World Journal of Engineering

A multi-period joint energy scheduling algorithm in smart home based on prediction of the residents energy consumption

Jijun Zhao[1], Siyuan Gao[1], Danping Ren[1*], Zhihua Li[1], Liang Xue[1]

World Journal of Engineering 12(2) (2015) 135-148

World Journal of
Engineering

A multi-period joint energy scheduling algorithm in smart home based on prediction of the residents energy consumption

Jijun Zhao, Siyuan Gao, Danping Ren*, Zhihua Li and Liang Xue

School of Information and Electrical Engineering, Hebei University of Engineering, Handan, 056038, P.R. China.

**E-mail: rendanping@hebeu.edu.cn*

(Received 4 December 2014; Accepted 25 March 2015)

Abstract

In this paper, considering a tradeoff between consumers comfort and energy efficiency, a multi-period joint energy scheduling algorithm (MPJ-ESA) based on prediction of residents energy consumption is proposed, which includes long-period preliminary sch eduling, short-period preliminary scheduling, and real-time fine-tuning scheduling. First, by analyzing historical data of energy consumption, preferred usage profile of consumers is inferred, and the dynamic comfort level is presented. Then the paper uses the wavelet neural networks (WNNs) prediction algorithm to predict the operation of the appliances which are classified into appliances with unschedulable mode and schedulable mode. Based on the energy consumption prediction and dynamic comfort level, home appliances running state are scheduled according to the prediction of renewable energy available amount and real-time pricing (RTP). The simulation results show that scheduling algorithm effectively improves the energy efficiency and enhances user satisfaction with the operation of scheduled appliances and let the consumers comfort and energy efficiency achieve a better tradeoff.

Key words: *Smart home, Energy consumption scheduling, Energy consumption prediction, Dynamic comfort level*

1. Introduction

In the past few years, rapid developments of the global economy and technology have brought a sharp increase in the demand of energy. With the decreasing of non-renewable resources, the energy crisis is imminent. So increasing utilization of renewable energy is not only an important way to solve the energy problem but also main direction of the energy area in the future (Qin *et al*., 2009; 2010; Ozturk, 2014). Under the trend of green energy saving, the traditional power grid is no longer able to meet the demand of low-carbon economy. So the smart grid emerged as the latest developments in current world energy industry reform. As the user side of the smart grid, smart home manage the energy in the house by a home energy management system (HEMS) (Arghira *et al*., 2012) to improve energy efficiency and provide comfortable and convenient living environment for residents. Reasonable scheduling algorithm is the key to

ISSN:1708-5284

decide the performance of the HEMS. Hence, the study of the scheduling algorithm in HEMS has attracted much attention.

A variety of technologies and countermeasures have been proposed for improving the energy efficiency and the users comfort (living environment for users) in smart home. An energy service system (Pedrasa *et al*., 2010) proposed by Pedrasa *et al*. was minimizing the cost of consumption. The function was achieved by using renewable energy in terms of energy use and particle swarm optimization (PSO) as strategy to find the optimal opening time of appliances. With the same function, an energy consumption scheduling scheme (Mohsenian-Rad *et al*., 2010) scheduled appliances running at low power prices period based on the change of the real-time pricing (RTP). The energy management systems (Becker *et al*., 2010; Chen *et al*., 2013) also scheduled appliances according to RTP. Above-mentioned studies using renewable energy instead of traditional energy or based the change of the RTP scheduled the appliances to avoid the electricity peak demand and decrease the carbon emissions. Yet these have not considered the users comfort.

In the previous researches, there were scheduling algorithms (Du and Lu, 2011; Bapat *et al*., 2011; Ren *et al*., 2011) considered users comfort while improving energy efficiency. This method for improving users comfort is decreasing the waiting time for operation of each appliance or guaranteeing the user demand for household environments. An appliance commitment algorithm (Du and Lu, 2011) minimized cost of consumption and guaranteed users requirements by scheduling thermostatic equipment. But it did not take the renewable energy into account and less designed in terms of energy saving. In order to reduce consumption costs and waiting time to open appliances, a scheduling algorithm (Bapat *et al*., 2011) scheduled appliances referencing the predicted operation of appliances. However these algorithms did not consider using renewable energy to reduce carbon emissions and lacked real-time scheduling to adjust the inappropriate arrangements as the difference between forecast information and real-time information.

In conclusion, previous scheduling algorithms can still not perfectly solve the problems about consumers' comfort and energy efficiency. These algorithms lacked the consideration about the tradeoff between consumers comfort and energy efficiency and most ignored the importance of prediction of energy consumption for intelligent scheduling.

This paper proposes a multi-period joint energy scheduling algorithm (MPJ-ESA) based on the prediction of residential energy consumption, which could solve the scheduling problem about energy efficiency and consumers comfort proposed in smart home. Unlike the balance between minimizing electricity costs and the scheduling time of the appliances (Mohsenian-Rad and Leon-Garcia, 2010), the main purpose of proposed algorithm is to make a tradeoff between energy efficiency and consumers comfort. The rule to measure degree of the comfort set in this paper is that the actual operation of appliances deviates farther from users' habits, the degree is lower. In order to achieve this object, firstly, in the prediction unit, by analyzing historical data of operation of single device, appliances are classified into two categories. Based on the categories, we use prediction algorithm to predict the energy consumption in the next 24 hours. Unlike energy consumption is predicted to make feedback to utility company to do demand response (DR) management and time-of-use (TOU) price decisions (Ozturk *et al*., 2013), the prediction information in this paper provides references and constraints for scheduling. Secondly, according to the operation of appliances in each hour, a dynamic comfort level is proposed, which is the dynamical setting about the energy efficiency and users comfort in the scheduling unit. Based on the energy consumption prediction, home appliances are scheduled according to energy information, RTP, and the dynamic comfort level. With the differences between forecast information and real-time information, the scheduling algorithm was divided into two parts including preliminary scheduling and real-time fine-tuning scheduling. Due to the difference of utilization frequency between appliances, the preliminary scheduling includes long-period scheduling and short-scheduling. Thirdly, in users feedback unit, users evaluate satisfaction level of scheduling result. Finally, evaluation information feeds back into prediction unit and scheduling unit to revise the algorithm.

The remainder of this paper is organized as follows. Section 2 describes a HEMS we proposed. In section 3, support work for proposed scheduling algorithm is introduced. We propose MPJ-ESA in section 4. In section 5 the scheduling results are analyzed to show the effectiveness of the proposed MPJ-ESA. The conclusion of this paper is in Section 6.

