Network Protocols and Algorithms
ISSN 1943-3581
2015, Vol. 7, No. 2

ZigBee Based Optimal Scheduling System for Home Appliances in the United Arab Emirates

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Received: May 25, 2015   Accepted: July 25, 2015   Published: July 31, 2015

DOI: 10.5296/npa.v7i2.7676   URL: http://dx.doi.org/10.5296/npa.v7i2.7676

Abstract

In this paper a smart energy management system for home appliances has been presented. Based on hourly load data the system sets an optimal operating schedule for home appliances. The paper is presented in two parts. In the first part a cost function has been derived based on practical data provided by two utility companies. In the second part an optimal scheduling system has been proposed for home appliances based on the derived cost function. A wireless system, based on ZigBee and LabVIEW, has been integrated with the proposed system so that home appliances can be controlled and monitored accordingly. The proposed system has been tested via simulation. The simulation results show that energy consumption in a household can be reduced by 30% by using the proposed system.

Keywords: *Smart grid, ZigBee, LabView, power generation, appliances, optimal scheduling, renewable energy*

1. Introduction

Modern society heavily depends on adequate and continuous supply of electrical power. Now-a-days, ensuring adequate and continuous power supply has become a prime concern for almost all countries of the World. The generation of electrical power depends on the availability of primary energy resources like oil, gas, and coal. It is obvious that the production of oil, gas, and coal cannot keep up in harmony with the growing World population, which is expected to reach nine billion by the year of 2050. It is imminent that there will be a gap between demand and supply of the energy resources and hence there will be slow down in the World's economic development. Most of the responsibility goes to the wealthy nations in the North America and Middle East for such a situation. These countries are the leading consumers of energy. A mix of energy resources are being used for the production of electrical power as shown in Fig.1. The situation is very alarming because the coal is being used at an increasing rate in the power generation causing an unprecedented rate of rise in Carbon-di-Oxide (CO_2) in the atmosphere.

In addition to environmental impact increasing demand for power has posed a serious challenge for electricity distribution systems. Aging infrastructure and insufficient utilities have become a bottleneck for the distribution systems. New power plants are being installed and commissioned. Additionally utility companies are exercising load shedding technique as an art for managing the demand. In order to avoid system failure and major breakdown utility companies are currently exercising this technique very frequently. Integration of renewable energy resources and application of efficient load management schemes are considered two alternatives of conventional load shedding. Wind, wave, tidal, and solar are the examples of renewable energy resources. But, it is evident that the current development in renewable energy sectors are not enough to play significant role in energy management. Traditionally load management schemes are generally carried out by the utility companies at the supply side. Now-a-days, the consumers are also playing an important at the demand side. Recent developments in technology are helping the consumers to play greater role for energy management and the concept of smart grid has emerged.

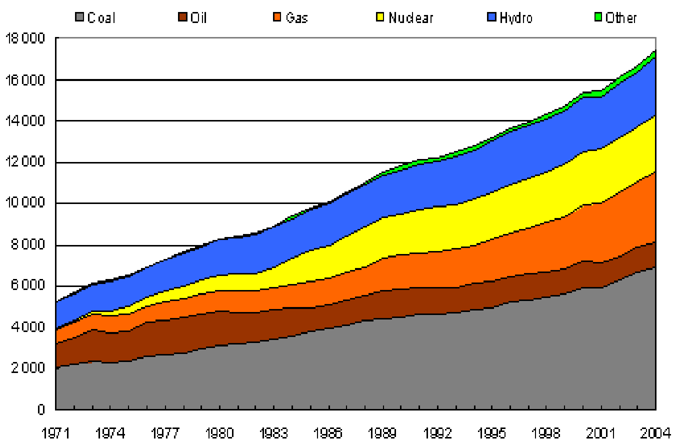

Figure 1 Mix of power Generation

Smart grid refers to integrating modern information, communication, control, and digital technologies with the current power grid system. Smart grid incorporates requirements and actions of all stakeholders in order to provide reliable, cheap, and safe electricity supplies [1]. The utility companies around the globe have employed their research and development activities for practical realization of the smart grid.

Smart grid assists utility companies and consumers to exercise their own load management scheme. Dynamic pricing is a key component in this regard. Dynamic pricing is being used by the utility companies to create time varying rate structures [2,3,4] for load management and consumers have given more responsibility to manage their appliances accordingly. Different techniques have been introduced for reducing residential energy consumption. Two popular of these techniques are (a) reducing power consumption, and (b) shifting load to off-peak hours [5].

In this paper we propose an energy management system for home appliances. The proposed system is not intended to reduce energy consumption of the users, but to shift the load to off-peak hours by using dynamic load scheduling. The system provide the consumers with an optimized solution to monitor and control their home appliances through a user friendly application developed in LabVIEW. The application has been integrated with a ZigBee based sensor network. The main goal is to optimize the scheduling of home appliances so that the energy consumption can be reduced [6].

The rest of the paper is organized as follows. Section 2 shows the related works. Section 3 presents the theoretical background of this work. Section 4 presents the methodology used in this work. Data analysis is presented in section 5. The system implementation has been presented in section 6. The paper is concluded with section 7.

2. Related Works

An optimization based residential energy management (OREM) system has been proposed in [7]. The main idea is to minimize the electricity cost by scheduling the operation of home appliances at appropriate times. In the proposed method a day has been divided into several time slots with different prices of electricity and home appliances are operated in a particular time slot. One of the limitations of the proposed method is delay in operation of the home appliances. In order to reduce this delay the authors have proposed a linear programming model and have proposed an In-Home Energy Management (iHEM). The performances of iHEM have been compared with those of OREM. It has been shown that iHEM not only saves same energy, but also provides flexibility due to a Sensor Home Area Network (WSHAN), which is associated with the OREM.

Application coordination (ACORD) scheme has been proposed in [8] to reduce the cost of energy consumption in a home. The aim of the proposed scheme is to shift the consumer

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ISSN 1943-3581
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demand to off-peak hours. The scheme is implemented by using an in-home Wireless Sensor Network (WSN) and an Energy Management Unit (EMU). According to this scheme the home appliances send a request to the EMU. The EMU fixes schedule for the appliances for minimizing the energy bill.

An optimal and automatic residential energy consumption scheduling framework has been proposed in [9]. The main idea is to minimize electricity consumption while maintaining minimum waiting time for the home appliances. The system is based on simple linear programming computation. The authors have presented an efficient weighted average price prediction filter to predict the price. The proposed system not only reduces the users' electricity bill but also reduces peak-to-average (PAR) ratio in load demand.

Appliance Coordination with Feed In (ACORD-FI) has been proposed for energy aware home in [10]. This is an extension of the work presented in [8]. The system consists of WSN, EMU, and smart meters. ACCORD-FI sets schedule for the home appliances based on the information about the peak hour, local energy generation, and other conflicting requests.

A decision support tool has been used in [11] for scheduling available distributed energy resources (DER) in a home. The decision support tool has been used for intelligent scheduling for the home appliances to save energy. The authors have chosen particle swarm optimization (PSO) to generate near optimal schedule for the home appliances.

Optimization based residential load management strategy has been presented in [12]. In this strategy an optimal relationship between hourly electricity bills and the operation of household appliances have been defined. For the optimization several factors have been considered namely electricity prices, energy demand, and renewable energy. The proposed load management strategy has been field tested. The test results show that the proposed strategy can reduce the energy bill of the house by 8-20%.

