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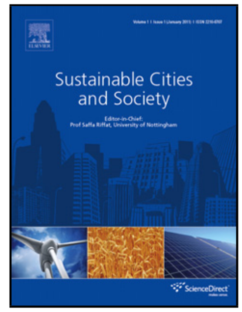

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Authors: Shakouri G. Hamed, Aliyeh Kazemi

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Multi-objective cost-load optimization for demand side management of a residential area in smart grids

Hamed Shakouri G.[1], Aliyeh Kazemi[2*]

[1] School of Industrial and Systems Engineering, College of Engineering, University of Tehran, Tehran, Iran.

[2] Department of Industrial Management, Faculty of Management, University of Tehran, Tehran, Iran.

Highlights

- SHC planning problem for energy management in a residential area is considered.
- A multi-objective mixed integer linear programming model is developed.
- Objectives include minimization of peak load and minimization of cost.
- Simulation results for six different scenarios with different objectives are provided.

Abstract

Demand side management (DSM) is one of the most interesting areas in smart grids, and presents households with numerous opportunities to lower their electricity bills. There are many recent works on DSM and smart homes discussing how to keep control on electricity consumption. However, systems that consider minimization of peak load and cost simultaneously for a residential area with multiple households have not received sufficient attention. This study, therefore, proposes an intelligent energy management framework that can be used to minimize both electrical peak load and electricity cost. Constraints, including daily energy requirements and consumer preferences are considered in the framework and the proposed model is a multi-

* Corresponding author. Tel:+982161117771; fax: +982188006477.
E-mail address: aliyehkazemi@ut.ac.ir
Address: Nasr Bridge, Chamran Highway, P.O. Box: 14155-6311, Tehran, Iran.

objective mixed integer linear programming (MOMILP). Simulation results for different scenarios with different objectives verified the effectiveness of the proposed model in significantly reducing the electricity cost and the electrical peak load.

Keywords: Demand side management; Smart homes; Load scheduling; Time of use tariffs; Optimization

Nomenclature Symbols

Sets

A	Set of appliances
H	Set of hours (24 hours in a day)
T	Set of electricity tariff
C^h	Set of c^hs
TSAs	Set of time-shiftable appliances
PSAs	Set of power-shiftable appliances
NSAs	Set of non-shiftable appliances

Indices

h	Time interval index
a	Household appliances' index
s	Start time index
e	End time index
n	Number of appliances

Functions

f_1 Electrical peak load function

f_2 Electricity cost function

Variables

EPL Electrical peak load

c_a^h Energy consumption of appliance *a* in a particular hour *h*

c^h Total energy consumption in hour *h*

u_a^h Binary variable: if time-shiftable appliance *a* operates in hour *h*, $u_a^h = 1$; otherwise, $u_a^h = 0$

U_a Binary integer vector of u_a^h

Parameters

DR_a Daily requirements of energy for appliance *a*

h_a^s Operation start time of appliance *a*

h_a^e Operation end time of appliance *a*

p_a^* Fixed hourly energy consumption of non-shiftable appliance *a*

$\underline{p_a}$ Minimum energy consumption of power-shiftable appliance *a*

$\overline{p_a}$ Maximum energy consumption of power-shiftable appliance *a*

p_a^h Fixed energy consumption of appliance *a* in hour *h*

P_a Fixed energy consumption pattern of time-shiftable appliance *a*

P_a^{total} Fixed consumption pattern of time-shiftable appliance *a*

t^h Electricity tariff for hour *h*

1. Introduction

Increasing population, urbanization, industrialization and technological developments throughout the world have increased energy consumption intensively. Increase in energy use has caused problems including depleting energy sources and creating pollution due to energy production process. For the solution of these basic energy issues, traditional grids are being transformed into smart grids (SG), which could be defined as the grid infrastructure that optimizes the energy efficiency while lowering both the energy sources' installation expenses and pollution effects on the environment (Ozkan, 2016). A research area that has been very popular within SGs is demand side management (DSM), as shown by the increasing number of publications over the recent years (Galvan-Lopez et al., 2014); More than 2000 scientific papers have been published in this area since the 1980s, with more than half in the recent decade (Galvan-Lopez et al., 2015).

DSM technique mainly relies on matching present generation values with demand by controlling the energy consumption of appliances and optimizing their operation at the user side (for instance, by shifting appliances such as dishwashers, washing machines and dryers from peak time to off-peak time).

