Chapter 89
Optimization for Family Energy Consumption in Real-Time Pricing Environment

Weipo Wu, Genke Yang, Changchun Pan and Changjiang Ju

Abstract In order to help consumers adapt to electricity consumption in real-time electricity pricing environment, an energy consumption scheme is proposed in this paper. This scheme focuses on the prediction, modeling and optimization for family energy consumption. A method based on support-vector machine (SVM) is used to predict the real-time price (RTP) and the optimization model divides every hour into equal time slots and thus provides more opportunities to schedule household appliances in proper working time. Then the simulation results show that the proposed optimal control model reduces the daily electricity expenditures.

Keywords RTP · Electricity consumption scheduling · Price prediction · Time slot

89.1 Introduction

Nowadays, real-time pricing model has been proposed in order to reflect the real supply—demand relationship in the electricity market more accurately. This pricing strategy not only reflects the actual wholesale prices but also encourages consumers to shift high-load household appliances to off-peak hours so that it can reduce their electricity payments and peak-to-average ratio (PAR) in load demand simultaneously [1, 2].

However, recent studies showed that there are two major limitations to implement the RTP strategy. On one hand, most consumers do not want to choose the RTP electricity supply system due to lack of the knowledge about it. On the other hand, the absence of automatic family energy management system is the

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W. E. Wong and T. Ma (eds.), *Emerging Technologies for Information Systems, Computing, and Management*, Lecture Notes in Electrical Engineering 236, DOI: 10.1007/978-1-4614-7010-6_89,

other element which limits the consumers to respond to the time-varying electricity prices more properly [3].

This paper focuses on the family energy consumption scheduling model which aims to solve the above problem. The second section explains details of an electricity prediction method based on SVM, and then gives the forecasting value based on the RTP data of Illinois Power Company (IPC) from January 2009 to December 2011 [4]. In the third section, it clearly describes how to schedule the consumption under different conditions. Then, it gives a model that could ensure the consumer spend the minimum payment but still finish the work in a comfort way. In the fourth section, this paper illustrates the simulation results. Finally, there is the conclusion.

89.2 Price PredictionModel

Clearly, electricity price mainly depends on the wholesale market prices, different time in the day and different weathers which determine the supply and demand of the electricity [5]. Since it has several input variables, the prediction model will be the non-linear mapping function. In order to be used in the Real-time pricing environment, this section will use the (SVM) Price Prediction Strategy [6].

Recent studies showed that hourly price of electricity is highly related with the historical price [7]. This part will analyze the RTP data by IPC from January 2009 to December 2011 [4].

The result has been showed in the Fig. 89.1, which plotted the correlation among the current hourly-prices with the same time in the past few days. Clearly indicated in the Fig. 89.1, the correlation coefficient is declining cyclically as it goes further back, and the prices have the highest correlation between two continuous days, e.g., today and yesterday. Additionally, the figure also represents a noticeable correlation between the prices today and those in the same day last week.

With consideration of these characteristics of the price series, the following vector of input features has been considered to forecast the price p_h at hour h

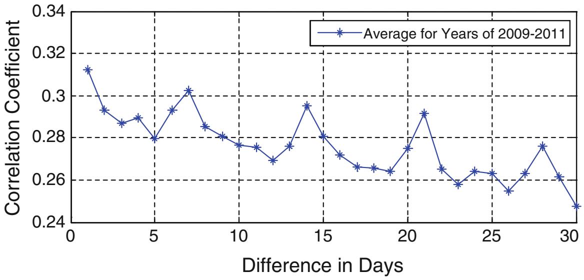


Fig. 89.1 The correlation coefficient between the same hour in different days

$$\begin{aligned} X_i = [&p_{h-1}, p_{h-2}, p_{h-22}, p_{h-23}, p_{h-24}, p_{h-25}, \\ &p_{h-26}, p_{h-167}, p_{h-168}, p_{h-169}, p_{h-192}, p_{h-193}] \end{aligned} \quad (89.1)$$

In (89.1), the first two terms that consist of price information of the two previous hours are used to model the trend of the price signal. The rest of the terms contain information about price in the previous period to model the multiple seasonality of the electricity price signal.

