ABSTRACT

The critical peak pricing plan is an active part in demand response program. Its technical perspective is to maximize the energy service provider profit as they can reduce the risks and maximize the outcomes further. As an incentive for electricity users to participate in a demand-side management program, this paper will discuss how to maximize the users’ payoff by rescheduling their energy consumption. A distributed demand-side management system among users will be presented with a two way digital communication infrastructure. Then using game theory to formulate, an optimization problem that deal with the total hourly load for each user is applied. The proposed algorithm is implemented on a real data taken from ISO market and by using genetic algorithm.

INTRODUCTION

Demand Side Management DSM is a large variety of programs that are employed to use the available energy more efficiently without installing new generation or transmission infrastructure [1]. As the goal of the DSM is to encourage the consumer to use less energy during peak hours, or to move the time of energy use to off-peak time.

Critical Peak Pricing (CPP) plan is one of the price based Demand response programs. Its objective is to flatten the demand curve by offering a high price during peak periods and lower prices during off-peak periods by applying tariffs to end-use customers. The price on peak time is more expensive and it usually related to the time when the market prices are more expensive [2], [3]. Direct load control is one of the residential load management in it the utility company make an agreement with the customers to remotely control the operation and energy consumption of some appliances in a household, but user privacy is a major concern in implementing this program as the customer owns and control the home area network.

A real time price based demand response management model for residential appliances that can help residential consumers to manage automatic their appliances for the optimal energy efficiency and economics, this model can be imbedded into smart meters and executed to determine the optimal operation in the next 5 minutes time interval with consideration of the future electricity price variation. To explore optimal real-time demand response decisions with respect to time varying electricity price variation scenario-based stochastic optimization and robust optimization approaches are used. The studies show a decrease in the electricity bill while using both of the demand response management techniques [4]. To balance the electricity bill payment and User’s privacy protection demand response energy management model is introduced in which future uncertainties do not depend on the decision made previously it learn from the past and anticipate the future for producing robust and optimal solutions [5].

User’s privacy raised the need of an alternative program which was achieved by smart pricing in which users are controlling individually and voluntarily their loads by reducing their consumption at peak hours and by shifting a large portion of load from a typical peak hour to a typical non peak hour. A good DSM program must satisfy that the total load at each hour is the only important issue, so interaction between users is needed they must coordinate their usage to minimize the energy cost and this interaction should not be manual but automatic through two-way digital communication [6].

The critical peak prices are detected based on predicted prices and all of these data are used as input to check the energy system provider profit, then an incentive-based energy consumption scheduling scheme for the future smart grid is proposed, by considering a scenario where one source of energy is divided between several customers each one of them is equipped with an automatic Energy Consumption Scheduler ECS which is installed inside the smart meters that are connected to the power line coming from the energy source and they are also connected to each other and to the energy source through a local area network. LAN through it are done all message exchanges between the smart meters[6]. Then these smart meters with ECS functions interact automatically by running a distributed algorithm to find the optimal energy consumption schedule for each user to minimize the energy cost in the system. The task of the ECS function in each user’s smart meter is to determine the optimal choice of the energy consumption for each appliance. In [6], game theories are used to provide the constraints of the genetic algorithm to show the ability of preventing users from cheating and misleading during their interactions with each other. The result shows that the system performance is improved and each user pays less.

This paper is divided into five parts: first part is to build the load price model with the help of three statistical
methods, second is to predict the critical peak pricing, by using the support vector machine, third is to built the net profit equation, fourth applying the game theory among users to increase the profit of each one, then at last the results and conclusions.

I. PRICE FORECASTING

The technical perspective of CPP plan implies a method to maximize the economic perspective. An (ESP) energy system provider should know when to call critical peaks to maximize her profit given the market prices. This requires a good prediction of market prices followed by a critical peak decision based on the prices predicted [3]. The ISO market data of PJM is used [7].