A distributed energy management system has been proposed in [13]. In this system a common energy source is shared by several subscribers. An energy consumption controller (ECC) unit is associated with each subscriber. Smart meters are connected to the power grid through a local area network. The authors have proposed a novel real-time pricing algorithm based on the interactions between the smart meters and the energy provider. Utility functions have been used based on the subscribers' preferences and their energy consumption patterns. The energy provider prescribes some desirable consumption patterns among the subscribers. The simulation results presented in the same work show that both the subscriber and the energy provider are benefited by the proposed algorithm.

A mixed integer nonlinear optimization model has been proposed in [14]. The idea is that a household should shift the electricity consumption depending upon prices and incentives. A case study has been presented in the same work. It is shown that an electricity cost can be reduced by 25% by using the proposed optimum technique. The authors have defined various weighting factors and a consumer can choose these factors according to their preference.

In order to reduce complexity of optimum scheduling algorithm of home appliances a simpler method, based on binary particle swarm optimization, has been proposed in [15]. The authors argued that other existing proposed methodologies are complex and resource consuming because they target a large group of residences. But, the proposed method in [15] targets individual residence. According to the proposed method a residence can set optimum schedules for the loads that can be shifted. The authors also proposed another modified version of the algorithm that can converge quickly.

A joint access scheduling approach for home appliances has been developed in [16]. In this work an area network has been used so that home appliances can coordinate with each other for power usage. The proposed protocol classifies the home appliances into two categories namely critical appliances and schedulable appliances. The authors argued that some home appliances have delay flexibility, but critical appliances have no delay flexibility. An energy management controller has been used to control the operation of home appliances by incorporating the variation of electricity prices. A two-dimensional Markov chain model has been used for determining the average delay of the home appliances.

In our paper we also propose an energy management system in a home. In contrast to other above mentioned related works we have designed our system based on the actual energy consumption data of two cities namely Fujairah and Khorffakhan, which are located in the United Arab Emirates (UAE). We analyzed the energy consumption data provided by Federal Electricity and Water Authority (FEWA) and Sharjah Electricity and Water Authority (SEWA). These two Government owned organizations are responsible for the electrical power distribution in Fujairah and Khorffakhan cities respectively. We have analysed the data to find a cost function for optimizing the energy consumption in a home. We then designed a LabVIEW based application for optimal scheduling of the home appliances. Based on the cost function the proposed system controls the operations of the home appliances. The idea is to shift the operation of the home appliances to off-peak hours. We also show via simulation that our proposed energy management system can save up to 30% of the energy consumed by a household. Since the optimal scheduling is implemented in LabVIEW, the proposed system is a flexible one and the consumers can modify the system according to their needs. We consider several cases namely worst case summer, worst case winter, and other cases in the simulations.

3. Theory

In this section, we first formally define the terminologies used in this paper. We then introduce the multiple knapsack problem (MKP) and finally we relate our scheduling problem with an instance of the MKP.

The consumers, in a smart grid community are charged depending upon the net power consumed from the smart grid based on a variable peak pricing model. The energy prices for a specific period of time is set in advance. Consumers, with smart appliances, define allowable period for the operation of their home appliances. In order to define appropriate operating time for the home appliances we classify the home appliances as into three classes namely must-run, fixed run, and flexible run.

The must-run appliances must be operational all the time during a day. Air conditioners operating in summer and heaters operating in winter are the examples of must-run appliances. The fixed run appliances must be operational at specific fixed time slots of a day. Lights operating in evening is an example of fixed-run appliances. The flexible run appliances must be operational for a specified duration at any time within a flexible interval. Washing machine is an example of flexible run appliances. The goal of these classifications is to optimally schedule the operation of all home appliances so that they meet the imposed constraints. A household may contain a mix of smart appliances and manual appliances. The smart appliances can be scheduled and operated by a computer program. The manual appliances are without inbuilt intelligence and are manually operated. In this work, we consider only the scheduling for smart appliances. Thus the goal of the proposed scheduler is to schedule the smart appliances so that they can be operated within a given time frame to minimize the electricity bill while satisfying the constraints such as users' preferences, price model, and requirements.

In this work we also use a Cost function denoted by *Cost(t)* that represents the cost associated with the consumption of certain amount of energy at a time instant *t*. It is assumed that a variable peak pricing model is followed. In this model the cost function varies with respect to time in a day. Generally, the cost of power consumption is high during the peak-hours (evenings and mornings) and is considerably low during periods of low power usage (afternoons and late nights). But, there may be some exceptions too. Heat wave is an example of such exceptions. During the heat wave energy consumptions in the afternoon may be large. It is also assumed that a day-ahead pricing model is used. Weather forecasting information is also available so that the cost function can vary in a quasi-dynamic way. Practically speaking the cost function is implemented as a discrete piecewise-constant. Per unit price is altered to discrete values at discrete time steps. In our exposition, we assume that the time slots are of equal length. It is rather simple to extend this approach to the case where the time slot lengths are not the same.

We also use the term locally generated power, which refers to any renewable sources of energy such as wind energy or solar energy that is generated on-site. These sources of energy are not deterministic, but may be reflected by their expected values. Again, weather forecasts are used to predict these values on a day ahead basis.

In this paper we map the home appliance scheduling problem to a multiple knapsack problem (MKP). The (single) knapsack problem is a combinatorial problem where a number of objects must be packed into a knapsack of a specific capacity so that the value of the objects within the knapsack is maximized. The objects are associated with a value and a weight. Single knapsack problem is a standard problem template in computer science, and numerous practical problems have been mapped on to this problem. The fractional version of the knapsack problem can be solved by using dynamic programming techniques in polynomial time. The integer problem is an NP-complete and a number of efficient polynomial-time approximation algorithms are available to provide near-optimal solution [17,8,22].

The multiple knapsack problem (MKP) [17–21] is a generalization of the single knapsack problem. In essence, the MKP is a resource allocation problem. There is a set of *m* resources (i.e., *m* knapsacks) and a set of *n* objects. Similar to a single knapsack problem each object *i* in this set of *n* objects has two important attributes associated with it namely the value and the weight. Each resource (knapsack) *j* has a capacity constraint C_j, which represents the maximum weight that the resource can support. The objective of the MKP is to find a subset of the objects that can be packed within the bins such that the net value of all objects within all knapsacks is maximized.