This paper uses LIBSVM software to perform experiments and choose Mean Squared Error (MSE) which is defined as follow to measure its prediction accuracy [8].

$$\mathrm{MSE} = \frac{1}{l}\sum_{i=1}^{l}(f(X_i) - y_i)^2 \quad (89.2)$$

where l is the number of prediction prices, y_i is the real price data and $f(X_i)$ is the forecasting price data. So it is easy to know X_i is the input vector of prediction model, f is the prediction function.

This paper chooses the data from 1st May to 31st July in 2011 as training data, and chooses the data in August as testing data as well as chooses cross-validation and grid search method to determine the penalty parameter c and kernel parameter g in LIBSVM [8]. The result about parameters is shown in Fig. 89.2(a, b) where they find the best penalty parameter $c = 0.5$ and kernel parameter $g = 4$. At the same time, the forecasting electricity price is shown in Fig. 89.3 and the prediction result approximates to the real data, where the MSE $= 0.0275$ is far less than the result of Back-Propagation Neural Network model, which is 1.1230.

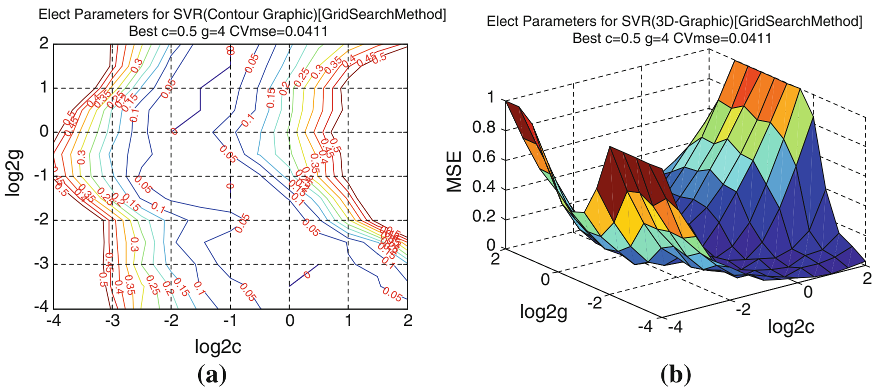


Fig. 89.2 Use cross-validation and grid search method to find the best parameters in SVM

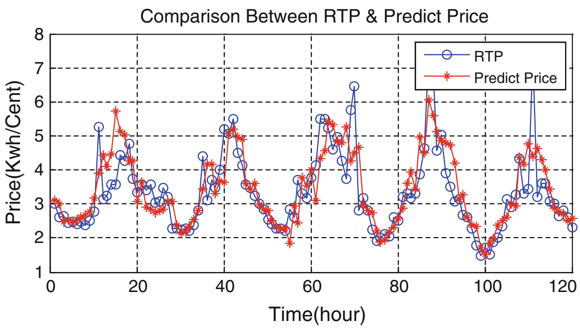


Fig. 89.3 Result when using SVM to predict the price from 5th to 9th August in 2011 of IPC

89.3 Model Formulations

This section will introduce the family energy consumption optimal control model, aiming to help each household to maximize the efficiency of electricity they are consumed, and meanwhile minimize the electricity payment they are supposed to spend.

89.3.1 Electricity Consumption Scheduling

This part will describe the energy consumption scheduling model including continuous electricity consumption and discrete electricity consumption. Additionally, the situation with uninterruptible electricity consumption will be discussed.

89.3.1.1 Continuous Electricity Consumption

Consider that each residential unit wants to optimize the electricity consumption in the next $H(H \geq 1)$ hours, where H represents the scheduling horizon and we define $\mathbf{H} = [1, \ldots, H]$. Let $\mathcal{A}$ denotes the set of appliances, which could include washing machine, refrigerator, air condition, etc. Because the working time of most household appliances does not occupy the whole hour, therefore, the time axis of each hour could be divided into equal time slots Δ. It has to ensure the number of time slots in each hour $N = 1/\Delta$ is an integer. Thus, the number of total time slots in scheduling horizon is $L = N * H$, where $\mathbf{L} = [1, \ldots, L]$.As a result, for each appliance $a \in \mathcal{A}$, we define an electricity consumption scheduling vector [7]

$$\mathbf{e}_a = \left[e_a^1, \ldots, e_a^n, \ldots, e_a^L\right] \tag{89.3}$$

where e_a^n means how much electricity the appliance a consumed in the n^{th} time slot. So it is easy to know $e_a^n \geq 0$ when $n \in \mathbf{L}$ and $a \in \mathcal{A}$.

