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A Research of Real-Time Pricing Mechanism and Its Characteristics

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Abstract

Real-Time Pricing (RTP) is proposed as an effective Demand-Side Management (DSM) to adjust the load curve in order to achieve the peak load shifting. At the same time, the RTP mechanism can also raise the revenue of the supply-side and reduce the electricity expenses of consumers to achieve a win-win situation. In this paper, a real-time pricing algorithm based on price elasticity theory is proposed to analyze the energy consumption and the response of the consumers in smart grid structure. We consider a smart grid equipped with smart meters and two-way communication system. By using real data to simulate the proposed model, some characteristics of RTP are summarized as follows: 1) Under the condition of the real data, the adjustment of load curve and reducing the expenses of consumers is obviously. But the profit of power supplier is difficult to ensure. If we balance the profits of both sides, the supplier and consumers, the profits of both sides and the adjustment of load curve will be relatively limited. 2) If assuming the response degree of consumers to real-time prices is high enough, the RTP mechanism can achieve the expected effect. 3, If the cost of supply-side (day-ahead price) fluctuates dramatically, the profits of both sides can be ensured to achieve the expected effect.

Keywords

Smart Grid, Demand-Side Management, Real-Time Pricing

1. Introduction

With development of the smart grid, real-time pricing (RTP) is considered as an effective measure of demand-side management (DSM). In a smart environment the information and data transmission between the power supply-side and demand-side is becoming much more effective. A framework of smart grid that consists of smart meters, two-way communication, local area network structure, is depicted in **Figure 1**. Each consumer is equipped with a smart meter and an energy management system that schedules his/her energy consumption in response to real-time prices. The meters are connected to the utility through a communication network such as local area network that allows two-way communication between electricity provider and the meter. With this capability, besides receiving real-time prices from the electricity provider, the electricity provider would have access to real-time information on the electricity consumption of each consumer.

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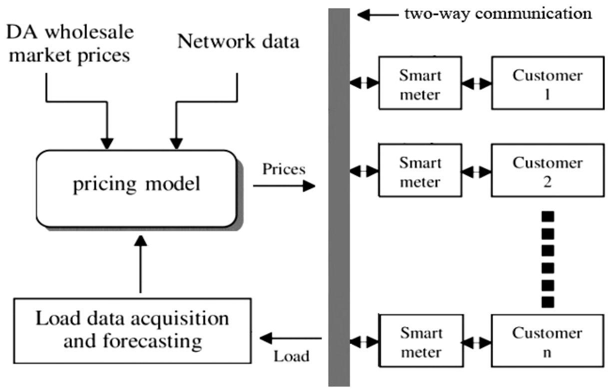

Figure 1. Real-time pricing framework in smart grid.

In traditional power system operation and management, more attention is given to supply-side compared to demand. Consumers are assumed to be unwilling or incapable of actively changing their consumption behavior. Therefore, massive demand during on-peak periods leading to higher generation costs. On the other hand, during off-peak periods, the phenomenon of power redundancy is gradually obvious. In addition to high variability of market prices, declining reserve margins, transmission congestion, and environmental issues increase the importance of improving the link between supply-side and demand-side [1].

By recent developments on smart metering technologies in smart grid, a number of utilities and states have executed a variety of time-based pricing programs. For instance, a day-ahead real-time pricing (DA-RTP) tariff used by the Illinois Power Company in the United States [2], several critical peak pricing pilots in California, Idaho, and New Jersey [3], and the three-level (on-peak, mid-peak, off-peak) TOU pricing tariff in Ontario, Canada [4]. However, recent studies have shown that exposing end-use consumers to hourly real-time prices is known as the most efficient tool that can urge consumers to consume more wisely and efficiently [5]. Given the recent increases in energy prices, RTP provides opportunity to consumers to reduce their energy bills by taking the advantage of lower energy prices in some periods and reducing their consumption when energy prices are high.

