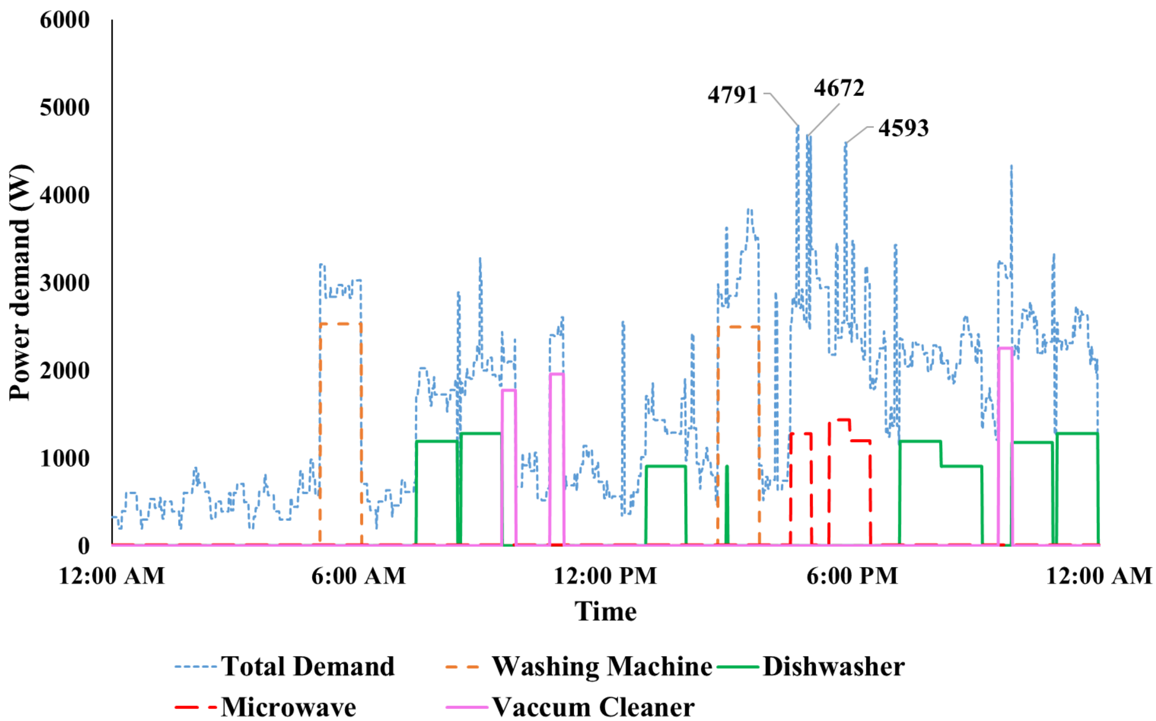

Figure 13. *Load profile for four appliances in the winter working day with the peak shaving algorithm*

Finally, Figure 14 shows the peak demand with a value of 9.4 kW happened later in the morning at about 9 AM for a winter weekend because of the simultaneous use of WM, DW and VC. After applying the algorithm, load profile is more flattened and the new peak value is decreased to about 6.5 kW which is illustrated in Figure 15.

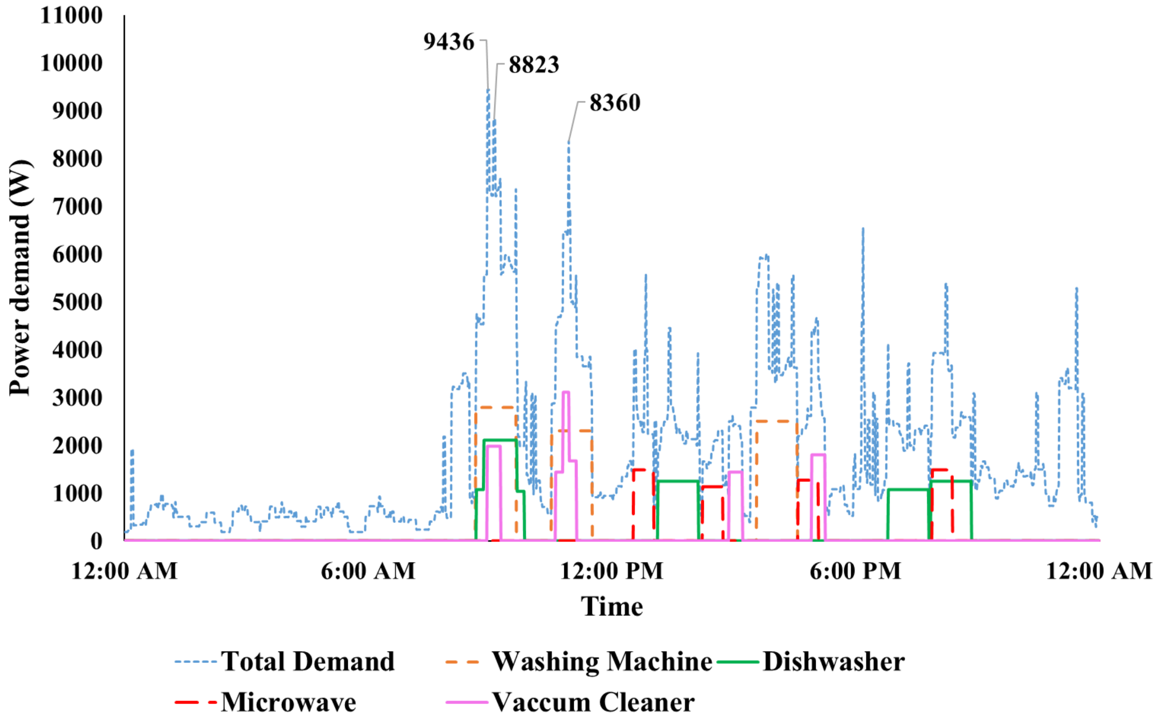

Figure 14. *Load profile for four appliances in the winter weekend day without algorithm*