Load and price data for April 2014 from ISO website are chosen to be used as the input data. A day ahead price will be used which means for each day 24 price forecasts are computed the applied assumptions in predicting the price are:

1. The testing period is 1 month, or 30 days.
2. The day-ahead market is running by one hour and the real-time market is running by 5 minutes.

To formulate the following price prediction equation

\[
\text{ln}(P(n)) = aL(n) + b + \sigma \sqrt{\Delta t} \alpha(L(n) - L(n-1)) + \eta(\text{ln}(P(n-1))(\kappa + \delta))
\]

(1)

three statistically forecasted methods will be used random walk, mean reversion, and jump diffusion but first Price-load relationship equation is formulated using least-squares estimation[8], [9]

\[
\text{ln}(P(n)) = aL(n) + b
\]

(2)

The value of “a” which is the slope of the regression line from the load-price relationship, and “b” is the intercept of the line as shown in Fig.1.

The following values are obtained:

\[a = 0.01359\]

\[b = 4.942\]

From the relationship of the price and load and by subtracting two equations of load-price relationship with only different time steps \(\text{ln}(P(n)) = aL(n) + b\) and \(\text{ln}(P(n-1)) = aL(n-1) + b\) the following equation is obtained

\[
\text{ln}(P(n-1)) = \frac{aL(n) - aL(n-1)}{\Delta t} - \sigma \sqrt{\Delta t}
\]

(3)

a) random walk model

A variable “\(z\)” follows a Wiener process if it has the following two properties [10]:

1. The change \(\Delta z\) during a small period of time \(\Delta t\) is: \(\Delta z = \sigma \sqrt{\Delta t}\)

Where \(\sigma\) is the standardized normal distribution which is between (0,1)

The values of \(\Delta z\) for any two different short intervals of time, \(\Delta t\), are independent.

b) mean reversion model

Over time the price path will drift towards the mean reversion level at a speed determined by the mean reversion rate [11]. To calculate the mean reversion rate, a particular price series had been chosen from the ISO data which is 10 consecutive hours which are from 11 to 20 from the day 10 in the selected month September 2012 then the mean reversion rate \(\alpha = \text{mean reversion rate} = 0.0056\)

c) Jump diffusion

To determine the jump diffusion parameters, first the threshold value which differs from study to another study has to be defined. In this paper the threshold is set to be the value which is greater than the mean price with triple the value of the standard deviation [12].

The following parameters are got:

1. the jump standard deviation \(\delta = 0.0127\)
2. the jump diffusion mean \(k = 0.0093\)

using this equation (1) to predict the price with the value of all constants extracted. A predicted price with a mean average percentage error =1.74 % is obtained. Table 1 shows the notation of the used variables.

Table 1 Variables and notations used in the price prediction equation [1]

| P(n) | Price at time step n |
| L(n) | Load at time step n |
| \(\Delta\) | Slope of the least-squares estimation on load and logarithmic price \(\text{ln}(P)\) |
| \(\Sigma\) | Volatility, error degree of the liner regression on loads and logarithmic price |
| \(\mathcal{M}\) | Interval of the time step (1 hour) |
| \(\Lambda\) | Mean reversion rate |
| \(\eta\) | Indicator variable on price spike (1: spike, 0: not spike) |
II. ENERGY PROFIT CALCULATIONS

A) Energy System Provider Profit Equation
The total profit can be formulated by subtracting the price paid by the energy system provider to buy energy at day ahead (non critical hours) at real time (critical hours) from the total revenue the energy system provider gets from selling the electrical energy to all customers

\[
\text{Max }\Pi = \sum_{n=1}^{NCP} \text{R}_{dj} - \sum_{k=1}^{24x30} \text{P}_{DA}(k) \cdot \text{Q}_{dj}(k) - \sum_{k=1}^{12x24x30} \text{P}_{RT}(k) \cdot \text{Q}_{dj}(t)
\]