2. The home energy management system

In this paper, HEMS includes three parts which are appliances information collection and storage (ICS) module, intelligent decision-making (IDM) module, and appliances operation display (AOD) module. As the external information providers, utility company and Internet provide real-time and predicted information of RTP and available amount of renewable energy for HEMS. The architecture of HEMS is shown in Figure 1. Real-time status and operation historical data of appliances are stored in ICS module that directly communicates with household appliances. Similarly, communicating with household appliances, the IDM module processes information data from ICS module, AOD module, and external to make decisions to schedule the appliances. The AOD module that is mobile phone or computer displays household appliances running state and provides a platform for users to evaluate satisfaction level of scheduling result. The evaluation information data feeds back into IDM module to revise the algorithm. The communication between HEMS and appliances relies on Wi-Fi or ZigBee wireless network protocol (Young and Stanic, 2009).

As the core of the HEMS, IDM module shown in Figure 2 consists of three parts, prediction algorithm unit, scheduling algorithm unit, and user feedback unit. The prediction algorithm unit analyzes data from ICS module and user feedback unit to predict the household energy consumption in next 24 hours. In more detail, the operation of single device predicted covers opening time, running time, and running power. The information include real-time status and predicted operation of appliances from ICS module and prediction algorithm unit, real-time and predicted RTP provided by utility, real-time and predicted available amount of renewable energy provided by Internet, feedback information from user feedback unit, and human intervention, which is provided for scheduling algorithm unit to schedule appliances. In the end of the day, user feedback unit analyzes and processes customer satisfaction level data provided by the AOD module to revise prediction algorithm and the scheduling algorithm. In section 3 and section 4, the IDM module will be described in detail.

3. Support work for proposed scheduling algorithm

3.1. The categories of home appliances

Based on the observations of the historical data from the Reference Energy Disaggregation Data Set (REDD), home appliances are classified into two categories in table 1, namely, appliances with unschedulable mode and appliances with schedulable mode. The operation of appliances with unschedulable mode like televisions, microwaves, refrigerators are directly related to consumer behavior and such appliances on-off events are difficult to be controlled. In other word, these devices must run immediately to meet the needs of users. Schedulable appliances include washing machine, dishwasher, water heaters, air condition etc. These appliances should complete their work

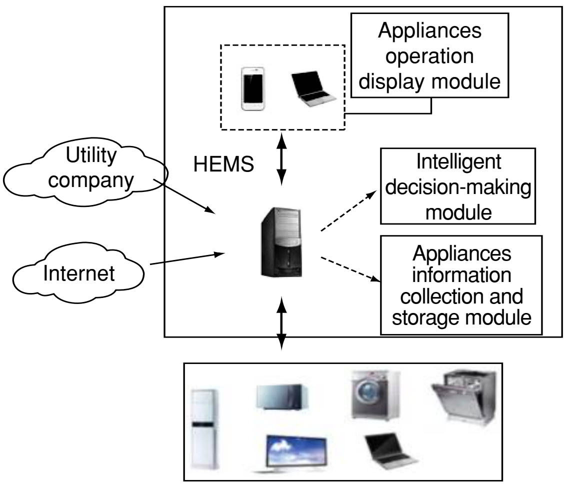

Fig. 1. Architecture of HEMS.

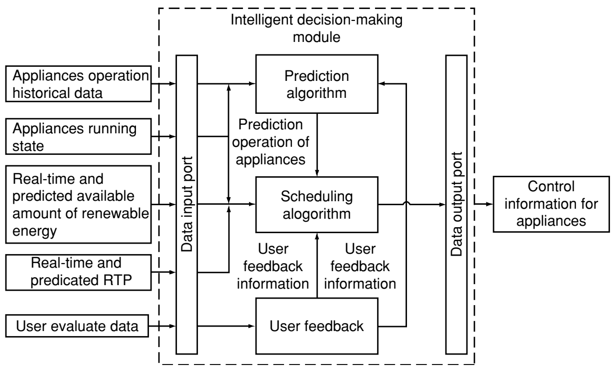

Fig. 2. Architecture of intelligent decision-making module.

Table 1.
Home appliances categories

Category	Appliances with unschedulable mode	Appliances with schedulable mode: High-scheduling range and low-time limit appliances	Appliances with schedulable mode: Low-scheduling range and high-time limit appliances
Examples	Microwave refrigerators, desktop computers without battery, printers, lights, TV sets, DVD players	Pool pumps, plug-in hybrid electric vehicles, laundry machines, dishwashers	Water and space heaters, air conditioners, laptop computers and other appliances with battery
Frequency		Two or three times a week; lower frequency	Two or three times a day; higher frequency
Scheduling rang and Limit		High-scheduling range and low-time delay limit	Low-scheduling range and high-time delay limit

before a particular moment or there is no need to start them immediately for the requirements of costumers.

There is a user tolerance range for the opening time advance or delay the optimizing starting moment, which is achieved by analyzing operation of the appliances. This tolerance range is the opening time range of appliances. The acceptance extent of the appliances opening time for users differs according to actual starting to run time. So a user comfort level curve shown in two figures that are Figure 3 and Figure 4 is proposed. The vertical axis represents satisfaction or comfort degree of users, while the horizontal axis represents the appliances opening time. The scope between starting point and ending point of the curve is the opening time range. The time that corresponds to the highest point of the curve is the optimizing starting moment. According to the opening time range and user comfort level curve, the appliances with schedulable mode are further classified into high-scheduling range and low-time delay limit (HR-LL) appliances and low-scheduling range and high-time delay limit (LR-HL) appliances. As shown in the Figure 3, the HR-LL appliances can start to work either earlier or later than the optimizing starting moment. What is more, the float time from the actual starting time to the optimizing starting moment has little impact on the customer satisfaction and the advance and delay rang is wide, which lead to a wide range and few limits for scheduling. As an example, washing machine has a low working frequency—running two or three times a week and a low limit for time. The other type, LR-HL appliances, as shown in the Figure 4, can start to work only earlier than the optimizing starting moment and customer can suffer the earlier starting of these appliances. When the actual starting time is earlier than the optimizing moment, the float time has little impact on the customer comfort. However, when the actual starting time is later than the optimizing starting moment, the customer comfort will fall rapidly. Taking water heater and air-condition as examples, these appliances have a narrow range for the earlier time and little time to delay with a high working frequency relative to the HR-LL appliances.