Now, assume consumers set their own scheduling horizon for each household appliance. For example, consumers want the automatic clean machine start to clean the house at their working time. Hence, they set the machine's scheduling horizon from 8:00 A.M. to 17:00 P.M. Then, electricity consumption *Ea* is expressed as follow,

$$\sum_{n=\alpha_a}^{\beta_a} e_a^n = E_a \tag{89.4}$$

where $\alpha_a \geq 1$ is the beginning of time interval, and $\beta_a \geq \alpha_a$ is the ending of time interval of the scheduling horizon for appliance a.

However, as we know, the household appliance is working in a limited power. So the constraint could be expressed as

$$\gamma_a^{min}/N \leq e_a^n \leq \gamma_a^{max}/N, \forall n \in [\alpha_a,\ \beta_a] \tag{89.5}$$

which means the scheduled energy consumption of appliance a in hour h is bounded between γ_a^{min} and γ_a^{max}.

Due to the assigned electricity load for each family at each hour is limited, so the limited equation is

$$\sum_{a \in \mathcal{A}} e_a^n \leq \boldsymbol{E}_{max}/N, \quad \forall n \in \boldsymbol{L}, h \in \boldsymbol{H} \tag{89.6}$$

where $E_{max} \geq 0$ is the upper limited power in hour h for a family.

89.3.1.2 Discrete Electricity Consumption

So far it considers the household appliances consume electricity in a continuous way. However, some households work with discrete electricity consumption level, which $\mathcal{A}_D$ denotes. In other words, the scheduled electricity consumption for some appliance may only take the discrete values γ_a^{min}/N and γ_a^{max}/N when the appliance is "off" and "on".

In order to describe this kind of households, let y_a^n denote an auxiliary binary variable, when $y_a^n = 1$ the appliance a is "on" and when $y_a^n = 0$ the appliance a is "off". By definition, the former requires an energy consumption level of $e_a^n = \gamma_a^{min}/N$ while the latter is $e_a^n = \gamma_a^{max}/N$. Therefore, for each appliance $a \in \mathcal{A}_D$, the relationship between the energy consumption scheduling vector $\boldsymbol{e_a}$ and the auxiliary $y_a = [y_a^{\alpha_a}, \ldots, y_a^n, \ldots, y_a^{\beta_a}]$ can be expressed as follows:

$$e_a^n = y_a^n * \gamma_a^{max}/N + \left(1 - y_a^n\right) * \gamma_a^{min}/N \tag{89.7}$$

89.3.1.3 Uninterruptible Electricity Consumption

Under another circumstance, the household may have some appliances that have to work in uninterruptible electricity consumption condition. We call them uninterruptible loads which mean once the appliances start operation, their operation need to continue until they finish. This paper defines them as $\mathcal{A}_U$.

Consider an uninterruptible load $a \in \mathcal{A}_U$ working in discrete energy consumption level, let θ_a denote the duration of time, in number of time slots, the appliance a needs to operate at power level γ_a^{max}/N. Let's impose z_a^n as an auxiliary binary variable as well. When the uninterruptible load starts to operate, $z_a^n = 1$, otherwise $z_a^n = 0$. So equations are expressed as follow,

$$\begin{aligned} &\sum_{n=\alpha_a}^{\beta_a-\theta_a+1} z_a^n = 1, \qquad \forall a \in \mathcal{A}_U \\ z_a^n = 0, \quad &\forall n \in \mathbf{L} \backslash [\alpha_a, \ldots, \beta_a - \theta_a + 1], \end{aligned} \tag{89.8}$$

that is, the operation of appliance a is to begin working between time slot α_a and $\beta_a - \theta_a + 1$.We can relate the start time vector $z_a = [z_a^{\alpha_a}, \ldots, z_a^n, \ldots, z_a^{\beta_a - \theta_a + 1}]$ with auxiliary vector $\mathrm{y_a}$ as

$$\mathrm{y_a^n \geq z_a^n, \ldots, y_a^{\beta_a - \theta_a + 1} \geq z_a^n, \forall n \in [\alpha_a, \ldots, \beta_a - \theta_a + 1]} \tag{89.9}$$

from (89.8), if $\mathrm{z_a^n} = 1$, $\mathrm{y_a^n = y_a^{n+1} = \ldots = y_a^{n+\theta_a-1}} = 1$. On the other hand, from (89.7) and (89.9), it is easy to get $\mathrm{e_a^n = e_a^{n+1} = \ldots = e_a^{n+\theta_a-1}} = \gamma_a^{max}/N$.