The importance of energy usage optimization in a smart house can be inferred from the statistical information, which indicates that the electricity consumption in the residential sector represents over 27% of the global energy consumption in 2014 (Ministry of Energy of Iran, 2016). Therefore, a large number of research efforts have been devoted to the application of DSMs in the residential sector (Tascikaraoglu, Boynuegri & Uzunoglu, 2014; Esther & Kumar, 2016). For example, a mixed integer linear programming (MILP) model was formulated by Sou et al. (2011) to minimize the total electricity cost for operating the appliances. The cost calculation was based on a given 24-hour ahead electricity tariff. Tascikaraoglu et al. (2014) put forward a scheduling approach of operation and energy consumption of various electrical appliances in a grid-connected smart home system, which utilized wind and solar power predictions, electricity tariff information, states of storage systems and load priorities for deciding the optimal operation times of appliances. It was aimed to minimize the monetary expenses with autonomous decisions while avoiding to buy electricity at high-price times by shifting the deferrable loads to the times with higher renewable energy potential and/or with cheaper electricity price. Gottwalt et al. (2011) introduced an algorithm that simulated residential load shifting under time of use (TOU) regimes using previously generated profile data to model realistic demand response behavior. Different groups of household appliances were included into the model with their technical and practical usage patterns and operation constraints. Giorgio and Pimpinella (2012) addressed the design of a smart home controller strategy providing efficient management of electric energy in a domestic environment. The problem was formalized as an event driven binary linear programming problem, the output of which specified the best time to run smart household appliances under a virtual power threshold constraint, taking into account the real power threshold and the forecast of consumption from non-plannable loads. Ma et al. (2016) proposed an optimization power scheduling scheme to implement demand response in a residential unit when the electricity price was announced in advance. Adika and Wang (2014) presented appliance scheduling and smart charging techniques for household electricity management. They proposed an intelligent energy management framework that can be used to implement both energy storage and appliance scheduling schemes. Two variants of evolutionary algorithms were used by Galvan-Lopez et al. (2014) to search for efficient charging schedules for fleets of electric vehicles (EVs); they achieved good results in terms of reducing peak demand and reducing consumers' electricity costs, while maintaining a high overall state of charge of EVs' batteries. Chavali et al. (2014) described a distributed framework for demand response based on cost minimization. Each user in the system could find an optimal start time and operating mode for the appliances in response to the varying electricity prices. Galvan-Lopez et al. (2014) surveyed the use of Monte Carlo tree search in SG technologies with the ultimate goal of learning the optimal times to switch electric devices on or off to minimize electricity cost by learning and predicting the electricity price based on a pricing history in a dynamic price environment. A MILP model was put forward by Steen et al. (2016) to schedule the load demand for residential customers with the objective being minimization of their electricity cost. Bae et al. (2014) focused on a system architecture and an algorithm for DSM using information and communications technology (ICT). As the first step, the objective function was based on electricity bill, and the usage pattern was formulated. Then the electricity bill was minimized, and the usage similarity was maximized. In the second step, a load balancing algorithm was applied to avoid blackout and to minimize rebound peak. Mesaric and Krajcar (2015) developed a mixed-integer program to reach maximum amount of renewable energy sources, scheduling optimal power and operation time for EVs and appliances. Muralitharan et al. (2016) presented a multi-objective evolutionary algorithm, which resulted in the cost reduction for energy usage and minimizing the waiting time for appliance execution. Pallotti et al. (2013) discussed the use of genetic algorithm (GA) to find the optimal planning of energy consumption inside 246 smart homes in a neighborhood. For this purpose, a multi-objective optimization problem was formulated aiming at reducing the peak load as well as minimizing the energy cost and its impact on the users' satisfaction. An appliance control algorithm, called appliance-based rolling wave planning, was developed by Ozkan (2016) with the aim of reducing electricity cost and improving energy efficiency while maintaining user comfort. Vardakas et al. (2014) presented and analyzed four power-demand scheduling scenarios that aimed to reduce the peak demand in a smart grid infrastructure. Caprino et al. (2015) addressed an approach to the peak shaving problem that leveraged the real-time scheduling discipline to coordinate the activation/deactivation of a set of loads. A multi-objective mixed integer nonlinear programming (MOMINLP) model was developed by Anvari-Moghaddam and Rahimi-Kian (2015) for optimal energy use in a smart home, considering energy saving and a comfortable lifestyle. Elma and Selamogullari (2015) introduced a home energy management algorithm for smart home environments to reduce peak demand and increase the energy efficiency. A system that produced a real time solution to reduce the electricity cost and to avoid the high peak demand problem for a smart home which, was equipped with smart electrical appliances, power units, a communication network and a main controller was proposed by Ozkan (2015). Bradac et al. (2015) focused on an optimal scheduling of domestic appliances by using MILP. The aim of the proposed scheduling was to minimize the total energy price paid by the consumer. Missaoui et al. (2014) developed a global model based on anticipative building energy management system in order to optimize a compromise between user comfort and energy cost by taking into account occupant expectations and physical constraints like energy price and power limitations. A mixed-integer nonlinear programming (MINLP) approach was used by Lu et al. (2015) to solve the optimal scheduling problems of energy systems in the buildings integrated with energy generation and thermal energy storage. The optimal scheduling strategy minimized the overall operation cost day-ahead, including the cost of operation energy and the cost concerning the plant on/off penalty. Zhang et al. (2015) proposed an MILP model to schedule the energy consumption within smart homes by coupling the environmental and economic sustainability in a multi-objective optimization with ε-constraint method that employed electricity tariff and CO_2 intensity profiles of UK and obtained the Pareto curve for cost and CO_2 emissions in order to present the trade-off between the two conflict objectives. A smart home energy management model was developed by Shirazi et al. (2015) in which electrical and thermal appliances were jointly scheduled. The proposed method aimed at minimizing the electricity cost of a residential customer by scheduling various types of appliances considering the residents' consumption behavior, seasonal probability, social random factor, discomfort index and the appliances' starting probability functions. Ogunjuyigbe et al. (2017) suggested a demand side load management technique that was capable of controlling loads within the residential building in such a way that the user satisfaction was maximized at minimum cost.

A short review of the existing literature reveals that most of the articles exploring a residential DSM model focus on minimizing electricity cost (Ozkan, 2016; Galvan-Lopez et al., 2014; Sou et al., 2011; Gottwalt et al., 2011; Giorgio & Pimpinella, 2012; Ma et al., 2016; Adika & Wang, 2014; Chavali, Yang & Nehorai, 2014; Steen, Tuan & Carlson, 2016; Missaoui et al., 2014; Lu et al., 2015; Zhang et al., 2015; Shirazi, Zakariazadeh & Jadid, 2015; Ogunjuyigbe, Ayodele & Akinola, 2017) or minimizing electrical peak load (Ozkan, 2016; Galvan-Lopez et al., 2014) for a home energy management unit (Caprino, Vedova & Facchinetti, 2015; Anvari-Moghaddam & Rahimi-Kian, 2015; Tascikaraoglu, Boynuegri & Uzunoglu, 2014; Sou et al., 2011; Gottwalt et al., 2011; Giorgio & Pimpinella, 2012; Ma et al., 2016; Bae et al., 2014; Mesaric & Krajcar, 2015; Muralitharan, Sakthivel & Shi, 2016; Caprino, Vedova & Facchinetti, 2015; Anvari-Moghaddam & Rahimi-Kian, 2015; Elma & Selamogullari, 2015; Ozkan, 2015; Bradac, Kaczmarczyk & Fiedler, 2015; Missaoui et al., 2014; Lu et al., 2015; Zhang et al., 2015). In this research, we propose an MOMILP model to minimize electrical peak load and electricity cost simultaneously considering the users' preferences and for a residential area with multiple households.