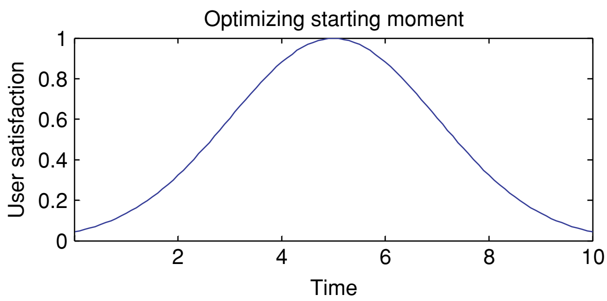

Fig. 3. The user comfort level curve of HR-LL appliances.

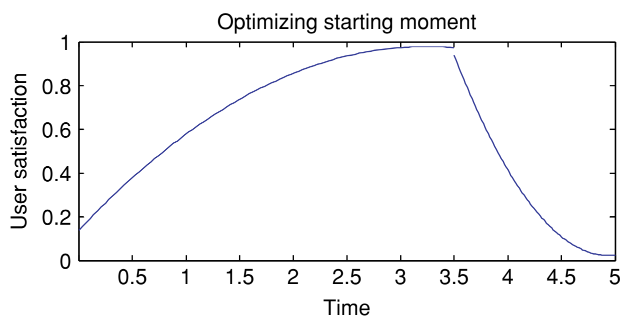

Fig. 4. The user comfort level curve of LR-HL appliances.

The optimal opening time of the appliance is predicted by the prediction algorithm. And the earliest opening time and latest opening time of the opening time range are determined by calculating the frequency that an appliance starts to run at each hour over all the historical data from REDD. Like the opening time frequency of bathroom gfi shown in the Figure 5, we determine that the opening time range of this appliance is 5:20 a.m. to 7:20 a.m. The comfort level is closely related to the operation of appliances. Appliances are scheduled based on the prediction of the operation of appliances, so the low precision of prediction has an impact on the comfort degree of users for the scheduled appliances operation. Setting the opening time range and user satisfaction level curve as the reference and limiting condition for scheduling algorithm can effectively reduce the impact mentioned above. And the operation of appliances scheduled by scheduling algorithm will not deviate too much from users' habits, which can better guarantee the demands of users for the appliances.

3.2. Prediction algorithm

As the on-off event of the appliances with unschedulable mode cannot be control, only the operation of appliances with schedulable mode is predicted. HR-LL appliances have a low operating frequency. For example, the washing machine work two or three times per week. So, the cycle of the prediction for HR-LL appliances is set each week. On the other hand, the prediction period of the LR-HL appliances is one day (24 hours) because these appliances, such as electric water heater and air conditioners, have a high operating frequency.

Using wavelet neural networks (WNNs) prediction method forecast the operation of HR-LL appliances and LR-HL appliances separately in this paper. And the WNNs is continuous wavelet neural network. Network model is trained with the historical data from the REDD and the future values are predicted based on the learning. Because the habits of users for using the appliances are difference between workday and weekend, the network is trained with workday data and weekend data separately to decrease the training time. And on this basis, the network model is further trained by the two type appliances operation data separately, where the input data includes data, day of the week, weather situation of the day, operational duration, and running power of the appliances. The outputs of LR-HL appliances are operational duration, and running power and the outputs of HR-LL appliances are day of week, operational duration, and running power

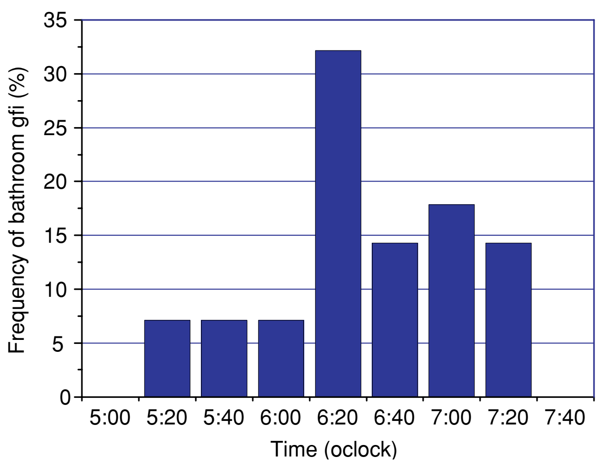

Fig. 5. The opening time frequency of bathroom gfi in a day.

3.3. Dynamic comfort level

In order to make a tradeoff between energy efficiency and users comfort, a dynamic comfort level is proposed in this paper. This conception is the dynamic relationship between them in a day. There are differences in opening time and useful frequency of appliances between workday and weekend, which is achieved by analyzing the historical data of home energy consumption from REDD, as is shown in Figure 6 and Figure 7. So the 24 hours a day are divided into several periods to set dynamic comfort (relationship between comfort and energy efficiency), as is shown in table 2. In workday, the dynamic comfort in low-comfort high-energy efficiency status is set during the two periods 09:00-18:00 and 00:00-06:00. Requirement for comfort is relatively low and the energy efficiency is relatively high in the two periods. At the period 09:00-18:00 users are generally working or at school, so the requirement of users for household environment is not high. At the period 00:00-06:00, users in the state of sleeping do not have too many activities, so the demands for running status of most appliances are not exact. In the two low comfort periods, the energy can be saved better. In other periods, the statue is set dynamic comfort in high-comfort low-energy efficiency. In this time, the demand of users for the operations of appliances are more exact, so energy saving must be done on the premise of the guarantee of users comfort. Since in this period the majority of users are at home, the comfort requirement is high. At weekends, the dynamic comfort at the period 00:00-06:00 is the

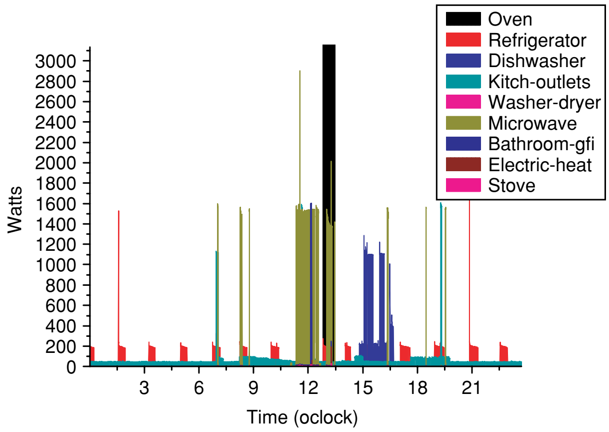

Fig. 6. The operation of appliances in a house at a weekend.