4. Methodology

Let us consider there are *n* home appliances within a smart grid and these appliances have to be scheduled in *m* time slots. Recall that the cost function, *Cost(t)*, is a piecewise constant function that reflects the cost of power consumption at a time slot *t*. The maximum power capacity of the system is denoted by *Capacity(t)* in time slot *t*. Let $T_{req,i}$ be the time duration of an appliance A_i to complete its task. This time duration is specified in units of the number of time intervals. This value of $T_{req,i}$ will be the same across all time slots for an appliance *i* because the power consumed by an appliance is a constant. We now relate the optimization formulation as a discrete linear program that has the form of a MKP. We introduce the Boolean integer variable, X_{ij}, defined as

X_{ij}= “1” if appliance is ‘on’ in time slot *j* and “0” if appliance is ‘off’ in time slot *j*

The objective function is now formulated as

$$\min\left(\sum_{i=1}^{n} E_i\left(\sum_{j=1}^{m} X_{ij}\cos t(j)\right)\right) \tag{1}$$

Here, X_{ij} is an indicator variable that states whether the *Cost(j)* term in slot *j* should contribute to the cost function or not. If so, this term represents the unit cost in that slot multiplied by the energy usage during that period. There are several constraints that must be obeyed. Specifically completion constraints are designed to ensure that each task is completed during the time period in question (e.g., one day). For each appliance *i*, these can be formulated as

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ISSN 1943-3581
2015, Vol. 7, No. 2

$$\sum_{j=1}^{m} X_{ij} = T_{req,j} \tag{2}$$

This equation states that an appliance *i* must be provided with enough time slots to complete its function. Clearly, this constraint support non-contiguous time slots for various appliances as long as the total $T_{req,i}$ constraint is met. Capacity constraints may be used to control the total energy usage of a home and to help incentivize energy usage that is more distributed in time and uniform. For each time slot *j*, these are stated as

$$\sum_{j=1}^{m} E_i X_{ij} \leq Capacity(t) \tag{3}$$

In this work we define the cost function as:

$$Cost(j) = (NP)^n \times Max.Cost \tag{4}$$

,where NP is the normalized power, *n*=1,2, and 3. Based on the available data provided by the two utility companies we choose *n*=3 and Max. Cost=0.33 Dirham. The reason for choosing *n*=3 has been explained in the next section.

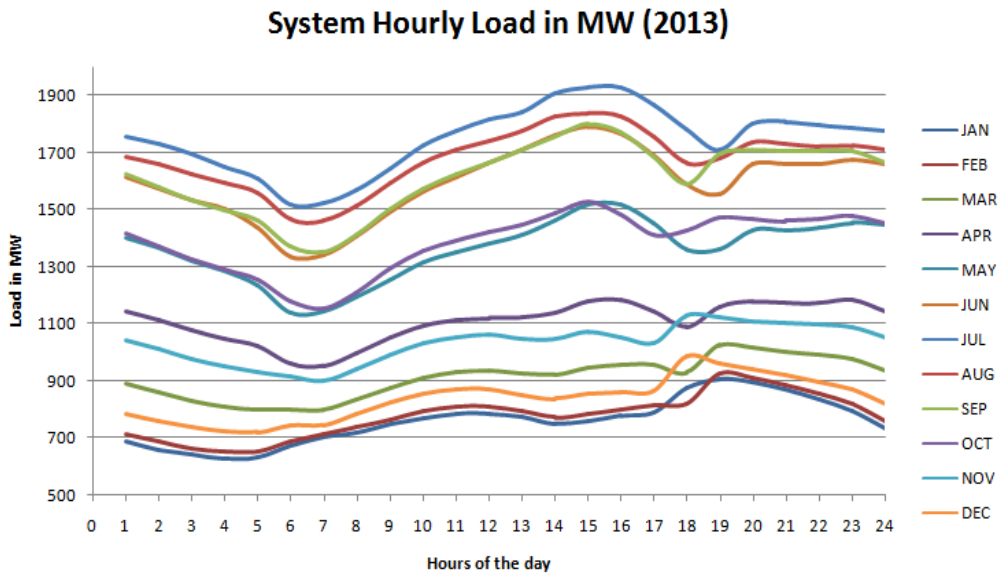

Figure 2 Average day hourly load of Fujairah city in different months for the year 2013

5. Data Analysis

We collected data from the power distribution authorities of two neighboring cities namely Fujairah and Khorffakhan located in the United Arab Emirates (UAE). Using the detailed hourly load data for the whole year, supplement by the Federal Electricity and Water Authority

(FEWA) and Sharjah Electricity and Water Authority (SEWA), the average day hourly load for each month is calculated. The average day hourly loads for the year 2013 of Fujairah city are shown in Fig. 2.

It is depicted in the figure that the energy consumption pattern in winter months is different from that in summer months. The power consumption for summer months (May-October) is higher than that of winter months (November-April). Also, the peak hours for summer months are from 1p.m. to 4 p.m. and for the winter months are from 7 p.m. to 10 p.m. The off-peak hours for both summer and winter months are the same (i.e., 4am - 7am).

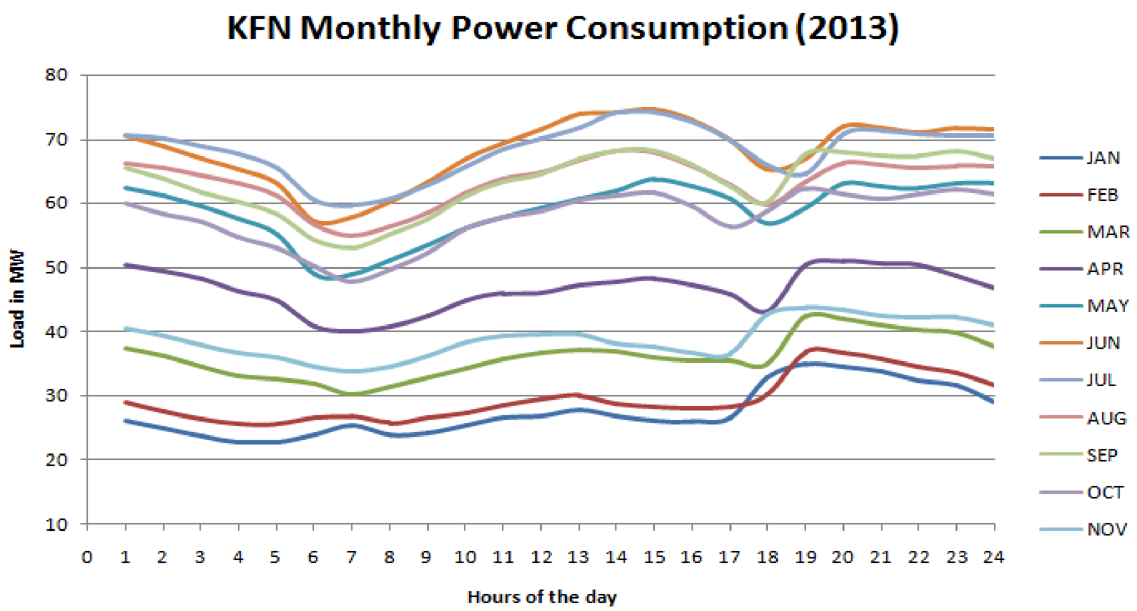

Figure 3 Average day hourly load of Khorffakhan city in different months for the year 2013

The average day hourly loads of Khorffakhan city for the year 2013 is shown in Fig.3. In this figure we notice that the energy consumption patterns in Fujairah and Khorfakkan are approximately the same. But, the monthly energy consumption in Khorffakhan is less than that in Fujairah. In Fujairah, the power consumption ranges from 580MW-1930MW, but in Khorffakhan, the power consumption ranges from 22MW-78MW. This reflects the difference in population sizes of Fujairah and Khoffakhan. It is worthwhile to mention here that the population size of Fujairah is 192,190 and that of Khorffakhan is 49,635. Since the power consumptions in the two cities are different we normalized the power consumption by dividing each curve by its maximum value. The normalized power consumptions in Fujairah and in Khoffakhan are shown in Fig.4 and Fig.5 respectively. We presented only six months' sample data here. But, we used twelve months' data in our actual analysis.