The paper is organized as follows: Section 2 introduces system architecture. Multi-objective optimization model for appliance scheduling is explained in Section 3. Applicability of the proposed model is provided in Section 4. Section 5 shows the simulation results. Finally, conclusions are presented in Section 6.

2. System architecture

In this section, we provide smart grid residential system architecture. The overall system architecture is depicted in Fig. 1. The predominant component is the smart home controller (SHC), which is responsible for managing the appliances inside the house in order to achieve the objectives such as minimizing the electrical peak load along with minimizing the electricity cost based on TOU tariffs, appliance specifications, and the information collected from the consumer preferences. SHC can monitor and control appliances by means of communication networks like general packet radio service (GPRS), wireless fidelity (WiFi) or long term evolution (LTE).

Home appliances are categorized in three classes based on their intrinsic characteristics:

1) Time-shiftable appliances (TSAs)

TSAs such as washing machines can be shifted in time. SHC generates scheduled starting commands to turn them on. These loads consume electric power according to their power.

2) Power-shiftable appliances (PSAs)

PSAs consume electric energy in a certain range between their minimum and maximum power. Most of rechargeable devices like electric vehicles are included in this category. SHC decides how much energy these loads consume in their working period.

3) Non-shiftable appliances (NSAs)

For NSAs such as lights, which have fixed power consumption requirement and working period, SHC considers their energy consumption according to the consumer preferences.

3. Multi-objective optimization model for demand side management

The load scheduling mechanism can be described as a MOMILP model, which aims to minimize the electrical peak load and the electricity cost simultaneously, as shown below:

$$\min f_1 = EPL \tag{4}$$

$$\min f_2 = C^h \times T \ , \qquad C^h = [c^1, c^2, \dots c^{24}] \ , \qquad T = [t^1, t^2, \dots, t^{24}]^T \tag{5}$$

s.t:

$$c^h = \sum_{a=1}^{n} c_a^h \ , \qquad \forall h \in H \tag{6}$$

$$\sum_{a=1}^{n} c_a^h \leq EPL, \qquad \forall h \in H \tag{7}$$

$$\sum_{h=1}^{24} c_a^h = DR_a \ , \qquad \forall a \in A \tag{8}$$

$$c_a^h \geq p_a^* \ , \quad \forall a \in NSAs \ , \quad \forall h \in \left[h_a^s, h_a^{(s+1)}, \dots, h_a^e\right] \tag{9}$$

$$\underline{p}_a \leq c_a^h \leq \ \overline{p}_a \ , \quad \forall a \in PSAs \ , \quad \forall h \in \left[h_a^s, h_a^{(s+1)}, \dots, h_a^e\right] \tag{10}$$

$$P_a^{total} = \begin{bmatrix} p_a^1 & p_a^{24} & \dots & p_a^3 & p_a^2 \\ p_a^2 & p_a^1 & \dots & p_a^4 & p_a^3 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_a^{24} & p_a^{23} & \dots & p_a^2 & p_a^1 \end{bmatrix} \tag{11}$$

$$\sum_{h=1}^{24} u_a^h = 1 \ , \qquad U_a \in \{0,1\}, \qquad \forall a \in TSAs \tag{12}$$

$$c_a^h = U_a \ P_a^{total}, \qquad U^h = [u_a^1, u_a^2, \dots u_a^{24}] \ , \qquad \forall a \in TSAs \tag{13}$$

$$c_a^h \geq 0 \tag{14}$$

The objectives of the above optimization problem are to minimize the hourly load EPL and to minimize the electricity cost, subject to the constraints (6)-(14). The hourly load should be greater than or equal to the sum of the scheduled power for all appliances at each hour (constraint (7)). To make sure that the energy phases fulfill their energy requirements, the constraint (8) is imposed. For non-shiftable appliances, the hourly power requirement is fixed at p_a^* during its working period from h_a^s to h_a^e (constraint (9)). The household user can set up the time preference constraints, specifying the time interval a particular appliance must be started and finished within.

Alternatively, this means that the PSAs cannot be run outside of the time preference interval. The constraints are written as (10). The constraints (11)-(13) are used to model the TSAs' power consumption. A TSA power consumption can be presented as $P_a = [p_a^1 \quad p_a^2 \quad \cdots \quad p_a^{24}]^T$. The operation can be postponed but the power consumption pattern should remain the same. Hence, the scheduling result c_a has to be exactly the same as one of the cyclic shifts of the pattern p_a. All possible shifts can be put together in a matrix as in Eq. (11). The binary integer vector $U_a = [u_a^1 \quad u_a^2 \quad \cdots \quad u_a^{24}]^T$ is defined as switch control for the TSA. There is only one non-zero element in vector U_a, which is equal to one. Vector U_a is an optimization parameter that chooses the appropriate column of P_a^{total} to optimize the energy consumption. According to constraint (14), the power consumption c_a^h must be non-negative value.

The model is solved for a residential area with multiple households. However, because of their different time of use preferences, their energy consumption behavior varies. The various consumption patterns for all households are monitored over discrete hourly intervals h in a total observation period H. It is further assumed that every household can define its time of use preferences via a smart scheduling device embedded in its smart meter to coordinate the appliances' electricity expenditure. Denoting the hourly electricity requirement for each appliance $a \in A$ as c_a^h, the power demand for the customer is computed as an aggregate power for all appliances in each time slot over H [9].