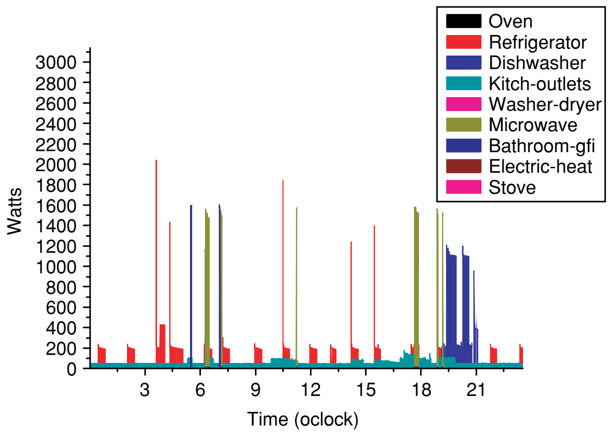

Fig. 7. The operation of appliances in a house at a workday.

same as the periods 09:00-18:00 and 00:00-06:00 at workdays. And 06:00-24:00 in weekend is the same as 06:00-09:00 and 18:00-24:00 in workday.

3.4. Other prediction information

The prediction information includes available amount of renewable energy, and RTP besides the prediction of the operation of appliances. The generation of most renewable energy is associated with the weather, so predicting the available amount of renewable can be done by analyzing the hour-by-hour weather forecast (Liu *et al.*, 2012). In this paper, the change of the available amount of renewable energy is set in each hour. Electricity market price forecasting can be divided into medium and long-term electricity price forecasting and short-term electricity price forecasting. Day-ahead electricity market price forecasting belonging to short-term electricity price forecasting is the focus of them. The existing main short-term electricity price forecasting methods include neural network (Catalao *et al.*, 2011) and time sequence prediction method (Hickey *et al.*, 2012). In this paper, appliances are scheduled based on the day-ahead electricity market price forecasting and hour-ahead electricity market price forecasting. As shown in Figure 8, the prediction information of RTP changes in every hour.

3.5. REDD dataset

The Reference Energy Disaggregation Data Set (REDD), a freely available data set which is used in this work contains detailed power usage information from six homes in the USA collected in April and May 2011 (Kolter and Johnson, 2011). The raw data contain total power consumption, and running time and power consumption of each load in every house, which are logged at a frequency about once a second for mains and once every three seconds for circuits. Because 3 houses raw data are not enough to use for this work, a list about other 3 houses raw data is made based on the appliance categories. The list contains data, appliance name, starting time, running time, running power, and the appliance categories. We use the list to judge the performance of the algorithm proposed in this paper.

Table 2.
The distribution of the dynamic comfort level

Type	Time	Comfort requirements	Energy efficiency
Workday	06:00-09:00 18:00-24:00	high	low
	00:00-06:00 09:00-18:00	low	high
Weekend	06:00-24:00	high	low
	00:00-06:00	low	high

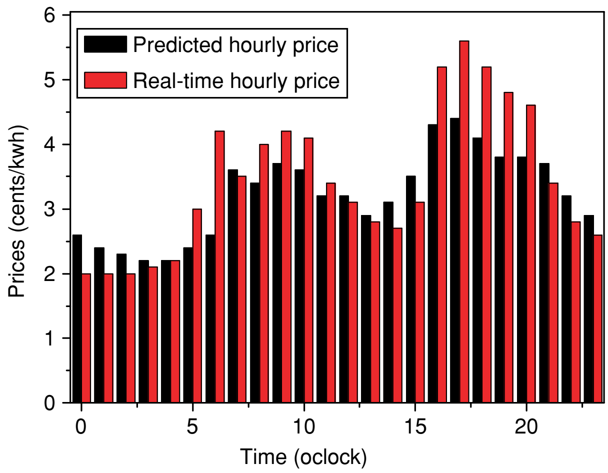

Fig. 8. Day-ahead electricity market forecasting price and actual price on a typical day.

4. The multi-period joint energy scheduling algorithm

MPJ-ESA proposed in this paper is divided into two steps that are the preliminary scheduling and real-time fine-tuning scheduling. Preliminary scheduling schedules the operation of the appliances according to the users comfort level curve, dynamic comfort level, and prediction information. Real-time fine-tuning scheduling adjust the inappropriate arrangements which preliminary scheduling have made based on the real time information. The causes of inappropriate arrangements are the difference between forecast information and the real-time information.

4.1. Preliminary scheduling

At the beginning of each day, the preliminary scheduling will judge whether it is workday or weekend, because dynamic comfort level is different between workdays and weekends. Then appliances are scheduled by preliminary scheduling. Preliminary scheduling is divided into two steps, due to the difference of utilization frequency between the HR-LL and LR-HL appliances. The period of the first step is 24 hours, named long-period scheduling and the second step is every hour, named short-period scheduling. In the first step, the HR-LL appliances are scheduled. The LR-HL appliances are scheduled in the second period after completion of scheduling HR-LL appliances. The procedure of preliminary is described in the subsection. Because most appliances' switch power are far more than running power, we set that in scheduling process the operation status of running appliances cannot be changed unless user intervene.

4.1.1. The long-period scheduling of HR-LL appliances

Assume that appliances except for HR-LL appliances begin to run in optimizing starting moment predicted by prediction algorithm. Then the opening times of HR-LL appliances are determined by the users comfort level curve, dynamic comfort level, prediction information about renewable energy, RTP, and HR-LL appliances operation statues. And to compute the opening times of HR-LL appliances aims at the cost lowest. The reason for doing this is that such devices use frequency is low and schedulable scope is bigger. For example, washing machine is arranged running in the 4 a.m. to 5 a.m., because the available amount of renewable energy and RTP in this period is good for washing machine running to decrease the cost.

4.1.2. The short-period scheduling of LR-HL appliances

The procedure of scheduling LR-HL appliances is described in this subsection. The RTP changes in every hour and the scheduling scopes of LR-HL appliances are relatively small. So the scheduling appliances in every hour can control the operation of appliances better. In the process of scheduling, the scheduling algorithm considers the feedback information from the users for the operations in last 24 hours.