There has been much attention paid to pricing programs in recent years. A novel real-time pricing model based on smart metering and demand-side management is presented in [1] [6]. The model in [1] is used price elasticity theory to depict the response degree of consumers. A distributed framework for demand response and user adaptation in smart grid networks is proposed in [7]. In paper [8] the problem of grid-to-vehicle energy exchange between a smart grid and plug-in electric vehicle groups (PEVGs) is studied using a noncooperative Stackelberg game. In [9] [10], the formulation and critical assessment of a novel type of demand response program targeting retail customers who are equipped with smart meters yet still face a flat rate.

2. Mathematical Formulation

2.1. Objective Function

The objective function is formulated as (1) here. It aims to maximize the energy provider's profits, which is defined as the difference between its revenue due to selling energy to consumers and the cost of purchasing energy from the day-ahead electricity market.

$$\text{Max}\sum_{t=1}^{24}\left\{\left[\sum_{c=1}^{n} d_c(t)\rho_c(t)\right]-p_{sub}(t)\rho_E(t)\right\} \quad (1)$$

where $P_{sub}(t)$ is the amount of power purchased by the energy provider from DA energy market at Hour *t*; $\rho_E(t)$ is the DA energy market price at Hour *t*; $d_c(t)$ is the consumption that customer response to the real-time prices at Hour *t*; $\rho_c(t)$ is the real-time price at Hour *t*; and *n* is the number of consumers.

In this paper, the demand response model is set by using price elasticity theory. The self and cross elasticity represent the response of consumers at each period respectively.

Consumer response to RTP:

$$d_c(t)=d_{0c}(t)\left\{1+\frac{\varepsilon_c(t)\left[\rho_c(t)-\rho_{0c}(t)\right]}{\rho_{0c}(t)}+\sum_{\substack{h=1\\h\neq t}}^{24}\varepsilon_c(t,h)\frac{\left[\rho_c(h)-\rho_{0c}(h)\right]}{\rho_{0c}(h)}\right\} \quad (2)$$

where $\varepsilon_c(t)$ and $\varepsilon_c(t,h)$ are self and cross price elasticity of the demand respectively; $\rho_{0c}(t)$ is base energy price set by the historical data; $d_{0c}(t)$ is the initial demand forecast.

2.2. Constraints

Constrains are composed of following several components. The first is the load flow of the power grid. The feeders flow limits (3), bus voltage limits (4) and grid ramping constraints (7) are taken into account in the model. Secondly, implementing RTP is in order to change the consumption habit of consumers, not to reduce the power consumption. So the limits on daily consumption (5) ensure the consumption is unchanged after implementing the RTP model. As mentioned in (6), the real-time prices have to be considered hedge consumers against high energy prices. The last constraints ensure the profits of consumers (8).

Subject to:

Feeders flow limits:

$$\left|S_{t,ij}(V_t,\delta_t)\right|\le S_{t,ij}^{\max} \quad (3)$$

$S_{t,ij}$ is the apparent power flow between node *i* and *j*; V_t and δ_t is voltage amplitude and voltage angle; $S_{t,ij}^{\max}$ is the capacity of the line between node *i* and *j*.

Bus voltage limits:

$$V_{t,i}^{\min}\le V_{t,i}\le V_{t,i}^{\max} \quad (4)$$

$V_{t,i}^{\min}$ and $V_{t,i}^{\max}$ are maximum and minimum voltage magnitude at node *i*.

Limit on daily consumption:

$$\sum_{t=1}^{24}d_c(t)=d_c^{\text{day}} \quad (5)$$

d_c^{day} is the daily consumption set by historical data.

Price limits:

$$\rho_c^{\min}(t)\le\rho_c(t)\le\rho_c^{\max}(t) \quad (6)$$

$\rho_c^{\max}(t)$ and $\rho_c^{\min}(t)$ is the price cap and the price floor of the RTP.

Grid ramping constraint:

$$(70\%)\left|S_{t\text{-}1}\right|\le\left|S_t\right|\le(130\%)\left|S_{t\text{-}1}\right| \quad (7)$$

The constraint represents the power amplitude is pegged at 30 per cent between two neighboring hours.
Limit on consumers' revenue:

$$\sum_{t=1}^{24}d_c(t)\rho_c(t)<\sum_{t=1}^{24}d_{0c}(t)\rho_{0c}(t) \quad (8)$$

The constraint represents the expenses of consumers are reduced by implementing RTP. Consumers enjoy a low price when they respond the RTP actively.