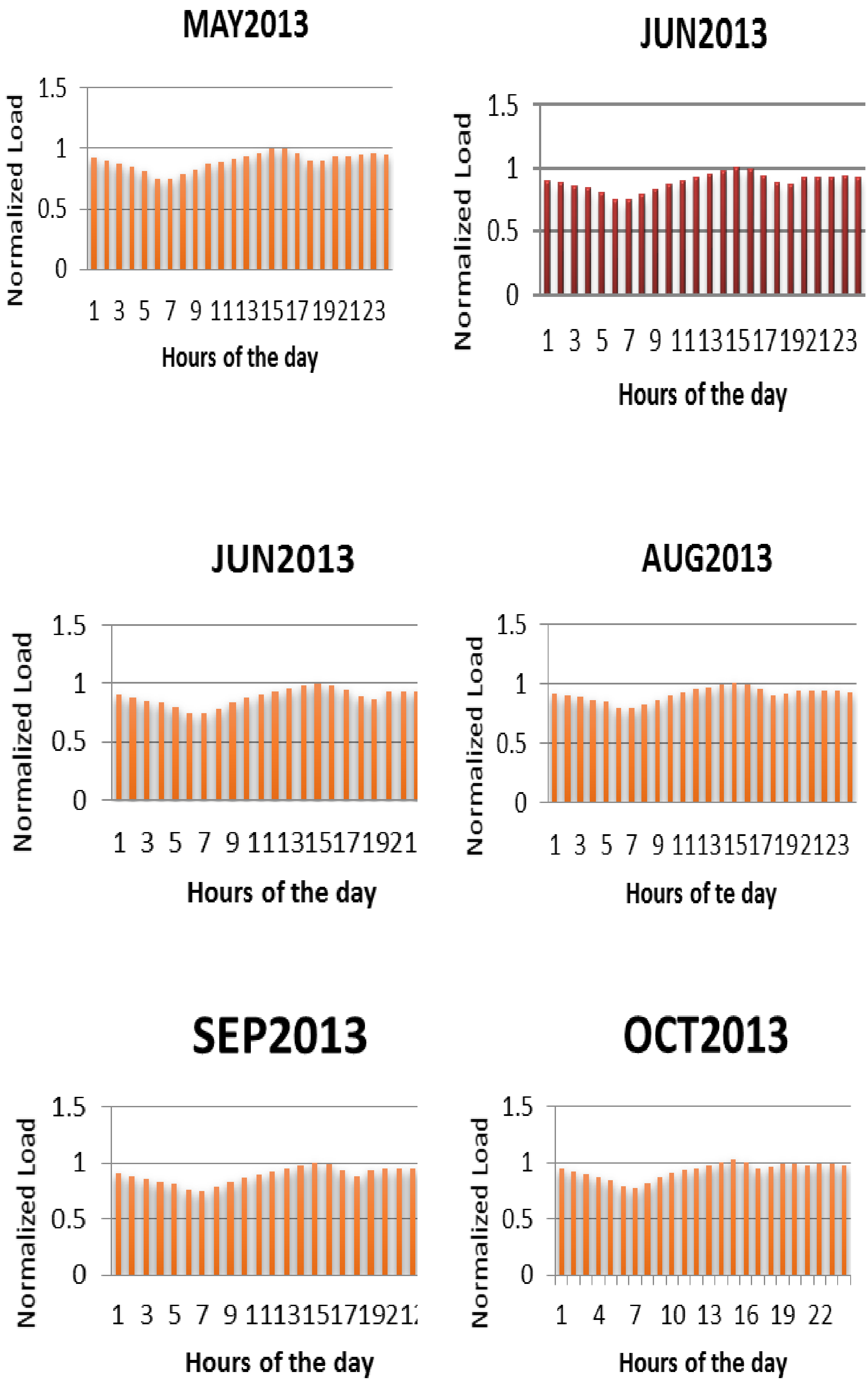

Figure 4 Normalized sample data for Fujairah in year 2013

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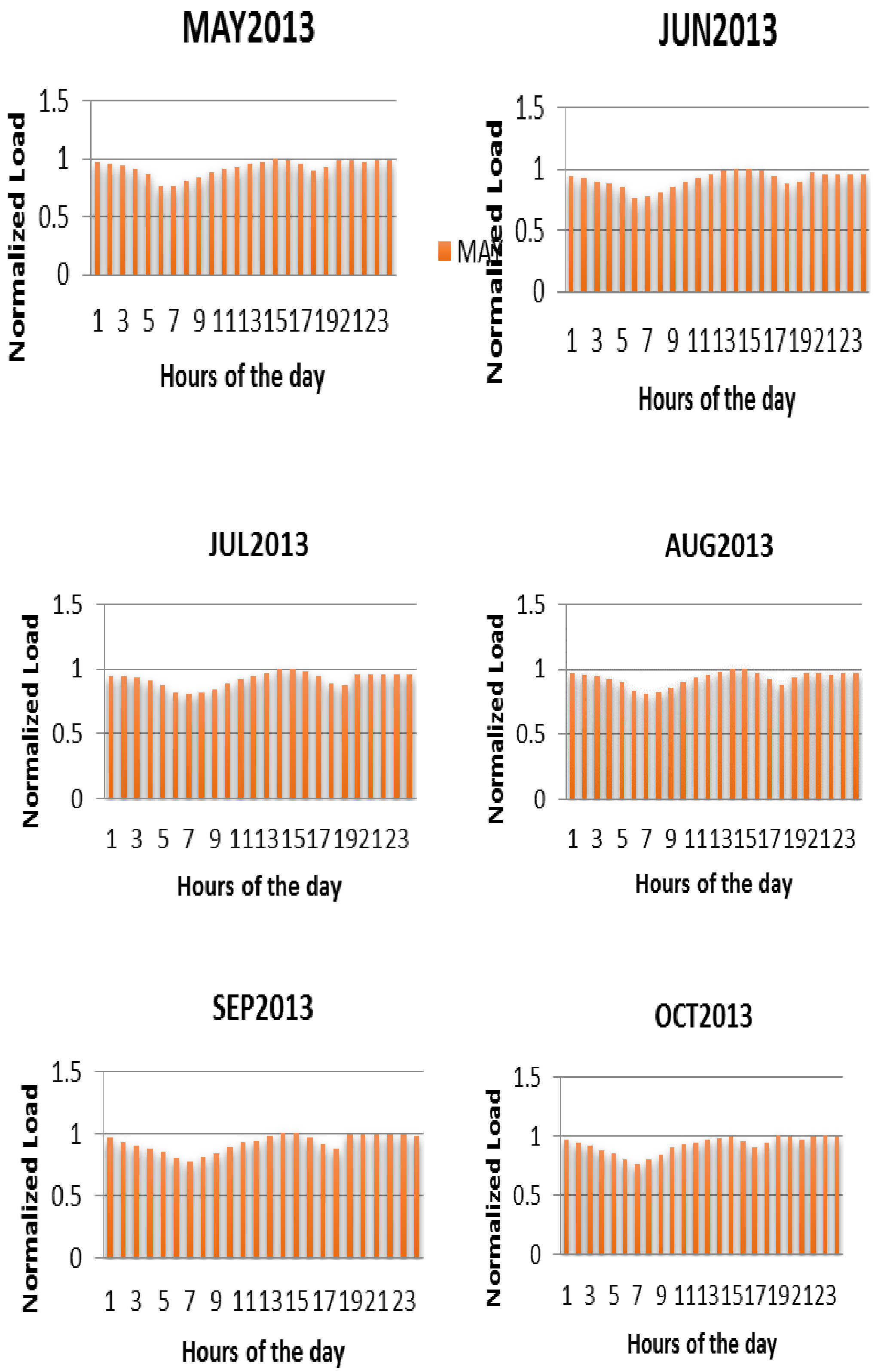