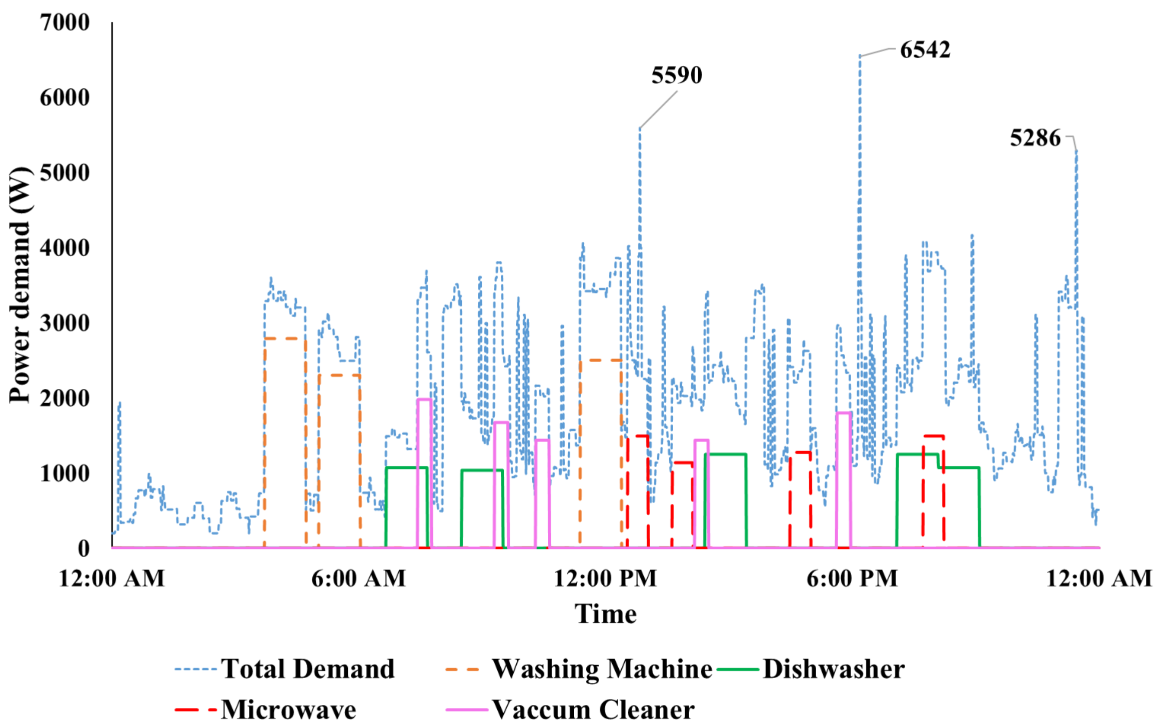

Figure 15. *Load profile for four appliances in the winter weekend day with the peak shaving algorithm*

A summary of the above results is given in Table 3 for the four-story building electricity demand before and after the implementation of the peak shaving algorithm.

Table 3. *Peak demand values before and after applying appliance schedule algorithm*

Season and day type	Peak demand before using algorithm (W)	Peak demand after using algorithm (W)	Reduction (%)
Summer-working day	9 031	5 913	34.5%
Summer-weekend	10 595	5 851	44.7%
Winter-working day	7 643	4 791	37.3%
Winter-weekend	9 436	6 542	30.6%

The results in Table 3have shown that in case the appliance scheduling is being applied based on the proposed algorithm, the summer weekends followed by winter working days, have had the most potentiality for peak reduction. It is necessary to pay attention to this fact that the total demand for building has not changed, and only by applying the algorithm to shift the loads for four electrical appliances, the best mode of use has been selected in such a way that the electricity demand of the houses in these four cases has had the least synchronization during the day. using this peak shaving algorithm, a plan might be compiled for the time of using these four appliances for each dwelling with different numbers of occupants; Moreover, a dynamic pricing structure for electricity use at different times of the day along with incentives could encourage occupants to use the appliances during the optimal time interval.

4 Conclusions

In this study a load shifting algorithm was proposed for analyzing the appliance scheduling impact on the overall peak demand. Since the load shifting strategies might have increased the occupant discomfort, average waiting time (AWT) index was delineated to investigate whether the appliance scheduling for decreasing peak demand worth risking the OC or not.

According to the results, the summer weekend showed the highest potentiality for the peak demand reduction by 44.7% and the winter working days by 37.3%. It shall be noted that these amounts of reduction for an urban neighborhood, could have a great impact on the main electricity grid or off-grid networks. To manage the load demand with dynamic pricing policy, future work would extend this algorithm to integrate the standalone or grid-connected systems.

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