3. Numerical Case Study

3.1. Simulated Network

The proposed model is simulated in a 33-node radial distribution system shown in **Figure 2** references [12]. The loads in this system are characterized based on consumer type. Each consumer belongs to one of the 4 categories (residential, commercial, industrial and some new type of power consumers). Consumers are divided into 4 categories in **Table 1**. The new type of power consumers is considered as a group of users who respond to the RTP more actively than the other type of consumers, such as charging of electric vehicles, etc. which is introduced in [11]. References [13]-[15] the self and cross elasticity of different consumers in shown in **Table 2**. On-peak time is (7 - 11, 17 - 19), mid-peak is (11 - 17), off-peak is (19 - 7).

3.2. Simulation Data

The power market data of this paper is from Ontario, Canada. Feb.4.2011. The average market prices during February and August were 3.3 ¢/kWh and 3.5 ¢/kWh, respectively. The average global adjustments were 3.5 ¢/kWh and 3.6 ¢/kWh during February and August 2011, respectively. Therefore, average RPP prices were

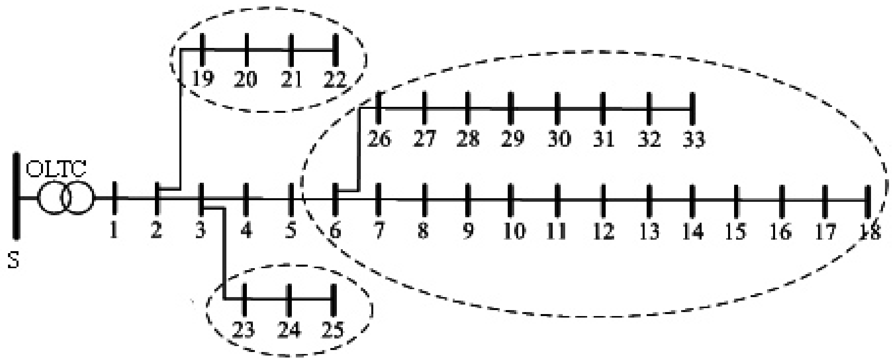

Figure 2. IEEE 33-node distribution network.

Table 1. Load types at different buses of the 33-node distribution test system.

Type of consumer	load buses
Residential	2, 4,5, 8, 9, 10, 12, 14, 15, 16, 17, 18, 19, 20, 21, 25, 26, 27, 30, 31, 32
Commercial	1, 3, 6, 7, 13, 28
Industrial	23, 24
New type of consumers	11, 22, 31

Table 2. The self and cross elasticity of different consumers in 24 hours.

Type of consumers		on peak	mid peak	off peak
	on peak	−0.15	0.08	0.07
residential	mid peak	0.08	−0.13	0.05
	off peak	0.07	0.05	−0.12
commercial	on peak	−0.13	0.05	0.08
	mid peak	0.05	−0.13	0.08
	off peak	0.08	0.08	−0.16
industrial	on peak	−0.13	0.08	0.05
	mid peak	0.08	−0.13	0.06
	off peak	0.05	0.06	−0.16
	on peak	−0.22	0.10	0.12
New types of consumers	mid peak	0.10	−0.17	0.07
	off peak	0.12	0.07	−0.19

6.8 ¢/kWh and 7.1 ¢/kWh during February and August 2011, respectively as reported in [13]-[16]. The average RPP prices are assumed as base energy price (tariff) in the numerical studies. The load curve and day-ahead price is shown in **Figure 3** and **Figure 4**.

3.3. Simulation Results

The simulation is assumed that all the nodes of test system are the residential, industrial, commercial and new type of consumers respectively. Then demand curve data is shown in **Figure 5-8**. Then add a weight value according to the **Table 2**. to calculate the data of whole society (33-node) in **Figure 9**. The proposed model is simulated in Matlab with yalmip toolbox which is based on primal-dual interior point algorithm.