Figure 5. Normalized sample data for Khorffakhan in year 2013

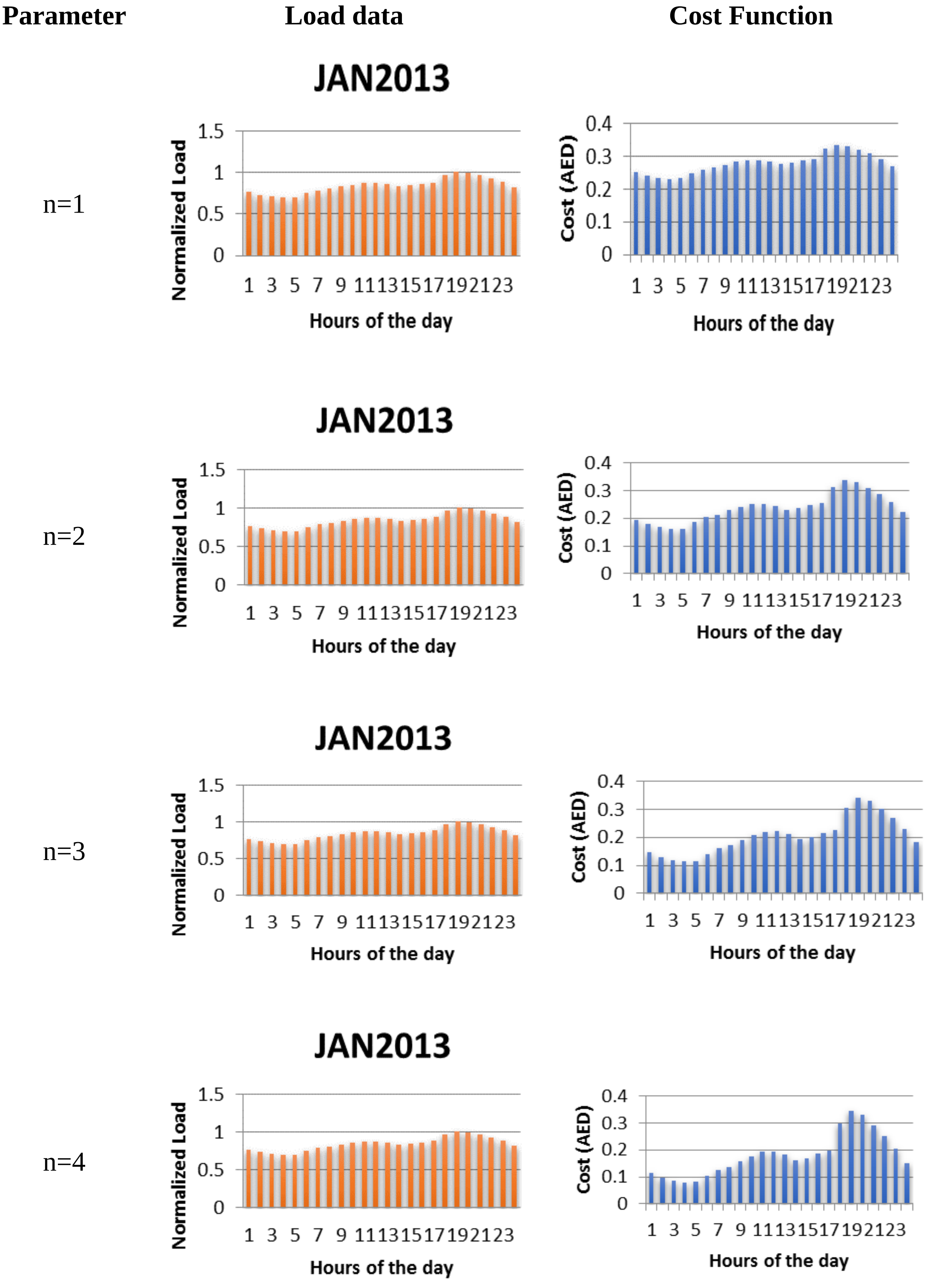

Figure 6. Sample cost function calculation

For cost function calculation we arbitrarily choose the data for the month of January 2013 as sample data and present here. The cost function is calculated based on (4) and we choose n=1,2,3,4, and the Max. Cost value is set to 0.33 Dirhams. The cost function calculation is illustrated in Fig. 6. It is shown in this figure that when n=1 there is very small difference between the cost of peak hours and off peak hours. Hence the consumers will not be benefited from using the cost function. Similar conlusions can be drwan for n=2, and n=4. Exception occurs when we set n=3. For this value of *n* we notice a significant difference between the cost of the peak hours and off-peak hours and we notice the best variation of the cost function throughout the day. So we set the value of *n* to 3 for the analysis in the rest of this paper.

We divided each monthly curve of Fujairah for the year 2013 into two parts: from 0-17 hours and 17-24 hours. The detail calculations are shown in Table 1 and Table 2.

Table 1. General equations of 2013 from **0-17hrs**

	X4	X3	X2	x	c
Jan-Mar	-0.01493m² + 0.04460m + 0.01999	0.51663m² - 1.56581m - 0.94381	-5.35475m² + 16.72916m + 15.02777	14.80481m² - 50.99886m - 80.71764	62.58071m² - 150.50877m+ 876.90702
Apr-May	-0.04166m + 0.14503	1.33728m - 4.94965	-11.84589m + 50.35482	23.51693m - 158.46669	246.00941x + 233.71313
Jun-Sep	-0.00017m³ - 0.00099m² + 0.04406m - 0.27357	0.01154m³ - 0.13738m² + 0.10572m + 4.02746	0.04489m³ - 1.48859m² + 14.29623m - 53.33152	-2.34771m³ + 48.83262m² - 328.63238m + 680.26002	40.23208m³ - 953.22202m² + 7,417.89598m - 17,198.52058

Table 2. General equations of 2013 from **17-24hr**

	X4	X3	X2	x	c
Jan-Mar	-0.42401m² + 2.14456m - 2.06686	34.93071m² - 177.37660m + 172.34381	-1,071.78168x² + 5,468.28084x - 5,367.74907	14,515.56490m² - 74,460.19973m + 73,980.10304	-73,159.95485m² + 377,661.78759m - 379,590.31028
Apr-May	0.45692m - 1.28933	(-38.71559m + 109.35257	1,228.52490m - 3,482.54401	-17,290.91904m + 49,313.08032	91,266.32321m - 261,566.11876
Jun-Sep	-0.09168m³ + 2.10410m² - 15.94173m + 40.94808	7.29951m³ - 167.60383m² + 1,271.09834m - 3,274.95582	-216.32006m³ + 4,968.46724m² - 37,715.78980m + 97,492.02212	2,824.80140m³ - 64,887.15603m² + 492,976.17107m - 1,278,771.38128	-13,653.55885m³ + 313,551.85469m² - 2,383,735.24874m + 6,208,947.87849

The scheduling is done on a day ahead tariff basis. User specifies the loads that need to be scheduled. The optimal scheduling is determined with the user preferences. We specify a number of home appliances with different energy consumption pattern. Table 3 shows the list of the home appliances we considered in our simulation. This table also shows the power consumed by each appliance. It also shows the time required for each home appliance. We consider different scenarios in our simulation, which are depicted in Fig. 7. We considered three cases namely worst case summer, worst case winter, best case summer and winter. The schedule of the appliances and their power consumption are shown in the same figure. The optimal schedule of the appliances has been determined by our proposed algorithm is shown in Fig. 8. The energy consumed by different appliances are also shown in the same figure. The energy cost saving is illustrated in Fig. 9. The data presented in Fig. 9 shows that our proposed system can save up to 30% electricity bill.