Where \(\text{R}_{dj} = \sum_{k=1}^{24x30} \text{P}_{DA}(k) \cdot \text{Q}_{dj}(k) + \sum_{k=1}^{12x24x30} \text{P}_{RT}(k) \cdot \text{Q}_{dj}(t)\)

Table 2 shows the notation of the used variables in the profit equation.

| K | Time on day ahead market (unit: Hour) |
| T | Time on real time market (unit: 5 minutes) |
| D_{nj} | Index for a critical peak pricing customer (demand) |
| Q_{t} | Quantity of electricity demand by customer dj |
| N_{cpp} | Number of critical peak pricing customers |
| P_{DA}(k) | Electricity price of day-ahead market |
| P_{RT}(k) | Electricity price of real-time market |
| P_{pp} | Price of critical peak pricing for critical peak times |
| P_{pp-ncp} | Price of critical peak pricing for non critical peak times |

B) Support Vector Machine
Support vector machine can be simply described as a technique for transformation of data from vector form to a function that can be represented in a linear feature space as shown[13, 14,15 & 16]. To apply SVM technique, 2 days from April 2014 has been chosen as example day 1&2 Tuesday and Wednesday which are 2 working days. The load exceeding 15 MW will be considered as heavy load. Then grouping the data into digits by assuming that the heavy load is set to be 1 and the light load is set to be 0. Finally by using the support vector machine the following data shown in Fig. 2 is obtained.

In the profit equation an assumption is made which is that quantity an ESP bought from a market should be equal to the summation of quantity of electricity demand by all customers. Assuming that there are 4 customers who share the load by the following ratio:
- Customer 1 by 25%
- Customer 2 by 25%
- Customer 3 by 15%
- Customer 4 by 25%

A total revenue is obtained from all the customers by selling the energy by the predicted price that had been already calculated for the tested sample of 2 days by 123.77 then by subtracting from this number the total price the ESP bought by which the energy from the market using the market price a positive profit equal +14.53 is obtained which indicate that a profit is realized.

III. GAME THEORY PROBLEM FORMULATION

Table 3 Variables and notations used in the optimization problem

| N | set of users |
| n or m | each customer |
| H | 24 hours |
| h | each hour |
| l^n | Total load at hour h by user n |
| l^d | Daily load for user n |
| L_{all} | Total load across all users at each hour of the day |
| L_{max} | Daily peak load level |
| L_{ave} | Average load level |
| PAR | Peak to average ratio |
| C_{n}(l_n) | Cost of generating or distributing electricity by the energy source at each hour h \epsilon H |
| A_{n} | Set of household appliances |
| A | Each appliance |
| x_{n,a}^h | One-hour energy consumption that is scheduled for appliance a by user n at hour h |
| X_{n,a} | Energy consumption scheduling vector |
| l^H | Total load at hour h by user n |
| x_n | The vector containing the energy consumption schedules of all users other than user n |
| b_n | daily billing amount in dollars for user n charged to him by the utility at the end of each day |

Assuming that unit of time is one hour the daily load of user n is described by \(l^H_n = l^h_n, \ldots, l^H_n\)

Total load across all users at each hour of the day \(h \epsilon H\) can be calculated as :

\[
L_n = \sum_{n \epsilon N} l^h_n
\]

Daily peak load level

\[
L_{peak} = \max_{x \epsilon [0,1]} l_n
\]

Average load level

\[
L_{ave} = \frac{1}{H} \sum_{h=1}^{H} l_n
\]

For each user \(n \epsilon N\); and for each appliance \(a \epsilon A\) an energy consumption scheduling vector can be defined as

\[
X_n,a^h = \{x_{n,a}, \ldots, x_{n,a}\}
\]

Total load at hour \(h\) by user \(n\) is determined by

\[
l^h_n = \sum_{a \epsilon A} X_n,a^h
\]
An efficient energy consumption scheduling can be expressed in terms of minimizing the energy costs to all users which can be expressed as the following optimization problem

\[
\text{minimize}_{x_{n1}^{N}} \sum_{h=1}^{H} \text{Ch}(\sum_{n \in N \text{ and } A_n} x_{h,a}^{n}) \quad (9)
\]