The equipment classification in scheduling: Define unit hour is $t^{'}$ $(e^{'}, f^{'})$ and opening time range of appliance is t (e, f). The t_{nh} denotes the optimal opening time of the appliance n and the $t^{'}_{nh}$ is the optimal opening time in i^{th} unit time. Based on the relationship between t_{nh} and $t^{'}_{nh}$, LR-HL appliances are classified into three classes in the scheduling process: a. $t^{'}_{nh} > t_{nh}$; b. $t^{'}_{nh} = t_{nh}$; c. $t^{'}_{nh} < t_{nh}$.

Objective function: The problem of minimizing electricity cost in every hour can generally be formulated as:

$$\min Cost_i = x_i\left(E_i - C_i\right), \quad i = 1,2,3......24 \tag{1}$$

where $Cost_i$ is the total electricity cost during the i^{th} unit hour. x_i is the electric price in the i^{th} unit hour.

C^i denotes the available amount of the renewable energy in the i^{th} unit hour. E_i is total energy consumption of appliances during the i^{th} unit hour calculated as follows:

$$E_i = \sum_{n=1}^{m} p_n h_{ni} + \sum_{k=1}^{j} p_k h_{ki}, \quad n,m \in \alpha, \quad k,j \in \beta, \quad (2)$$

where p_n and p_k denote the average power of the appliance n and k, respectively. h_{ni} and h_{ki} denote the running time of the appliance n and k in the i^{th} unit hour, respectively. In this paper, the calculating time is hour. The set β represents the ID of the appliances i^{th} unit hour, and the set β represents the ID of the appliances which are running at the beginning of the i^{th} unit hour. The running time h_{ni} and h_{ki} are determined by adjusting the opening time t_n. In the i^{th} unit hour, h_{ni} and h_{ki} is respectively given by:

$$h_{ni} = \begin{cases} 1 - t_{nt} & t_{nt} + h_n \geq 1 \\ h_n & t_{nt} + h_n < 1 \end{cases} \quad (3)$$

$$h_{ki} = \begin{cases} 1 & \left(h_k - \sum_{t=0}^{i-1} h_{kt} \right) - 1 > 0 \\ h_k - \sum_{t=0}^{i-1} h_{kt} & \left(h_k - \sum_{t=0}^{i-1} h_{kt} \right) - 1 \leq 0 \end{cases} \quad (4)$$

where h_n and h_k denote the prediction running time about the appliances n and k, respectively. In the equation (4), the $\sum_{t=0}^{i-1} h_{kt}$ denotes the already running time before the i^{th} unit hour. In the equation (3), the t_{nt} denotes the rest of the appliance open time t_n after removing the hour, shown as follow:

$$t_{nt} = t_n - [t_n], \; t_n \geq 0 \quad (5)$$

Constraint conditions and processes of solving the open time t_n: In the beginning of the scheduling, the first task is working out the energy consumption of the appliances that are running at the beginning of the i^{th} unit hour in this unit hour. The second task is working out the residual amount of the renewable energy in the i^{th} unit expressed as $C_i^{'}$ which is the residual amount after renewable energy providing the energy for the appliances which have already run. Then the energy consumption of the appliances not running at the beginning of the i^{th} unit hour in this unit hour is expressed as $E_i^{'}$ shown as follow:

$$E_i{}' = \sum_{n=1}^{m} p_n h_{ni}, \quad n,m \in \alpha, \quad (6)$$

According to the constraint conditions which include the relationship between $E_i^{'}$ and $C_i^{'}$, the opening time range, the users comfort level curve, and the dynamic comfort level, we solve the opening time t_n of the appliance n

In the unit hour, if the appliances start run at the beginning of the opening time range in this unit hour, the $E_i^{'}$ is the maximum shown as follows:

$$E_i' = E_{i\max}' \quad (7)$$

If the appliances start to run at the end of the opening time range in this unit hour, the $E_i^{'}$ is the minimum shown as follows:

$$E_i' = E_{i\min}' \quad (8)$$

The constraint conditions of solving the open time t_n are classified into the following two cases.

(1) If the comfort level requirement is high in the i^{th} unit hour, constraint condition is guaranteeing users' comfort and scheduling steps shown as follow:

The open times of the appliances except for c. type appliances are the $t_{nh}^{'}$. Because in the i^{th} unit hour, the comfort level requirement is high and the optimal opening time of the c. type appliances is not in this unit time, whether the c. type appliances start to run in this unit time is decided by whether the available amount of the renewable energy is abundance. If the available amount of the renewable energy is abundant, the c. type appliances will open in this unit hour. And the t_n of c. type appliances are solved by using the (2)–(6) formulas with the constraint $E_i \leq C_i$. If the available amount of the renewable energy is not enough, the c. type appliances do not start to run in this unit hour.

(2) If the energy efficiency is high in the i^{th} unit hour, the constraint conditions and scheduling processes are shown as follows:

(a) When $E^{'}_{imax} \leq C^{'}_{i}$, the constraint is that h_{ni} is the longest, i.e., the running time of the appliances are the longest in this unit time. We arrange the appliances opening to run at the beginning of the opening time range in this unit time. Pseudocode is shown in Figure 9.

(b) When $E'_{imin} < C'_i < E'_{imax}$, the constraints are $E'_i = C'_i$ and the opening time to be close to t'_{nh}. The steps are as follow: In the beginning we will judge the state of the unit time which the c. type appliances optimal opening time t_{nh} is in. If the state is high comfort level requirement, the c. type appliances will not open to run in this unit time. Conversely, if the state is not high comfort level requirement, the c. type appliances will open to run in this unit time. Then make $E'_i = C'_{imax}$, and firstly postpone the opening time of the c. type appliances (if the c. type appliances will open to run in this unit time) up to $E'_i = C'_i$. If the status is still $E'_i > C'_i$, up to the opening time of the c. type appliances put off the end of the opening time range in this unit time, the b. type appliances opening time is postponed up to $E'_i = C'_i$,. If the status is still $E'_i > C'_i$, up to the opening time of the b. type appliances postponed the $t = t_{nh}$, the a. type appliances opening time is postponed up to $E'_i = C'_i$. If the status is still $E'_i > C'_i$ up to the opening time of the a. type appliances put off the end of the opening time range in this unit time, a. type appliances opening time is postponed up to $E'_i = C'_i$. The pseudocode of this step is depicted in Figure 10.

(c) When $E'_{imin} \geq C'_i$, the constraint is making the $Cost_i$ smallest in this unit hour and the scheduling steps are shown as follow.

When $x_{i+1} < x_i$, we make $E'_i = E'_{imin}$. Appliances start to run at the end of the opening time range in this unit time. Where the x_{i+1} denotes the electric price in the $i + 1^{th}$ unit hour.