Table 3: Appliance parameters

	A1	A2	A3	A4	A5
$T_{req,i}$ (hrs)	4	4	4	4	4
E_i (KW)	1.5	2	2	1.5	4
	A1	A2	A3	A4	A5
$T_{req,i}$	4	4	4	4	4

A1: vacuum cleaner
A2: washing machine
A3: Iron
A4: Heater
A5: Dishwasher

Worst Case Summer

Time	P1	P2	P3	P4	P5
0-1	0	0	0	0	0
1-2	0	0	0	0	0
2-3	0	0	0	0	0
3-4	0	0	0	0	0
4-5	0	0	0	0	0
5-6	0	0	0	0	0
6-7	0	0	0	0	0
7-8	0	0	0	0	0
8-9	0	0	0	0	0
9-10	0	0	0	0	0
10-11	0	0	0	0	0
11-12	0	0	0	0	0
12-13	0	0	0	0	0
13-14	0	0	0	0	0
14-15	1.5	2	2	1.5	4
15-16	1.5	2	2	1.5	4
16-17	1.5	2	2	1.5	4
17-18	1.5	2	2	1.5	4
18-19	0	0	0	0	0
19-20	0	0	0	0	0
20-21	0	0	0	0	0
21-22	0	0	0	0	0
22-23	0	0	0	0	0
23-24	0	0	0	0	0

Worst Case Winter

Time	P1	P2	P3	P4	P5
0-1	0	0	0	0	0
1-2	0	0	0	0	0
2-3	0	0	0	0	0
3-4	0	0	0	0	0
4-5	0	0	0	0	0
5-6	0	0	0	0	0
6-7	0	0	0	0	0
7-8	0	0	0	0	0
8-9	0	0	0	0	0
9-10	0	0	0	0	0
10-11	0	0	0	0	0
11-12	0	0	0	0	0
12-13	0	0	0	0	0
13-14	0	0	0	0	0
14-15	0	0	0	0	0
15-16	0	0	0	0	0
16-17	0	0	0	0	0
17-18	1.5	2	2	1.5	4
18-19	1.5	2	2	1.5	4
19-20	1.5	2	2	1.5	4
20-21	1.5	2	2	1.5	4
21-22	0	0	0	0	0
22-23	0	0	0	0	0
23-24	0	0	0	0	0

Best Case Summer & Winter

Time	P1	P2	P3	P4	P5
0-1	0	0	0	0	0
1-2	0	0	0	0	0
2-3	0	0	0	0	0
3-4	1.5	2	2	1.5	4
4-5	1.5	2	2	1.5	4
5-6	1.5	2	2	1.5	4
6-7	1.5	2	2	1.5	4
7-8	0	0	0	0	0
8-9	0	0	0	0	0
9-10	0	0	0	0	0
10-11	0	0	0	0	0
11-12	0	0	0	0	0
12-13	0	0	0	0	0
13-14	0	0	0	0	0
14-15	0	0	0	0	0
15-16	0	0	0	0	0
16-17	0	0	0	0	0
17-18	0	0	0	0	0
18-19	0	0	0	0	0
19-20	0	0	0	0	0
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21-22	0	0	0	0	0
22-23	0	0	0	0	0
23-24	0	0	0	0	0

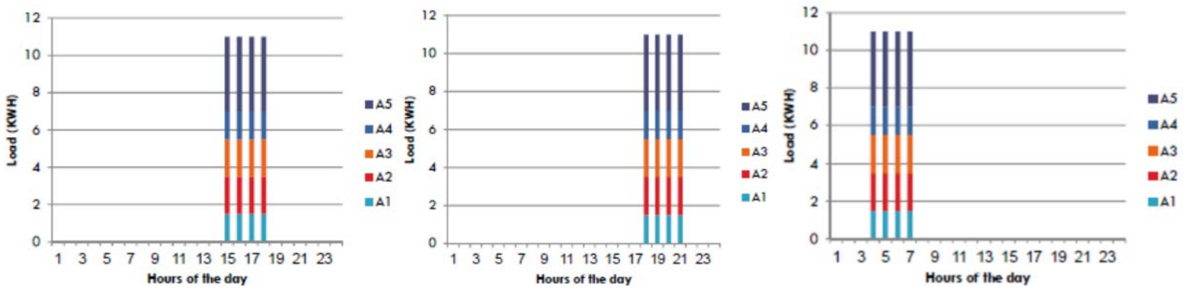


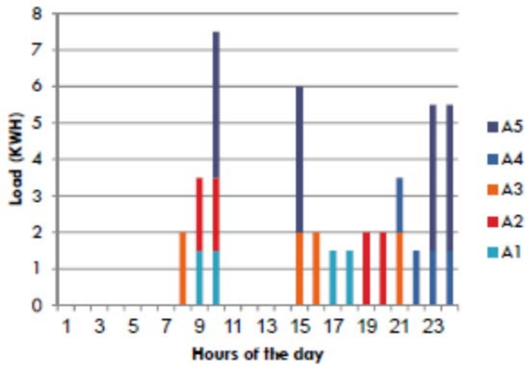
Figure 7 Different simulated scenarios

Suggested Scenario 1

Time	P1	P2	P3	P4	P5
0-1	0	0	0	0	0
1-2	0	0	0	0	0
2-3	0	0	0	0	0
3-4	0	0	0	0	0
4-5	0	0	0	0	0
5-6	0	0	0	0	0
6-7	0	0	0	0	0
7-8	0	0	2	0	0
8-9	1.5	2	0	0	0
9-10	1.5	2	0	0	4
10-11	0	0	0	0	0
11-12	0	0	0	0	0
12-13	0	0	0	0	0
13-14	0	0	0	0	4
14-15	0	0	2	0	0
15-16	0	0	2	0	0
16-17	1.5	0	0	0	0
17-18	1.5	0	0	0	0
18-19	0	2	0	0	0
19-20	0	2	0	0	0
20-21	0	0	2	1.5	0
21-22	0	0	0	1.5	0
22-23	0	0	0	1.5	4
23-24	0	0	0	1.5	4

Suggested Scenario 2

Time	P1	P2	P3	P4	P5
0-1	0	0	0	0	0
1-2	0	0	0	0	0
2-3	0	0	0	0	0
3-4	0	0	0	0	0
4-5	0	0	0	0	0
5-6	0	0	0	0	0
6-7	0	0	0	1.5	0
7-8	0	0	0	1.5	0
8-9	0	2	0	0	0
9-10	1.5	2	2	0	4
10-11	1.5	0	2	0	4
11-12	0	2	0	0	0
12-13	0	2	0	0	0
13-14	0	0	0	0	0
14-15	1.5	0	0	0	0
15-16	1.5	0	0	0	0
16-17	0	0	0	0	0
17-18	0	0	0	0	0
18-19	0	0	0	1.5	0
19-20	0	0	0	1.5	0
20-21	0	0	0	0	0
21-22	0	0	2	0	4
22-23	0	0	2	0	4
23-24	0	0	0	0	0