The SHC planning problem is a MOMILP problem that can be solved by well-established methods. Goal programming (GP) has been a popular theoretical method for dealing with multiple objective decision making problems. The basic approach of goal programming is to establish a specific numeric goal for each objective, and then seeking for a solution that minimizes the sum of deviations of these objective functions from their respective goals.

Moreover, in the literature, branch-and-cut method is presented as very successful techniques for solving a wide variety of integer programming problems providing a guarantee of optimality [8]. The above model is solved using both GP and branch-and-cut methods. By using GP method, two objectives are converted into a single goal, and by using branch-and-cut method the MILP model is solved.

4. Applicability of the proposed model

To evaluate the performance of the proposed model, the daily electricity use of four households in Tehran (capital of Iran), each with a set of different household appliances as listed in Tables 1-4, is simulated. It is worth mentioning each day is divided into 30-minute slots and simulations are performed by using GAMS/ CPLEX solver.

As discussed throughout the paper, we are interested in minimizing the electrical peak load, while at the same time minimizing the electricity cost for a residential area. Thus, we focused our attention on the performance of the proposed approach by analyzing six scenarios according to Table 5. The first scenario is based on minimizing the electrical peak load for each household. The second scenario includes minimizing the electricity cost for each household where each user independently minimizes his/her own cost. The third scenario is based on minimizing both the electrical peak load and the electricity cost for each household. The next three scenarios are similar to the first three scenarios except that the model runs for all four households at the same time.

4.1. Tariffs

There are two types of demand response mechanisms: one is based on pricing of tariff and the other is based on incentives for the consumer. In TOU tariffs mechanism, the tariffs are charged according to the time it is used. In a day, the time slots are divided as peak, off-peak and mid-peak. The rate of electricity changes in accordance with the time. This mechanism allows consumers to shift their activities to off-peak and mid-peak periods, thereby achieving financial savings. TOU usually leads to changes in consumption patterns. These TOU rates could be different for summer and winter as the consumption patterns also vary with season, leading to different peak periods (Thakur & Chakraborty, 2016). In this work, TOU, which is the most commonly utilized form of time-variant pricing, will be considered. Table 6 shows the information about the tariff details in Iran. In order to encourage consumers to shift their consumption from peak hours to mid-peak and off-peak usage times, the electricity price is lower than the standard electric service rates during the mid-peak and off-peak hours; however, during the peak hours, the prices are higher. After calculating the cost of electricity based on Table 6, an extra cost for peak hours or discount for mid-peak and off-peak times is calculated as follows:

Discount for off-peak hours (2 am-10 am)=Electricity consumption (kWh)×0.68 (Cent) (1)

Discount for mid-peak hours (12 am-2 am, 10 am-8 pm)=
Electricity consumption (kWh)×0.27 (Cent) (2)

Extra cost for peak (8 pm-12 am) hours =Electricity consumption (kWh)×1.36 (Cents) (3)

It is worthy to mention that in Iran, the electricity price varies in different sectors, cities and months. In this research, the electricity tariffs of residential sector in Tehran in September of 2015 are considered (Ministry of Energy, 2016). It should be noted that the official currency in Iran is Rial, and we have assumed one US dollar as equal to 30000 Rials. The TOU tariff is applied for billing. It is assumed that consumers select an appropriate schedule for the operation time of their appliance according to above three different tariffs to reduce the energy bill.

5. Simulation results

The obtained results have been represented for all scenarios. The first simulation is about Scenario 1. The aim of this simulation is to show how SHC plans the smart appliances' start times assuring overload management for each household separately. The second simulation concerns Scenario 2. The aim of this simulation is to show how SHC plans the smart appliances' start times assuring cost management for each household separately. The third simulation is about Scenario 3. The aim of this simulation is to show how SHC plans smart appliances' start times in such a way to optimize cost, while assuring overload management for each household separately. The next three simulations extend simulations 1-3 to Scenarios 4-6. The aim of these simulations is to show how SHC reacts to a DSM event by performing a new planning and checking for consumer convenience, while assuring overload/cost management for all households at the same time.

The schedules of the hourly electricity consumptions under Scenarios 1-3 are shown in Fig. 2. According to Scenario 3, the appliance profiles are smoother; while under Scenarios 1 and 2, the appliance profiles have one or more spikes. Scenario 1 tries to avoid peak hours; hence, it shifts the start time of appliances to the hours in which the price might be higher. Scenario 2 attempts to reduce cost; consequently, the start time of appliances shifts to the hours in which the price is lower. Since avoiding peak load is not important in this scenario, the start time of some appliances would be the same, causing the peak load to increase in those periods.

As mentioned in the previous section, Scenarios 3-6 are multi-user scenarios when the users adopt a coalitional approach. Such scenarios are provided to exhibit the scalability potential of the proposed method. On the other hand, in the present work, we have limited the number of coordinated households to four to simplify the presentation. Fig. 3. shows the schedules of the hourly electricity consumptions under Scenarios 4-6. As it can be seen, similar to Scenario 1, Scenario 4 intends to reduce the peak load with the difference that it tries to reduce the entire peak load for all the four households simultaneously. It is clearly beneficial for both the capital cost reduction and the stability of the power grid. Scenario 5 intends to lower the entire electricity cost for all the four households. As in this scenario, just cost reduction is important, the peak load of some households (e.g. household 1) is very high (above 4 kW). Scenario 6 attempts to decrease electrical peak load and electricity cost simultaneously. In this scenario, the appliance profiles are smoother, and similar to Scenario 3, there is not any high peak load.