When $x_{i+1} \geq x_i$, we assume $E'_i = E'_{imin}$. Under the hypothesis, if in the next hour $E_{i+1min} \leq C_{i+1}$, the assumption is confirmed, i.e., the appliances open to run at the beginning of the appliances opening

```
Process of scheduling appliance in E'imax ≤ C'i case
E'imax = the ith unit hour total maximum energy consumption of appliances not
running at beginning of this hour;
C'i = the residual renewable energy amount;
e = {a,b,c type appliances};
tne = appliance opening time;
tnhle = the opening time of apppliances at the beginning of opening time range
in this unit hour;
The energy efficiency is high in the ith unit hour;
begin
  tna = tnhla;
  tnb = tnhlb;
  tnc = tnhlc;
    //set opening time of appliances at the beginning of opening time range
in this unit hour
end
```

Fig. 9. Pseudocode of process of scheduling appliances in $E'_{imax} \leq C'_i$ case.

```
Process of scheduling appliance in E'imin < C'i < E'imax case
E'imin = the ith unit hour total minimum energy consumption of appliances not
running at beginning of this hour;
tnhe = appliance optimal opening time;
tnhre = the opening time of apppliances at the end of opening time range
      in this unit hour;
US = the unit hour state which the tnh of c. type appliances is in;
begin
    tna = tnhla;
    tnb = tnhlb;
    tnc = tnhLc;
    //set opening time of appliances at the beginning of opening time range
      in this unit hour
    if (US is not high comfort level requirment)
      while (E'i>C'i || tnc = tnhyc)
          tnc++;   // postpone c. type appliances opening time
      end while
      while (E'i>C'i || tnb = tnhb)
          tnb++;   // poStpone b. type appliances opening time
      end while
      while (E'i>C'i || tna = tnhya)
          tna++;   // poStpone a. tYpe appliances opening time
      end while
      while (E'i>C'i)
          tnb++;   // postpone b. type appliances opening time
      end while
    else
      while (E'i>C'i || tnb = tnhb)
          tnb++;   // poStpone b. type appliances opening time
      end while
      while (E'i>C'i || tna = tnhya)
          tna++;   // poStpone a. tYpe appliances opening time
      end while
      while (E'i>C'i)
          tnb++;   // posTpone b. type appliances opening time
      end while
     end if
end
```

Fig. 10. Pseudocode of process of scheduling appliances in $E'_{imin} < C'_i < E'_{imax}$ case.

time range in this unit hour. Where the C_{i+1} denotes the available amount of renewable energy in the $i + 1^{th}$ unit hour. If in the next hour $E_{i+1min} > C_{i+1}$ and the comfort level requirement is high in the unit hour which optimal opening time of the c. type appliances is in, the assumption is not confirmed. Then we schedule c. type appliances not opening to run in this unit time and other appliances opening to run at the beginning of the opening time range in this unit hour. If $E_{i+1min} > C_{i+1}$ and the comfort level requirement is not high in the unit time which optimal opening time of the c. type appliances is in, we schedule c. type appliances open to run in this unit hour and then schedule appliances that are need to run in this unit hour to make $E'_i = E'_{imax}$. The pseudocode of this steps is depicted in Figure 11.

4.2. Real-time fine-tuning scheduling

Real-time fine-tuning scheduling which is the second step of the MPJ-ESA adjusts the inappropriate arrangements preliminary scheduling have made based on the real time information. The causes of inappropriate arrangements are the difference between forecast information and the real-time information, and the interferences from the users. We classify the changes into interferences from the users, changes of the electric price, and the changes about the available amount of the renewable energy. Because the appliances with unschedulable are not scheduled, we defined the operation of this appliances belonging to the interference from users. We fine-tune the appliances scheduled by the preliminary scheduling based on the changes. The fine-tuning processes are shown as follow:

(1) Interferences from the users.

1) The increase of the appliances

We equate the increase of the appliances with the reduction of the available amount about the renewable energy. The appliances are rescheduled using the preliminary scheduling algorithm.

2) The decrease of the appliances

We equate the decrease of the appliances with the increase of the available amount about the renewable energy. Then appliances are rescheduled by using the preliminary scheduling algorithm.

(2) The changes about the available amount of the renewable energy and the electricity price.

Because the forecast errors are always there, we define error ranges of the prediction information to reduce the rescheduling times. The error rang of the electricity price is $\pm\delta$ and the available amount of the renewable energy is $\pm\varepsilon$. If the error is beyond the range, we reschedule the appliances based on the preliminary scheduling algorithm. Otherwise we don't do any adjustment about the appliances scheduled.

4.3. User feedback

At the end of the scheduling, the HEMS provide a platform for users to evaluate satisfaction level of scheduling result. Consumers will point out the appliances whose operation does not satisfy the users and give a satisfying operation state about this appliance. The operation state includes optimal opening time, running time, and opening time range that the users can tolerate. If the opening time range given contains the optimal opening time predicted, the feedback information will be fed back to the scheduling algorithm to revise the corresponding part. Otherwise the feedback information will be fed back to the prediction algorithm to retrain the network.

5. Simulation results

This section presents the simulation results of the performance of the scheduling algorithm described in the previous section. We use the information of the renewable energy from IRENA-Global-Atlas (http://globalatlas.irena.org/), RTP for residential customers from ComEd's RRTP program (https://rrtp.comed.com/) and the operations of the appliances from REDD to evaluate the effectiveness of the proposed scheduling algorithm. In the following simulations, we compare the status with and without the proposed scheduling algorithm in these aspects which are the total cost, the total energy consumption, and the grid's electricity consumption in one day and calculate the average offset of the opening time of appliances in every hour between scheduled operation state and user satisfied operation state.