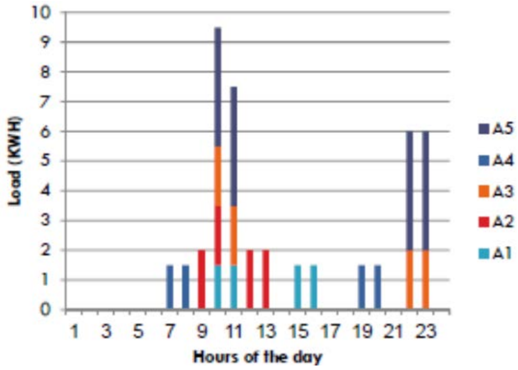


Figure 8 Suggested Scenario and power consumption

Scenarios	Load KWh /day	Cost (AED)								
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Worst Summer	44	311.9277	286.7608	368.6287	397.8663	390.3183	380.8529	402.4271	391.4211	376.5361
Worst Winter	44	421.5722	384.2308	427.1397	400.2525	336.9252	320.3762	339.903	345.9429	350.6283
Best Case	44	174.1357	170.9154	224.0132	260.4839	215.2714	211.3405	238.3827	247.1185	214.9985
Scenario 1	44	301.4268	294.3444	368.896	386.8788	346.5977	336.6001	345.8984	352.9277	344.0345
Scenario 2	44	299.3934	295.7993	361.5382	374.7651	323.45	321.8094	333.8773	343.8141	329.0778

Figure 9 The cost saving in the simulated scenarios

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ISSN 1943-3581
2015, Vol. 7, No. 2

6. System Implementation

The block diagram of our proposed system is shown in Fig. 10. The system has been designed to provide the following features for our system:

- Ability to extend the number of loads: Our system hardware can accept any number of loads from different sensor circuits attached with the appliances.
- Full monitoring, recording, controlling, and data processing features: Our programming environment is flexible enough to support the customer requirements.
- Low cost networking: The data from the controlling unit is transmitted over efficient and low cost (Zigbee) wireless network.
- Upgradability: The system hardware / software components can be easily upgraded to have enhanced operation. The monitoring units can also be upgraded to increase storage and computational capabilities.
- System economics: The system components are designed to achieve the minimum costs without scarifying accuracy

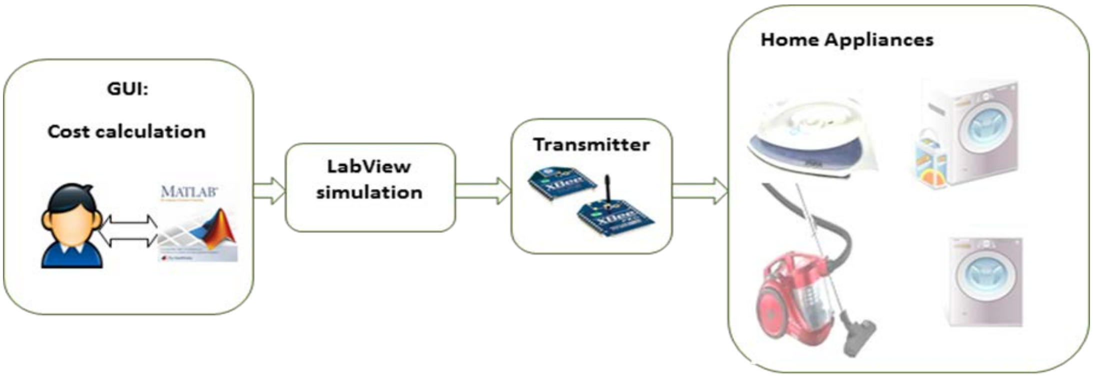

Figure 10 System block diagram

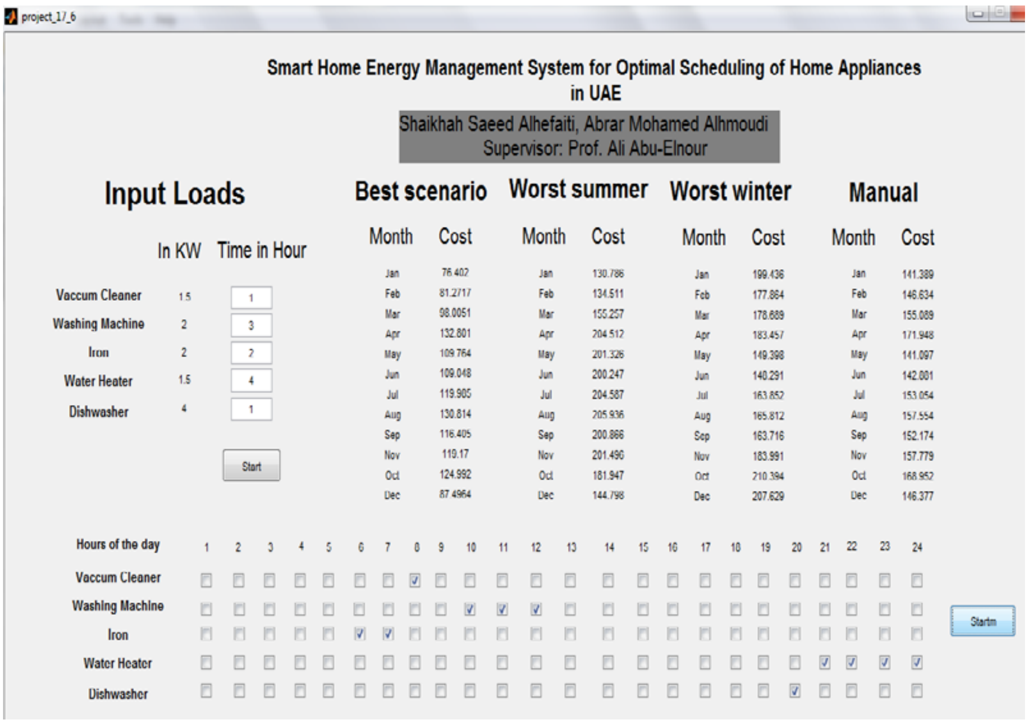

Figure 11 The Graphical user interface

The main components of the system are (a) Graphical user interface, (b) LabVIEW program, (c) ZigBee module, and (d) home appliances. Graphical user interface (GUI) is shown in Fig.11. It provides a two way communications between a user and the program. It also allows the user to choose the home appliance she/he wants and the time needed for that appliance.