The comparison of peak load (in kW) and cost (in $/month) for all the 6 scenarios is demonstrated in Fig. 4. Moreover, Fig. 5. illustrates the schedule of the hourly electricity consumption in a day for all households under Scenarios 1-6. Referring to Fig. 4. under Scenarios 1 and 4, the electricity cost for all the four households is higher than in the other scenarios. Furthermore, under Scenarios 2 and 5, the peak load of some households increases more than that of other scenarios. Although under Scenario 3, for some households like household 1, both the peak load and the electricity cost reduce more compared to Scenario 6, as shown in Fig. 5., the peak load for all households is reduced significantly under Scenario 6 in comparison to Scenario 3.

Table 7 details the reduction of electrical peak load and electricity cost in each scenario. By comparing the results of Scenarios 1-6, it can be noticed that the electrical peak load in Scenario 6 is lower than in Scenarios 1, 2, 3 and 5 by 11.2%, 33.8%, 36% and 48.6%, respectively. Moreover, comparing the results of Scenarios 4 and 6 reveals that the electricity cost for all households in Scenario 4 is 1.45% higher than that in Scenario 6. Therefore, Scenario 6 is recommended as the most suitable and the preferred one. By looking at this scenario from the viewpoint of a utility company, peak load reductions, as well as load shifting from peak hours to mid-peak and off-peak hours are achieved, and from the viewpoint of customers, substantial cost reductions are obtained. It is clear when the number of households in the residential area increases, more peak load and cost reduction can be achieved by applying this method.

Figs. 2-5 depict optimal schedule for each household according to Scenario 6. They clearly show how the energy consumption of time-shiftable and power-shiftable appliances is managed by DSM. Time-shiftable appliances like washing machine and dish washer are postponed from the afternoon to the morning periods, so the functionality of the household is preserved, since the work is done. Power-shiftable appliances such as electric vehicles and water pumps are charged more in the off-peak periods, as the demand is satisfied. Both of the mentioned appliance categories represent enormous potential to manage electrical peak load and electricity cost.

6. Conclusions

In this paper, the SHC planning problem for energy management in a residential area with multiple households was considered. The problem was formulated as an event driven binary linear programming problem, in which the decision variables represented the start times of appliances. The proposed model takes advantage of lower-cost pricing in the mid-peak and off-peak hours, and at the same time, reduces peak demand for residential households.

To verify the efficiency and robustness of the proposed model, a number of simulations were performed under different scenarios using real data, and the obtained results were compared in terms of total electricity cost and electrical peak load. The simulation results demonstrated the effectiveness of the mechanism.

In conclusion, this work provides a proof of concept about the advantages coming from the use of centralized energy management systems in residential areas, showing the possible benefits for both consumers and utility companies simultaneously.

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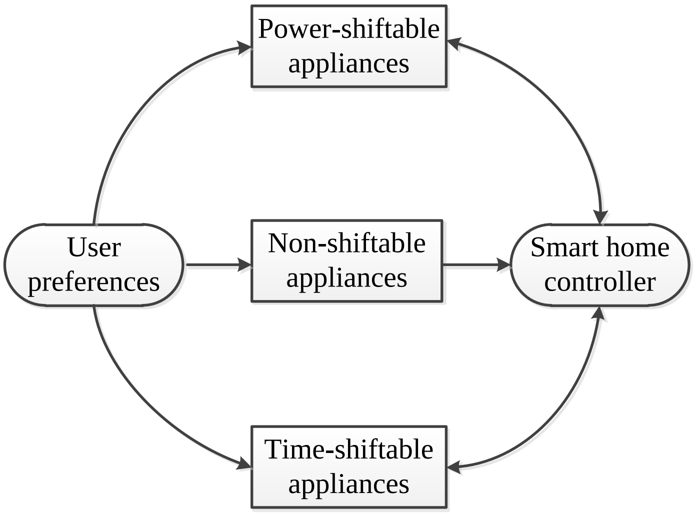

Fig. 1. System architecture.