Figure 12 depicts the comparison of daily cost between states with and without the scheduling algorithm. From the figure, the daily cost of state with scheduling algorithm is less than without scheduling algorithm. And compared with the state without scheduling algorithm, the state with scheduling algorithm can achieve over 22% daily cost in savings. Figure 13 and Figure 14 shows the difference of the hourly electricity consumption between the states with and without the scheduling

Process of scheduling appliance in $E'_{imin} \geq C'_i$ case

```
E'_{i+1min} = the i+1^{th} unit hour total minimum energy consumption of appliances;
C_{i+1} = available amount of renewable energy;
x_i = electric price in the i^{th} unit hour;
x_{i+1} = electric price in the i+1^{th} unit hour;
begin
    t_na = t_nhra;
    t_nb = t_nhrb;
    t_nc = t_nhrc;
    //set opening time of appliances at the end of opening time range
      in this unit hour
    if (x_{i+1}≥x_i&&E_{i+1min}≥C_{i+1})
        t_na = t_nhla;  // reset opening time of a type appliances at the beginning
        of opening time range in this unit hour
        t_nb = t_nhlb;  // reset opening time of b type appliances at the beginning
        of opening time range in this unit hour
        if(US is high comfort level requirement)
            t_nc = t_nhrc;  // reset c type appliances open in this unit hour
        else
            t_nc = t_nhlc;  // reset opening time of c type appliances at the beginning
            of opening time range in this unit hour
        end if
    end if
end
```

Fig. 11. Pseudocode of process of scheduling appliances in $E'_{imin} \geq C'_i$ case.

algorithm at workdays and weekends. Figures 13 and 14 with Figure 8 illustrate that the operation time of appliances scheduled with the scheduling algorithm avoid the time that are the peak hours of the RTP. The grid's electricity consumption comparison between the states with and without the scheduling algorithm at workdays and weekends is shown in Figures 15 and 16 separately. Using scheduling algorithm can save grid electricity more than 38% at workdays and 44% at weekends compared with not using scheduling algorithm. Taken together Figures 13, 14, 15 and 16 confirm that MPJ-ESA can help users decrease the cost and make a contribution to the greenhouse reductions and when the period of comfort level requirement is low the energy efficiency is high.

The average offset of appliances opening time in every hour between scheduled operation state and user satisfied operation state at workdays and weekends is shown in Figure 17. The average offset indicates how many time the actual opening time advance or delay relative to the user satisfied opening time. We guarantee the offset low in the period where the comfort level requirement is high, as shown in Figure 17. This confirms that the MPJ-ESA guarantees the comfort requirements for users.

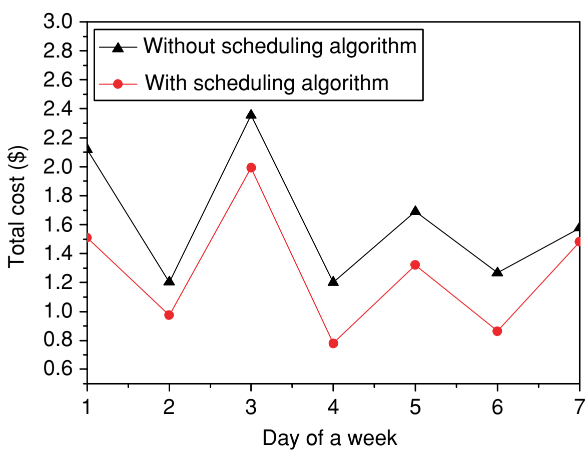

Fig. 12. The daily cost in a week.

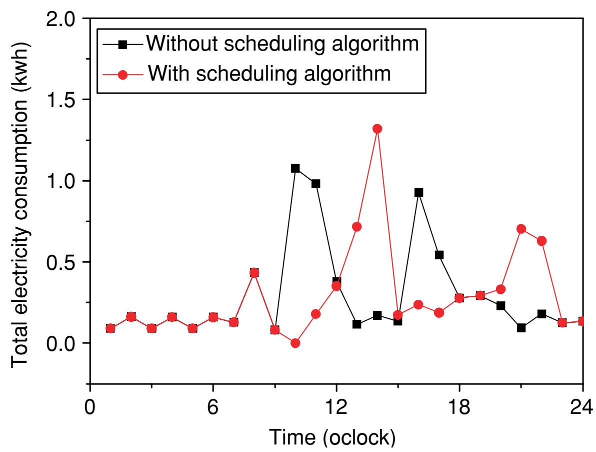

Fig. 14. The hourly electricity consumption in a weekend.

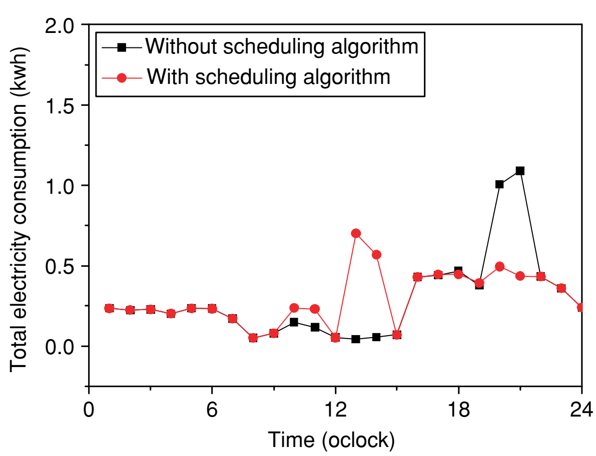

Fig. 13. The hourly electricity consumption in a workday.

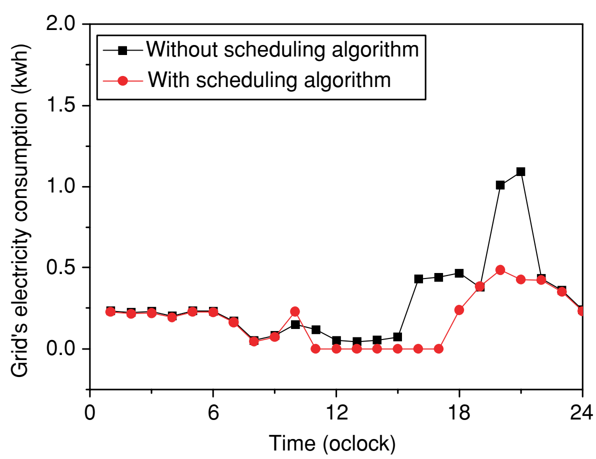

Fig. 15. The hourly grid's electricity consumption in a workday.

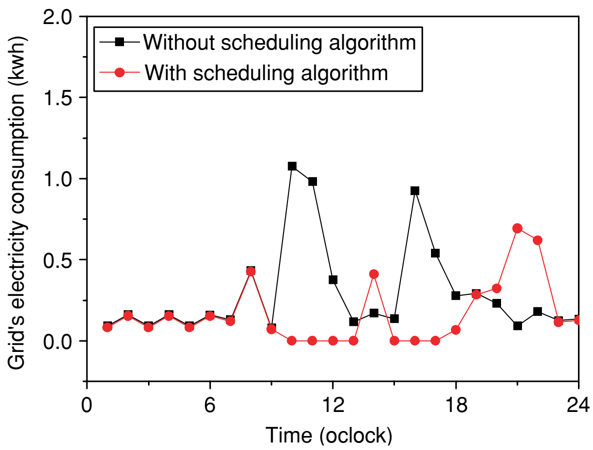

Fig. 16. The hourly grid's electricity consumption in a weekend.