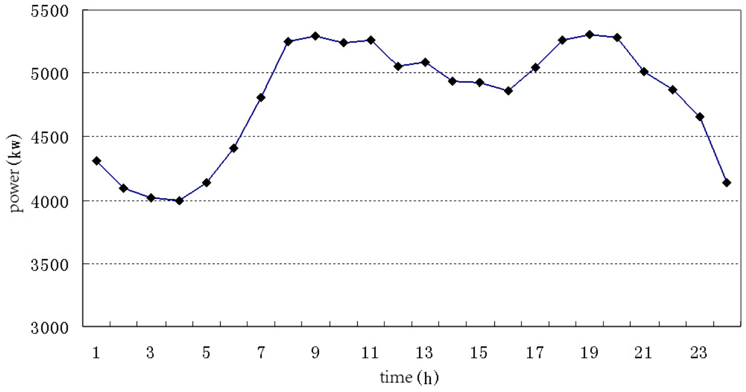

Figure 3. Daily demand curves (Ontario Canada) Feb.4th.2011.

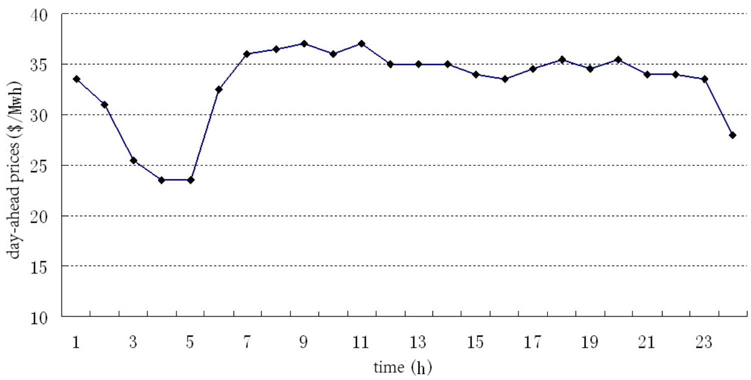

Figure 4. Day-ahead price (Ontario Canada) Feb.4th. 2011.

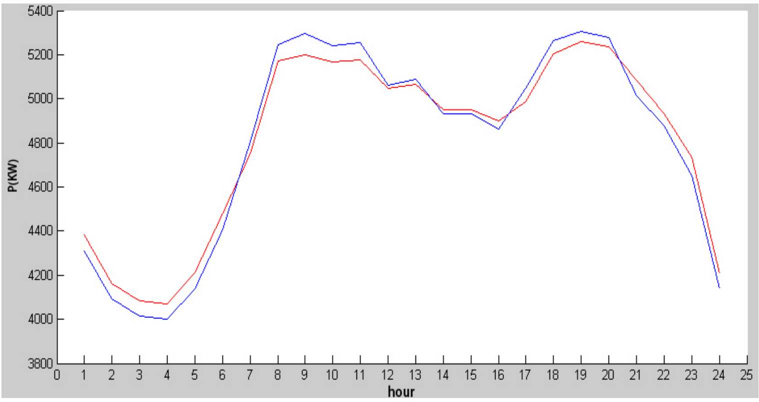

Figure 5. Daily demand curve (residential).

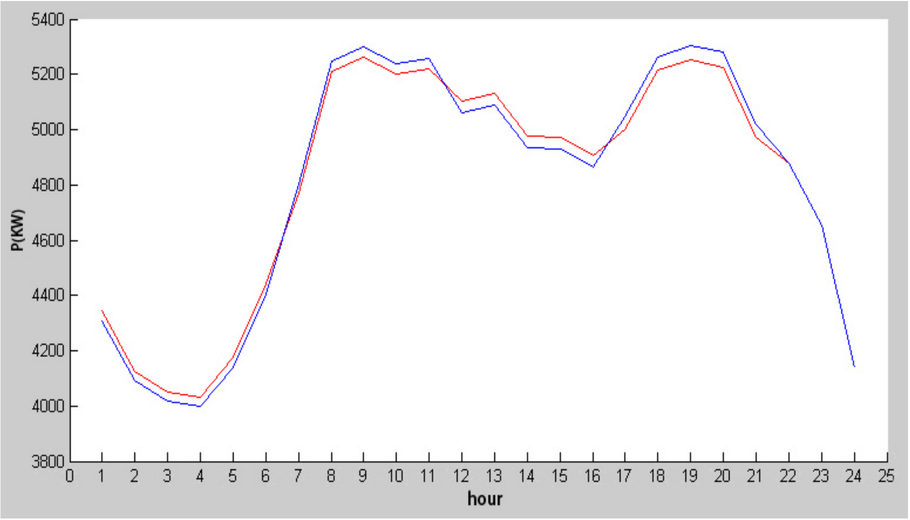

Figure 6. Daily demand curve (industrial).