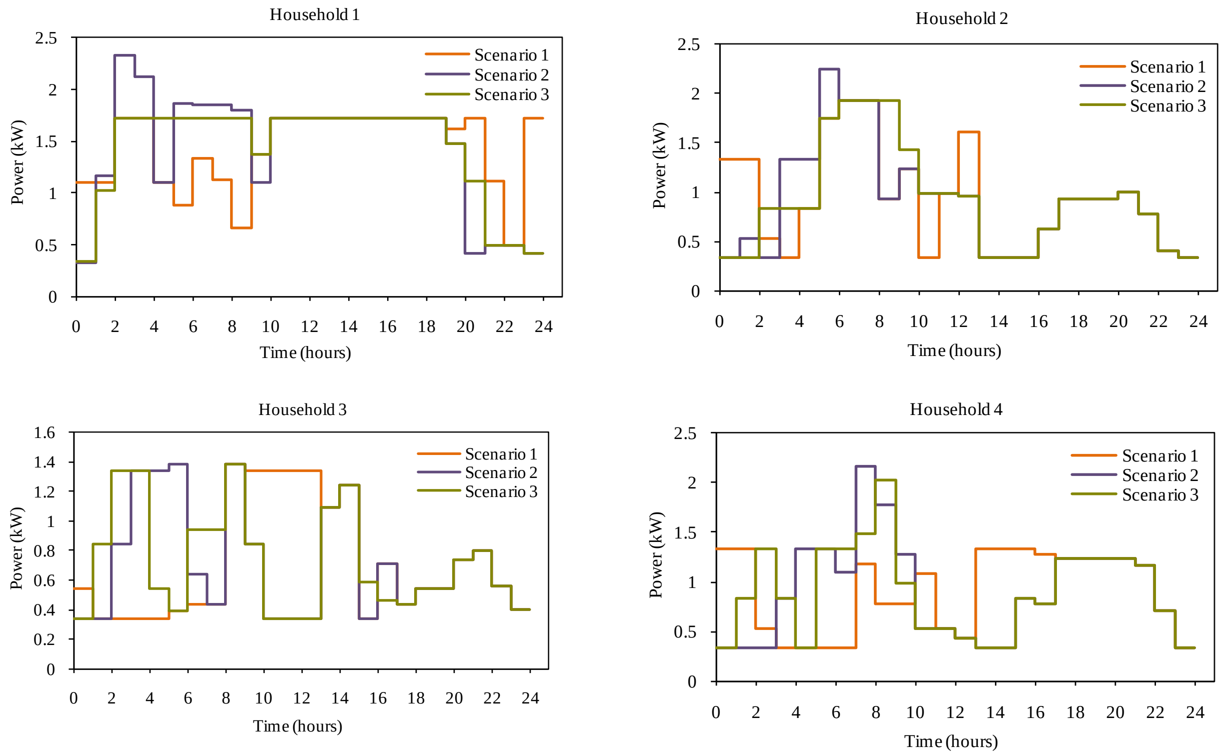

Fig. 2. Schedule of the hourly electricity consumption in a day for each household under Scenarios 1-3.

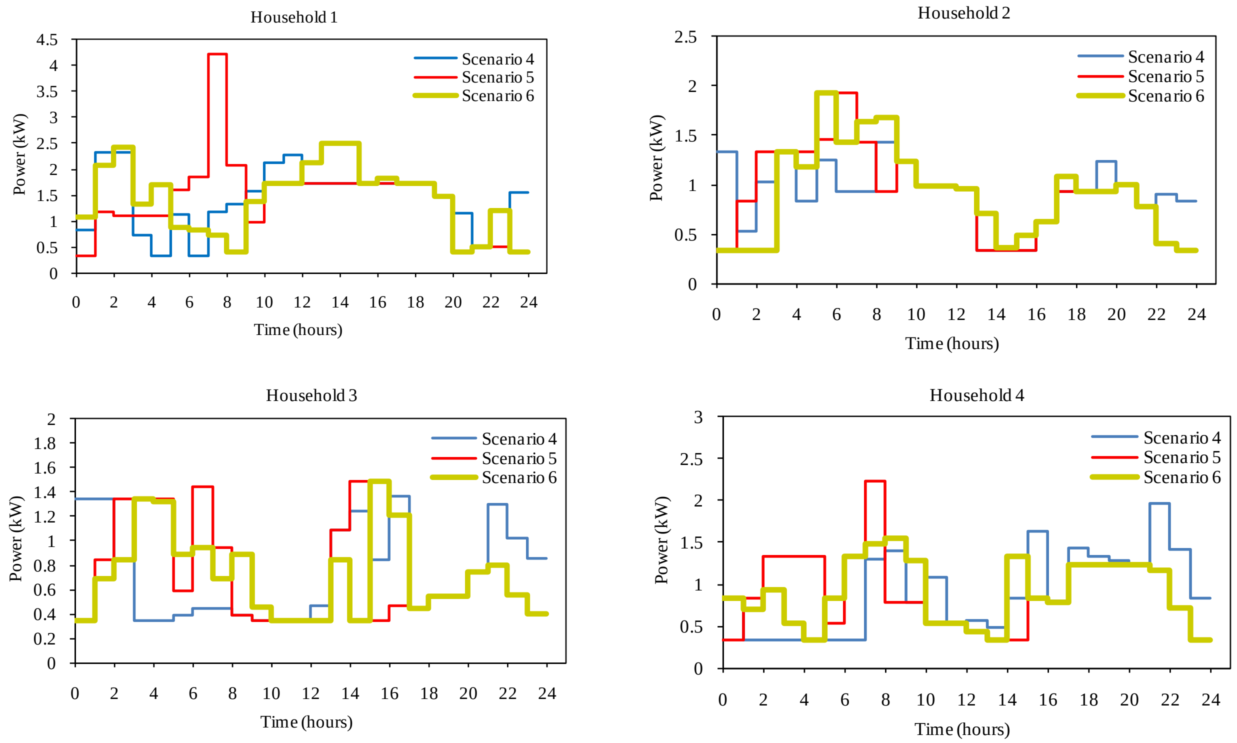

Fig. 3. Schedule of the hourly electricity consumption in a day for each household under Scenarios 4-6.