89.3.2 Problem Formulation

In this section, assume that each household is equipped with a smart meter with two-way communication and the real-time prices are provided by the utility company via local area network. The consumers choose their requirements by selecting parameters E_a, α_a, β_a, γ_a^{min} and γ_a^{max} as well as adjusted the appliance's energy consumption ways, such as continuous way, discrete way or interruptible way. Consequently, the electricity scheduler determines the optimal choice of electricity consumption scheduling vector $\boldsymbol{e}$. Then the resulting electricity consumption schedule is applied to all household appliances.

To minimize the energy payment, the optimal control model is

$$\min \sum_{h=1}^{H} p_h(E_h) * E_h \tag{89.10}$$

where H is the schedule horizon and $h \in \boldsymbol{H}$ as well as $p_h(E_h)$ is the electricity price of hour h. Additionally, Formulation (89.4–89.9) are the constraints of this model and how much energy is consumed in hour$h$ is calculated as follow:

$$E_h = \sum_{n=(h-1)*N+1}^{h*N} \sum_{a \in \mathcal{A}} e_a^n \qquad (89.11)$$

89.4 Simulations

This section will present the simulation results and evaluate the performance of the proposed model with price prediction. Consider a single household with different appliances and assume that it has adopted the RTP program. The test period is one month from 1st August to 31st August in 2011, which includes 31 days in total. For the purpose of this paper, assume that the number of appliances used in this household each day varies from 10 to 15. They include certain appliances with fixed consumption schedules such as lighting, heating, refrigerator, etc., and appliances with flexible energy consumption schedules such as house clean machine, dishwasher, clothes washer, and PHEV, etc [9]. Here assume that the scheduling horizon $H = 24$. As the user has subscribed for the RTP program adopted by IPC, this would require price prediction as discussed in Sect. 89.3.

89.4.1 Gains with Control Model

This paper simulates the energy consumption in two ways. In the first way, consider the household consume energy with the proposed optimal model while the other way is to use power as usual. As indicated in Fig. 89.4, the payment with energy optimal control and the parameter $N = 1$ is less than the expenditures without control. In the August 2011, the user only need to pay 29.26 dollars for the electricity consumption with scheduling optimal control, while 32.41 dollars will be cost if there was not an energy optimal control scheme, which is nearly 10 % cheaper. However, there still have some exceptions that in 3rd and 26th of August, the electricity charges with control are higher than that without control. It is easy to understand as the error of price forecasting. Nevertheless, the differences between those payments are not significant; therefore, this control scheme could be seen as useful.

89.4.2 The Influence of the Parameter N

Here discuss the influence of parameter N. it uses the optimal control model with different value of N. Figure 89.5 shows that the electricity payment with 4 time slot per hour ($N = 4$) will pay 4.585 % less than that with only 1 time slot per hour