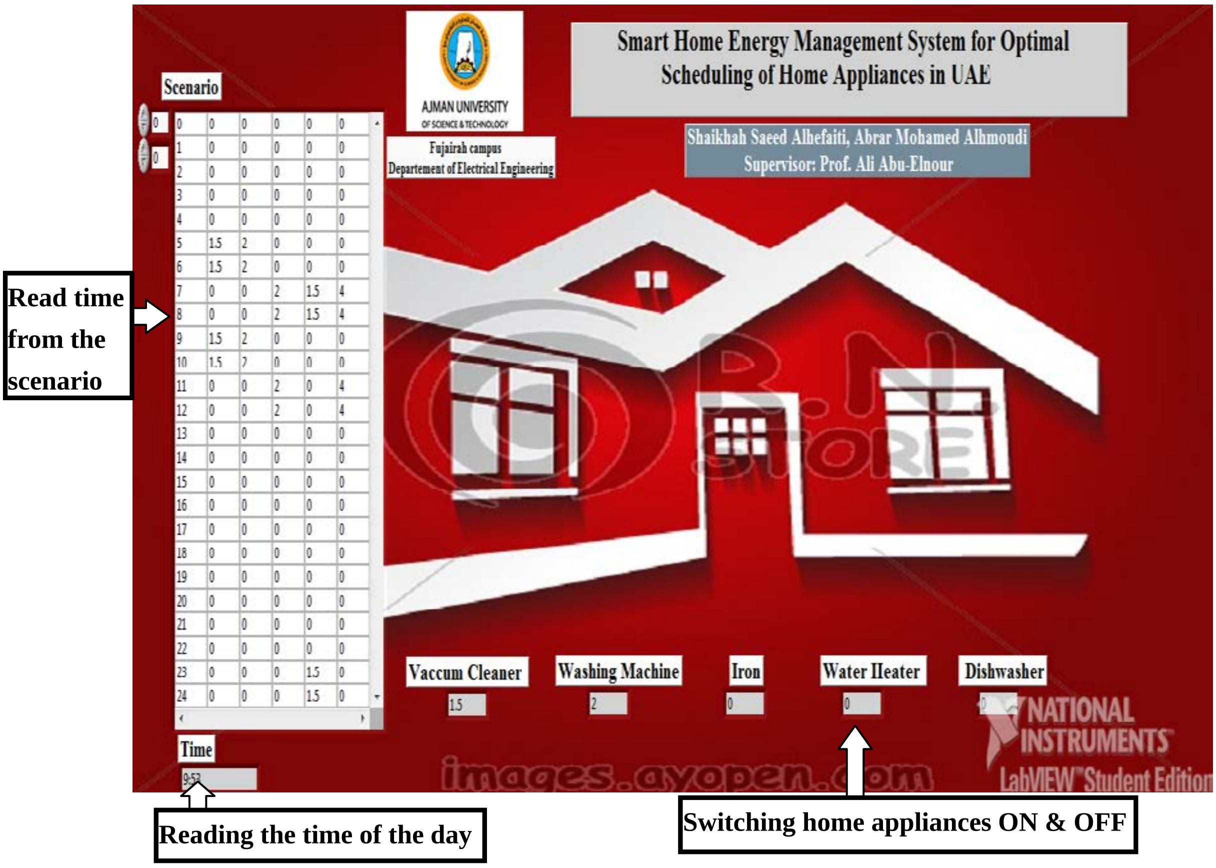

Figure12 The LabVIEW simulation of the system

The LabVIEW constitutes a graphical programming environment that allows input from user to program. Based on the provided user data the program is executed. The LabVIEW relies on graphical symbols rather than textual language to describe programming actions. The LabVIEW program works on the principle of dataflow, in which functions execute only after receiving the necessary data. Hence the program execution in LabVIEW is very straightforward. The front panel of the system and the complete flowchart are shown in Fig. 12 and Fig. 13 respectively. Figure 12 shows the status of the front panel at time 9:53 a.m. The scheduling of the home appliances and the status of the same are also shown in the front panel. It is depicted in the front panel that iron, water heater, and dishwasher are in OFF state at that time. Only the vacuum clear and washing machine are in ON state. The two appliances will be operational for 1.5 hours and 2 hours respectively as shown in the front panel. Fig. 14 shows the complete algorithm of our proposed system.

Network Protocols and Algorithms
ISSN 1943-3581
2015, Vol. 7, No. 2

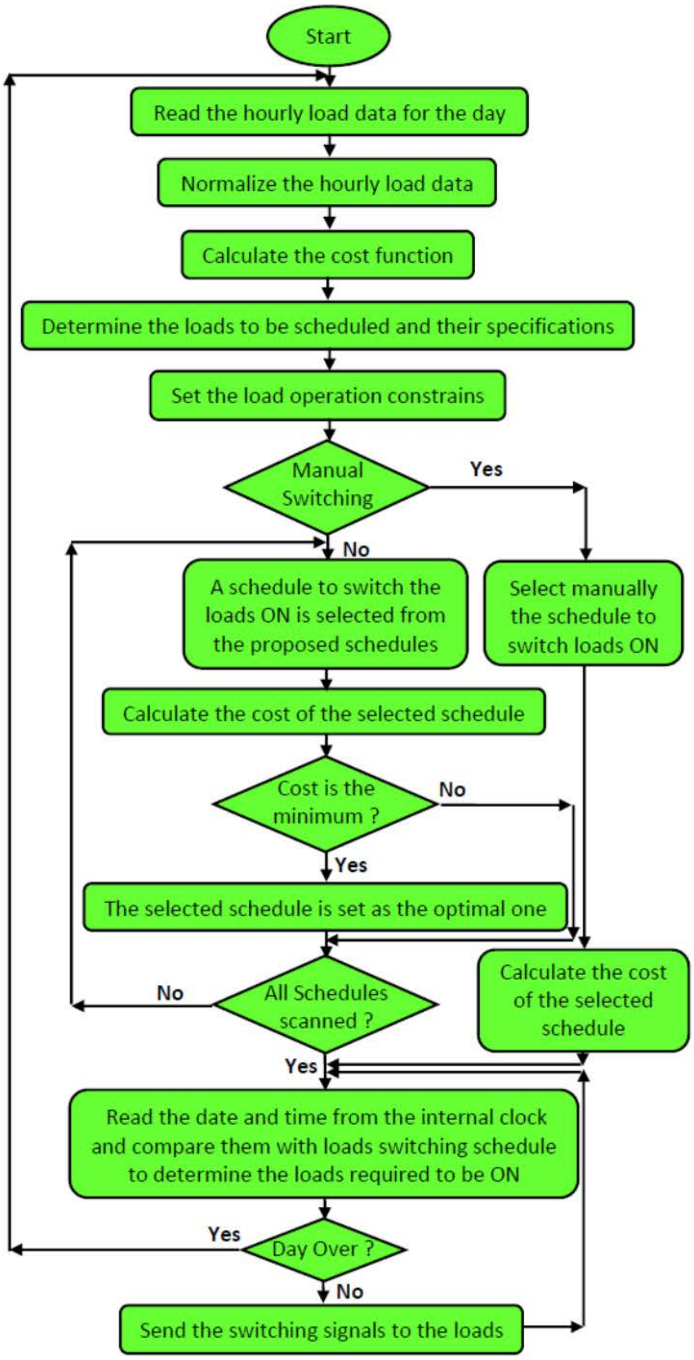

Figure 14 The flowchart of the program

7. Conclusions

In this paper an energy management system has been proposed for the household appliances. The energy management is achieved by using optimal scheduling of the home appliances. The proposed optimal scheduling is based on dynamic pricing paradigm. A cost function has been derived based on some practical data provided by two utility companies. Some experimental result has been presented in this paper. The results show that our system can help a household to save up to 30% of its energy consumption. Our system is flexible because of the LabVIEW program. The users can define their own cost function and can modify the scheduling accordingly. We also eliminated the use of wires by using ZigBee wireless technology. So, the users can deploy the system without any hassle related to new wiring. Due to the low cost of ZigBee network our proposed system is very cheap also.

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