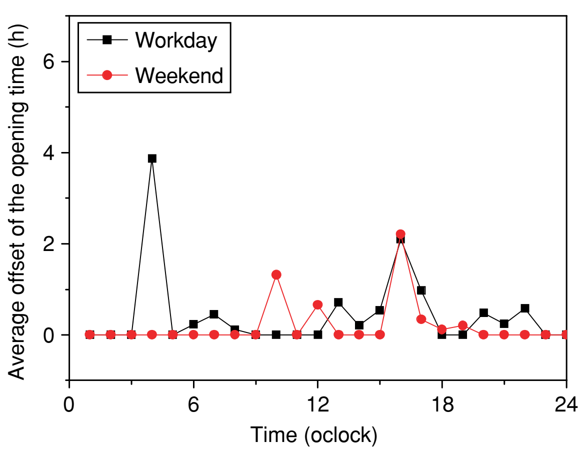

Fig. 17. The average offset of the opening time of the appliances.

6. Conclusion

This paper focused on a tradeoff between consumers comfort level and energy efficiency in smart home. Architecture of home energy management system and a novel MPJ-ESA based on the prediction of the operation of appliances were proposed. We classified the home appliances into two categories and use prediction algorithm to predict the operation of equipment to provide a reference and a limit for the scheduling algorithm. Based on the historical data from REDD, we presented a dynamic comfort level to provide a mode about the relationship between comfort level and energy efficiency to schedule the equipment. In addition, to effectively schedule the appliance, a real-time fine-tuning scheduling algorithm was proposed to adjust the inappropriate operations scheduled by preliminary scheduling. These were caused by the difference between forecast information and the real-time information and interferences from the users. In the end of the algorithm we make a user feedback to revise the algorithm. The obtained results and findings indicate that the scheduling algorithm effectively improves the energy efficiency under low comfort level requirement conditions and enhance users satisfaction with the operation of scheduled appliances and make the consumers comfort and energy efficiency achieve a better tradeoff.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (No.61304131), the Natural Science Foundation of Hebei Province (No.F2014402075), the Scientific Research Plan Projects of Hebei Education Department (No.BJ2014019, QN20131064, Q2012045), and the Science Technology Research and Development Fund of Handan (No.1121103137).

References

Arghira N., Hawarah L., Ploix S., Jacomino M., 2012. Prediction of appliances energy use in smart homes. *Energy* **48(1)**, 128–134.

Bapat T., Sengupta N.S., Ghai K., Arya V., Shrinivasan Y.B., Seetharam D., 2011. User-sensitive scheduling of home appliances. Proceedings of ACM SIGCOMM workshop on Green networking, Toronot, Canada: ACM, 43–48.

Becker B., Allerding F., Reiner U., Kahl M., Richter U., Pathmaperuma D., Schmeck H., Leibfried T., 2010. Decentralized energy-management to control smart-home architectures. Proceedings of Springer Internatonal Conference on Architecture of Computing Systems (ARCS), Hannover, Germany: Springer, 150–161.

Catalao J.P.S., Pousinho H.M.I., Mendes V.M.F., 2011. Hybrid Wavelet-PSO-ANFIS Approach for Short-Term Electricity Prices Forecasting. *IEEE Transactions Power System* **26(1)**, 137–144.

Chen C., Nagananda K., Xiong G., Kishore S., Snyder L.V., 2013. A communication-based appliance scheduling scheme for consumer-premise energy management systems. *IEEE Transactions on Smart Grid* **4(1)**, 56–65.

Du P., Lu N., 2011. Appliance commitment for household load scheduling. *IEEE Transactions on Smart Grid* **2(2)**, 411–419.

Hickey E., Loomis D.G., Mohammadi H., 2012. Forecasting hourly electricity prices using ARMAX–GARCH models: an application to MISO hubs. *Energy Economics* **34(1)**, 307–315.

Kolter J.Z., Johnson M.J., 2011. REDD: A public data set for energy disaggregation research. Proceedings of KDD Workshop on Data Mining Applications in Sustainability (SustKDD), San Diego, USA: ACM, 1–6.

Liu X., Ivanescu L., Kang R., Maier M., 2012. Real-time household load priority scheduling algorithm based on prediction of renewable source availability. *IEEE Transactions on Consumer Electronics* **58(2)**, 318–326.

Mohsenian-Rad A.-H., Leon-Garcia A., 2010. Optimal residential load control with price prediction in real-time electricity pricing environments. *IEEE Transactions on Smart Grid* **1(2)**, 120–133.

Mohsenian-Rad A.-H., Wong V.W., Jatskevich J., Schober R., 2010. Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid. *Proceedings of IEEE Innovative Smart Grid Technologies (ISGT)*, Gothenburg, Sweden:IEEE, 1–6.

Ozturk H.H., 2014. Energy Analysis for Biodiesel Production from Rapeseed Oil. Energy Exploration and Exploitation 32(6), 1031–1057.

Ozturk Y., Senthilkumar D., Kumar S., Lee G., 2013. An intelligent home energy management system to improve demand response. *IEEE Transactions on Smart Grid* **4(2)**, 694–701.

Pedrasa M.A.A., Spooner T.D., MacGill I.F., 2010. Coordinated scheduling of residential distributed energy resources to optimize smart home energy services. IEEE *Transactions on Smart Grid* **1(2)**, 134–143.

Qin S.J., Sun Y.Z., Yao H.W., Shi C.L. and Zhang S.X., 2009. Homogeneous production of biodiesels from vegetable oils. World journal of engineering 6(1), 139–142.

Qin Shenjun , Yuzhuang Sun, Xiaocai Meng, Shouxin Zhang, 2010. Production and analysis of biodiesel from non-edible seed oil of Pistacia Chinensis. Energy Exploration & Exploitation 28(1), 37–46.

Ren D., Li H., Ji Y., 2011. Home energy management system for the residential load control based on the price prediction. Proceedings of IEEE Online Conference on Green Communications (GreenCom), NewYork, USA: IEEE, 1-6.

Young S., Stanic R., 2009. SmartMeter to HAN communications. Smart Grid Australia Intelligent Networking Working Group.