Fig. 89.4 Payment comparison between control and uncontrol

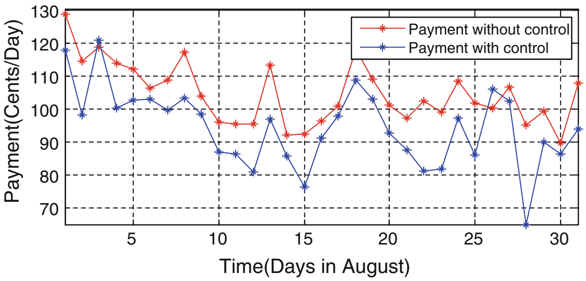


Fig. 89.5 Payment comparison between different numbers of time slots

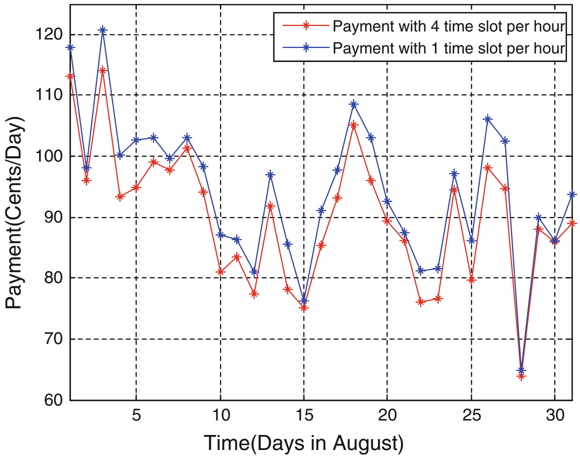
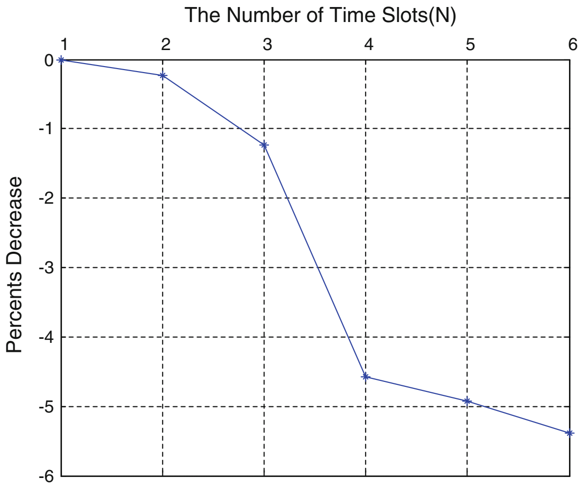


Fig. 89.6 Payment decrease with the increase of N



(parameter $N = 1$). This is mainly due to the fact that with more time slots, the control model will have more schedule range to ensure the appliances to work in more proper time, such as off-peak time.

According to Fig. 89.6, the payment is decreasing when parameter N is increasing. The reason is the same as above, i.e., with more time slot in an hour, the optimal control model will have more opportunities to schedule the household appliances in order to decrease the expenses. However, as presented in the Fig. 89.6, the decreasing rate of payment is lower when time slot s higher than 5. Thus, there must be a proper number of N could help the consumer to save maximum money. However, because different consumer will set their own parameters, therefore, the appropriate of N is hard to measure based on single benchmark. The graph here only describes the overall pattern.

89.5 Conclusion

This paper proposes a family energy consumption optimal control model which is applied in the environment installed smart meter and aims to minimize the electricity payment based on the needs declared by users. It argues that any load control in real-time electricity pricing environment essentially requires some price prediction capabilities to enable planning for the household energy consumption in advance. This paper uses SVM method with proper input values to forecast the hourly-based prices adopted by IPC from January 2009 to December 2011 and obtains the best parameters for the prediction model. Then it describes the electricity consumption scheduling model where it divides each hour into equal time slots. In the end, it makes a simulation whose results show that the optimal control model reduces the daily electricity expenditures, which will encourage the users to participate in the proposed control model.

Acknowledgments This research is supported by National Nature Science Foundation of China Grant 61074150 and Grant 61203178.

References

1. Kim, T., Poor, H.V.: Scheduling power consumption with price uncertainty. IEEE Trans. Smart Grid **2**(3), 519–527 (2011)
2. Ipakchi, A., Albuyeh, F.: Grid of the future. IEEE Power Energy Msg **8**(4), 52–62 (2009)
3. Ann-Piette, M., Ghatikar, G., Kiliccote, S., Watson, D., Koch, E., Hennage, D.: Design and operation of an open, interoperable automated demand response infrastructure for commercial buildings. J. Comput. Inf. Sci. Eng. **9**, 1–9 (2009)
4. Real-time pricing for residential customers, Ameren Illinois Power Co. http://www.ameren.com/sites/aiu/ElectricChoice/Pages/Home.aspx (2012)
5. Zhang, X., Wang, X.: Review of the short-term electricity price forecasting. Autom. Electr. Power Sys. **30**(3), 92–101 (2006)

6. Vapnik, V.: The nature of statistical learning theory. Springer, New York (1995)
7. Mohsenian-Rad, A.H., Leon-Garcia, A.: Optimal residential load control with price prediction in real-time electricity pricing environments. IEEE Trans. Smart Grid. **1**(2), 120–133 (2010)
8. Chang, C., Lin, C.: LIBSVM: a library for support vector machines. http://www.csie.ntu.edu.tw/cjlin/libsvm (2012)
9. Natural Resources Canada.: Energy consumption of major household appliances shipped in Canada. http://oee.nrcan.gc.ca/Publications/statistics/cama07/pdf/cama07.pdf (2007)