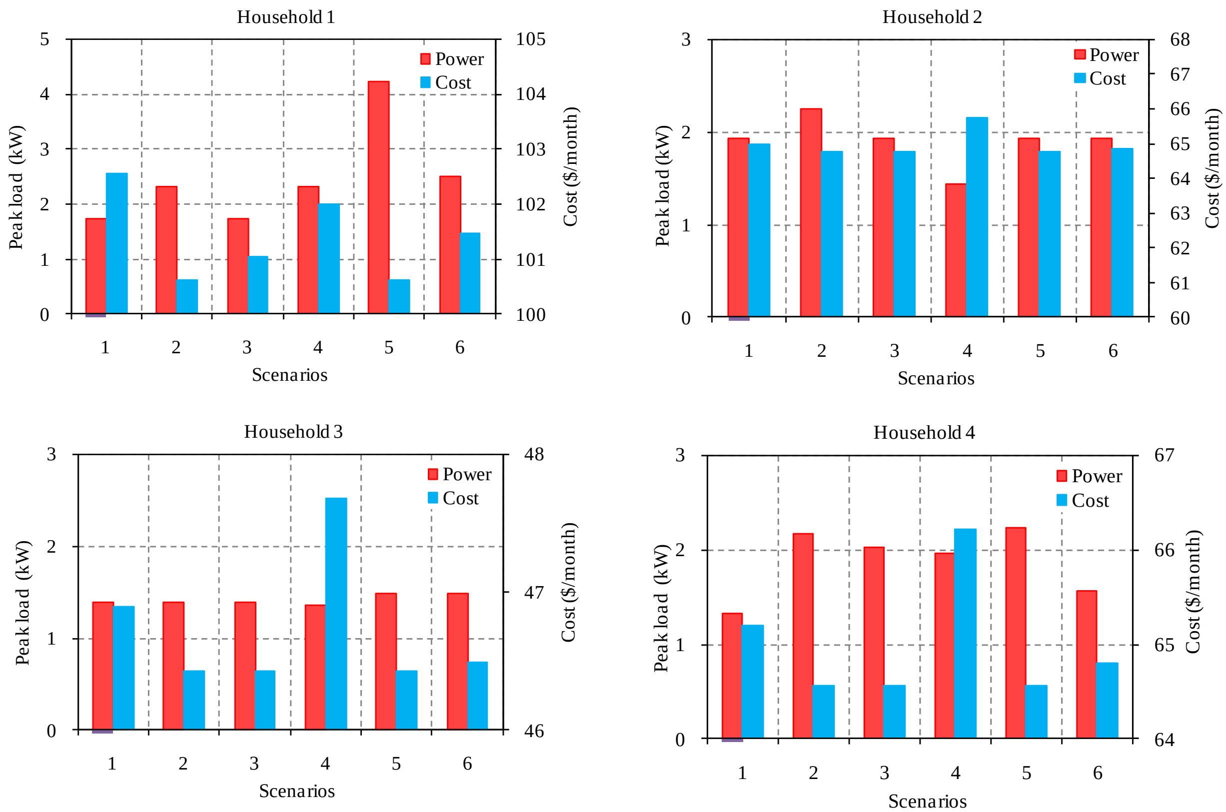

Fig. 4. Peak load and cost comparison among different scenarios.

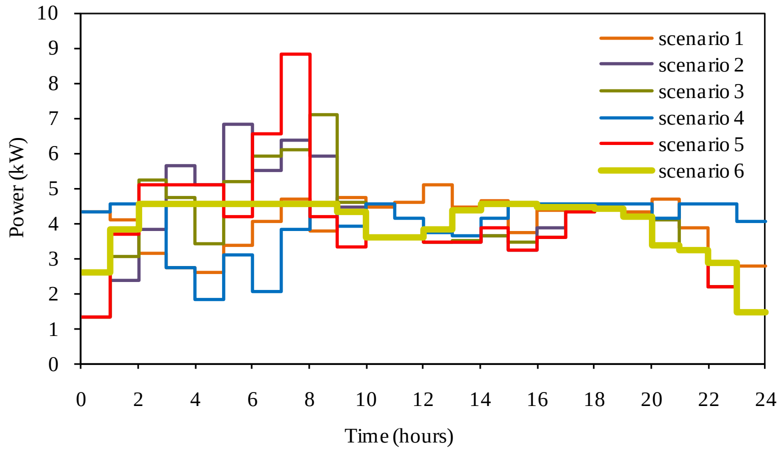

Fig. 5. Schedule of the hourly electricity consumption in a day for all households under Scenarios 1-6.