A) Energy consumption game

\(b_{n}\) denote the daily billing amount in dollars for user \(n\) charged to him by the utility at the end of each day, this price reflect the user’s total daily energy consumption

Assuming that

\[
\sum_{n \in N} b_{n} \geq \sum_{h=1}^{H} \text{Ch}(\sum_{n \in N} t_{h}^{n}) \quad (10)
\]

Where

\(\sum_{n \in N} b_{n}\) represent the total daily charge of all users and \(\sum_{h=1}^{H} \text{Ch}(\sum_{n \in N} t_{h}^{n})\) represent the total daily cost

\[
K = \frac{\sum_{n \in N} b_{n}}{\sum_{h=1}^{H} \text{Ch}(\sum_{n \in N} t_{h}^{n})} \geq 1 \quad (11)
\]

If \(k = 1\) so the utility company charges the users only with the same amount that generation and transmission energy costs for the utility but if \(k>1\) this indicate that the utility add a profit

Assuming that

\[
b_{n}/m = \frac{\sum_{h=1}^{H} t_{h}^{n}}{\sum_{h=1}^{H} t_{h}^{m}} \quad (12)
\]

by summing up the two sides of equation (12) across all users \(m \in N\), for each \(n \in N\) it is get

\[
\sum_{n \in N} b_{n} = \frac{\sum_{n \in N} b_{n}}{\sum_{h=1}^{H} t_{h}^{n}} \cdot \sum_{h=1}^{H} t_{h}^{m} \quad (13)
\]

\[
b_{n} = \frac{\sum_{h=1}^{H} t_{h}^{n}}{\sum_{m \in N} \sum_{h=1}^{H} t_{h}^{m}} \cdot \sum_{h=1}^{H} \text{Ch}(\sum_{n \in N} t_{h}^{n})
\]

\[
= \left(\frac{\sum_{h=1}^{H} t_{h}^{n}}{\sum_{m \in N} \sum_{h=1}^{H} t_{h}^{m}}\right) \cdot \sum_{h=1}^{H} \text{Ch}(\sum_{n \in N} t_{h}^{n})
\]

\[
= \sum_{h=1}^{H} \text{Ch}(\sum_{m \in N} \sum_{a \in A_{m}} x_{h,a}^{m}) \quad (14)
\]

This equation it is concluded that the charge on each user depend on how he and all other users schedule their energy consumption

The vector containing the energy consumption schedules of all users other than user \(n\)

\[
X_{n} = [X_{1}, \ldots, X_{n-1}, X_{n+1}, \ldots, X_{N}]
\]

The payoffs of each user \(n \in N\) can be expressed as

\[
P_{i}(X_{n}; X_{a}) = -b_{n}
\]

\[
P_{i}(X_{n}; X_{a}) = -\Omega_{n} \sum_{h=1}^{H} \text{Ch}(\sum_{m \in N} \sum_{a \in A_{m}} x_{h,a}^{m}) \quad (15)
\]

B) Game theories

It is a formal study of decision-making where several players which are agents who make the decisions in a game must make choices that potentially affect the interests of other players. This game has perfect information when at any point only one player make an action knowing the others actions until then. Each player when playing the game tends to maximize his own payoff. Game theories are used when the actions or decisions of several agents are interdependent as these games provide a language to formulate strategic scenarios [17, 18 & 19]. Taking into consideration the 4 principles and theory for co-operative gaming with restriction of players cheating, the algorithm implemented.