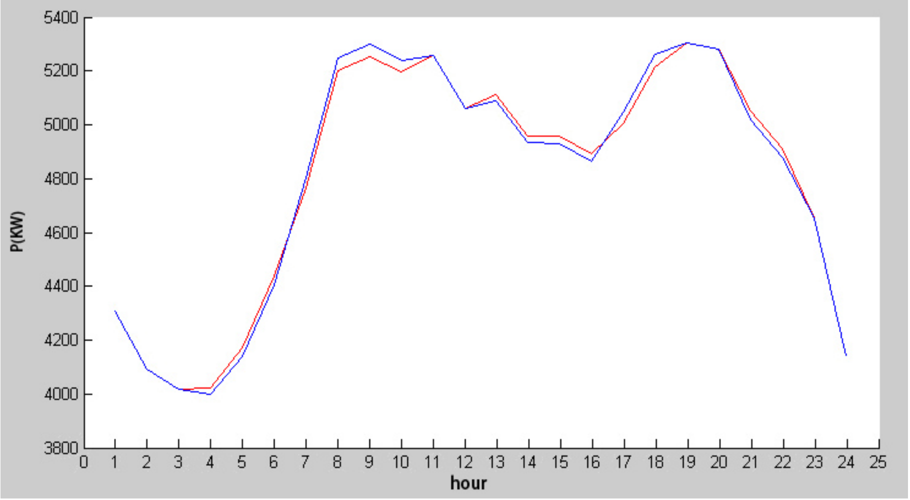

Figure 7. Daily demand curve (commercial).

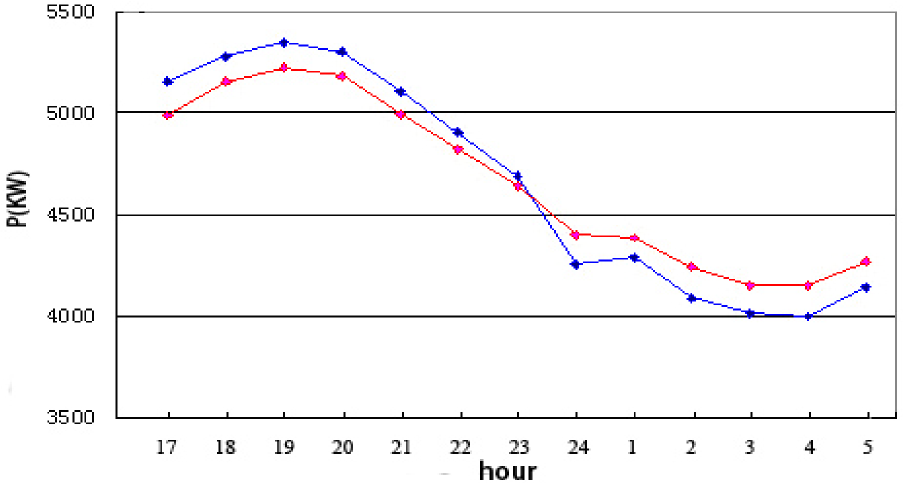

Figure 8. Daily demand curve (new type of consumer such as electric vehicle).