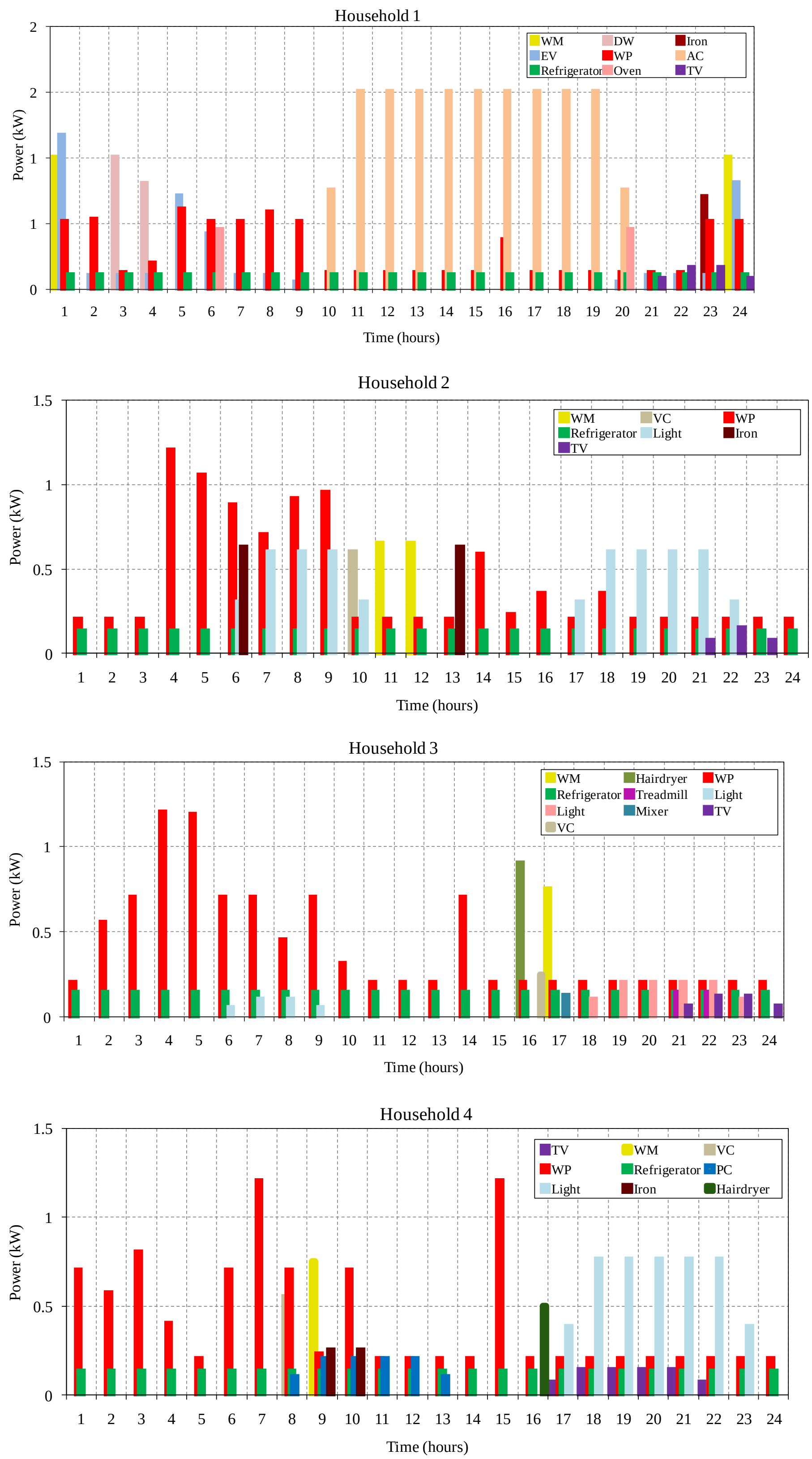

Fig. 6. Optimal schedule for households.

Table 1

Appliances and power consumption patterns for household 1.

TSAs	**Preferred time range**	**Duration (hour)**	**Power range (kW)**
Washing machine (WM)	24 hours	2	For the 1st hour: 1 For the 2nd hour: 1
Dish washer (DW)	24 hours	2	For the 1st hour: 1 For the 2nd hour: 0.8
Iron	6 am-6:30 am or 6 pm-11 pm	0.5	1.4
NSAs	**Preferred time range**	**Duration (hour)**	**Power range (kW)**
Air conditioner (AC)	10 am-8 pm	10	1.5
Refrigerator	12 am-12 pm	24	0.104
Oven	6 am-6:30 and 8 pm-8:30 pm	1	0.9
TV	9 pm-12 pm	3	0.16
PSAs	**Preferred time range**	**Daily energy requirement**	**Power range (kW)**
Electric vehicle (EV)	8 pm-9 am	4 kWh	0.1-1.6
Water pump (WP)	24 hours	7 kWh	0.125-0.9

Table 2

Appliances and power consumption patterns for household 2.

TSAs	**Preferred time range**	**Duration (hour)**	**Power range (kW)**
Washing machine	11 am-12 pm or 12 pm-1 pm	1	1.3
Vacuum cleaner (VC)	10 am-10:30 am or 11 am-11:30 pm	0.5	1.2
NSAs	**Preferred time range**	**Duration (hour)**	**Power range (kW)**
Refrigerator	12 am-12 pm	24	0.13
Light	6 am-10 am and 5 pm-10 pm	9	0.6
Iron	6 am-6:30 am and 1 pm-1:30 pm	0.5	1.25
TV	9 pm-11 pm	2	0.15
PSAs	**Preferred time range**	**Daily energy requirement**	**Power range (kW)**
Water pump	24 hours	10 kW	0.2-1.2

Table 3

Appliances and power consumption patterns for household 3.

TSAs	**Preferred time range**	**Duration (hour)**	**Power range (kW)**
Washing machine	2 pm-8 pm	0.5	1.5
Vacuum cleaner	3 pm-7 pm	0.5	0.5
Hairdryer	3 pm-5 pm	0.5	1.8
NSAs	**Preferred time range**	**Duration (hour)**	**Power range (kW)**
Refrigerator	12 am-12 am	24	0.14
Treadmill	9 pm-10 pm	1	0.28
Light 1	6 am-9 am	3	0.1
Light 2	6 pm-11 pm	5	0.2
Mixer	5 pm-5:30 pm	0.5	0.25
PSAs	**Preferred time range**	**Daily energy requirement**	**Power range (kW)**
Water pump	24 hours	10 kW	0.2-1.2

Table 4

Appliances and power consumption patterns for household 4.

TSAs	**Preferred time range**	**Duration (hour)**	**Power range (kW)**
Washing machine	8 am-11 am	0.5	1.5
Vacuum cleaner	8 am-11 am	0.5	1.1
NSAs	**Preferred time range**	**Duration (hour)**	**Power range (kW)**
Refrigerator	12 am-12 am	24	0.13
PC	8 am-1 pm	5	0.2
Light	5 pm-11 pm	6	0.76
Iron	9 am-10 am	1	0.5
Hairdryer	4 pm-4:30 pm	0.5	1
TV	5 pm-10 pm	5	0.14
PSAs	**Preferred time range**	**Daily energy requirement**	**Power range (kW)**
Water pump	24 hours	10 kW	0.2-1.2

Table 5

The specifications of scenarios.

Scenario	Households		Peak load	Cost	Peak load and cost
	Individually	All together	minimization	minimization	minimization
1	*		*		
2	*			*	
3	*				*
4		*	*		
5		*		*	
6		*			*

Table 6

Electricity tariffs in Tehran (September 2015) [25].

Electricity consumption (kWh/month)	**Electricity prices (Cents/kWh)**
0-100	1.36
100-200	1.59
200-300	3.41
300-400	6.14
400-500	7.05
500-600	8.87
>=600	9.78

Table 7

A summary of simulation results.

Scenario	**Electrical peak load for all households (kW)**	**Electricity costs for all households ($/month)**	**Electricity costs for each household ($/month)**			
			1	**2**	**3**	**4**
1	5.10	279.63	102.56	64.96	46.90	65.20
2	6.84	276.37	100.61	64.77	46.43	64.56
3	7.08	276.82	101.06	64.77	46.43	64.56
4	4.53	281.65	102.01	65.74	47.68	66.22
5	8.82	276.37	100.61	64.77	46.43	64.56
6	4.53	277.63	101.47	64.86	46.49	64.80