C) Principle of the algorithm

Consider any user \(n \in N\), given \(X_{n}\) and assuming that all other users fix their energy consumption schedule according to \(X_{n}\) by maximizing his payoff.

\[
\text{maximize}_{x_{n1}^{N}} \text{P}n( X_{n}; X - n) \quad (16)
\]

The only optimization factor is user’s \(n\) energy consumption scheduling vector as \(\Omega_{n}\) is fixed

So the maximization can be replaced by the minimization of the following equation

\[
\text{minimize}_{x_{n1}^{N}} \sum_{h=1}^{H} \text{Ch}(\sum_{a \in A_{m}} x_{h,a}^{m} + \sum_{m \in N \{n\}} t_{h}^{m}) \quad (17)
\]

User \(n\) can solve the problem if he knows the cost. \(C_{b}\) for each hour \(h \in H\) and \(1-n\)\{\[1,\ldots, In-1, In+1, \ldots, IN\]\] Each user start with some random initial conditions so he assume random vector \(l_{m}\) for any \(m \in N\) as at the beginning user \(n\) has no prior information about other users then the loop of the algorithm is executed until it converges. The new schedule is announced to the other users through broadcasting a control message and users only announce their total hourly usage and don’t announce the details about the energy consumption of their own appliances due to privacy concern.

In this paper, the ISO market datails are used [7] and no use of random values load and price data for April 2014 day 9 from ISO website are chosen to be used as the input data for total hourly load and price. Assuming that the load is divided between 4 users as assumed before. And by implementing the previous procedures on the 4 users by making some constraints that are raised from game theories:

- The sum of the 24 hour energy consumption value extracted from the calculation for user \(n\) minus the sum of the same 24 hour actual usage as extracted from the market should be an absolute value to assure that each user take his needed amount of energy
- Set a minimum and maximum value for each hour energy consumption for each user based upon previous experience of his usage
- Each user take one turn in each iteration then he announce his result to the others and the next user must take the previous user announcement as input in his calculation

By multiplying loads before the algorithm and after the rescheduling genetic algorithm with the price a total energy market profit of 615963.7$ is realized but not all users realize a positive profit one of them has negative profit as shown per the below table. By this result user no. 2 will not benefit from rescheduling his energy consumption as he will realize a negative profit so the correct decision will be to leave this user with his original
energy market will found realizing more profit to be 726207.8$ as the negative value of this user will be eliminated as shown per the below Tables 4 &5.

Table 4 Profit of each user after energy rescheduling for all users

<table>
<thead>
<tr>
<th>User</th>
<th>Total cost before optimization</th>
<th>Total cost after optimization</th>
<th>profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>User#1</td>
<td>1068046.7</td>
<td>797775.6</td>
<td>270271.1</td>
</tr>
<tr>
<td>User#2</td>
<td>640828.02</td>
<td>751072.1</td>
<td>-110244</td>
</tr>
<tr>
<td>User#3</td>
<td>1495265.4</td>
<td>1171632</td>
<td>323633.7</td>
</tr>
<tr>
<td>User#4</td>
<td>1068046.7</td>
<td>935743.7</td>
<td>132303</td>
</tr>
</tbody>
</table>

Table 5 Profit of each user after energy rescheduling for three users only

<table>
<thead>
<tr>
<th>User</th>
<th>Total cost before optimization</th>
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<tr>
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</tr>
<tr>
<td>User#4</td>
<td>1068046.7</td>
<td>935743.7</td>
<td>132303</td>
</tr>
</tbody>
</table>

CONCLUSION

By using actual market data to test, a price predictive model based on the critical peak pricing (CPP) is developed. The developed model tested using a real data to predict market prices. And the result shows a promising performance. By the integrating of heavy load detection, the profit of an energy service provider (ESP) is achieved. By using the CPP and the predicted price to calculate the profit to maximize the incentive of CPP, a method to optimize the profit of an ESP is explored. A positive profit is obtained which indicate to the success of all previous work. In this paper a way is proposed to encourage customers to implement demand response programs and rescheduling their energy consumption by proving the reduction of their bill that they will pay to the utility. An energy consumption scheduling algorithm is proposed to balance the total residential load when multiple users share a common energy source. Implementing this algorithm on a real data taken from market give results that confirm that this proposed distributed demand-side management strategy can reduce the energy cost of each user’s daily electricity charges.

REFERENCES