The blue line is the original load curve and the red one is the load data of response to RTP model. Residential consumers are willing to shift more load from on-peak time (7 A.M-11 A.M) to off-peak (7 P.M.-6 A.M.) than industrial and commercial. Commercial consumers are willing to shift more load from on-peak time to mid-peak (11 A.M.-5 P.M.) and the load shifting of industrial from on-peak to off-peak and mid-peak is relative to the average. The new type of power consumers like electric vehicle is considered as a high elasticity group in 5 P.M. to 6 A.M. Because of the charging of electric vehicle will be controlled by smart meter in the future in reference [11]. Due to the new type of consumers is set by a higher elasticity than other categories, the shifting of the load curve is more obvious. By adding the weight value, the curve data of whole society is shown as follow: The load is shifted about 1.47% during on-peak time and the load of off-peak and mid-peak is increased about 1.69% and 0.16% respectively. The real-time prices are shown in **Figure 10**. The electricity bills of consumers are reduced about 0.49%, but the profits of supply side are also reduced about 0.88%. So that is not a expected result. If we set a constraint that the profits of supply side must be raised, then there is no optimal solution in this simulation. In the follow section three cases are proposed to analyze the model in which situations the real-time pricing model can ensure the profits of supply-side to achieve the expected result.

4. Further Analysis of the Simulation Result

The initial result is not expected because of the profits of supply-side can be ensure even with the risk of loss. Therefore, there are some limitations to the real-time pricing mechanism. Three cases are proposed to analyze the RTP in which situations can achieve a win-win situation.

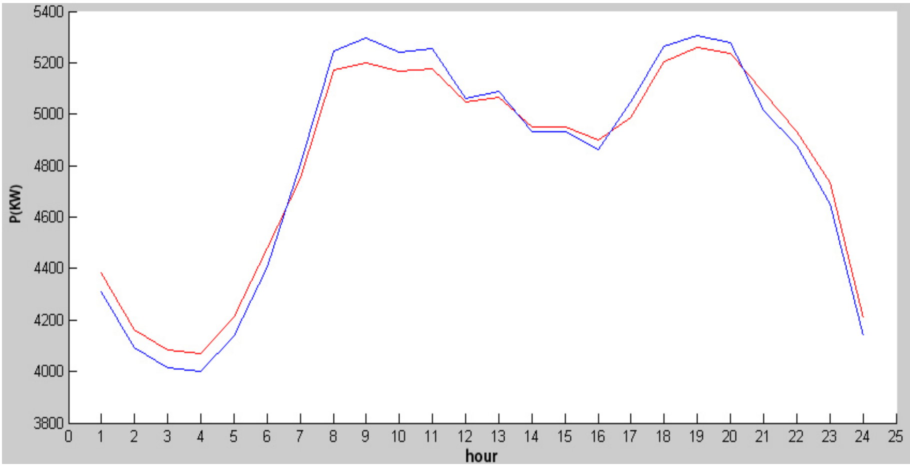

Figure 9. Daily demand curve (whole society 33-node).

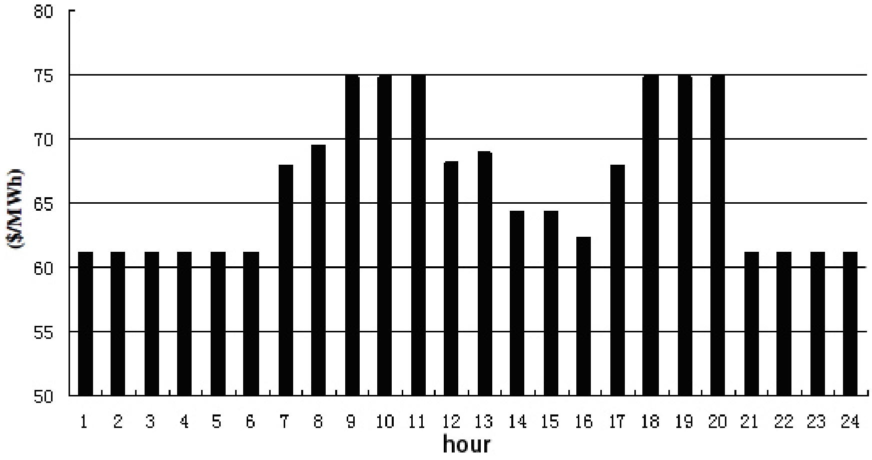

Figure 10. Real-time prices in 24 hours.

4.1. Raise the Range of Real-Time Prices to Balance the Profits between Two Sides

Due of the RTP is different value for each kind of consumers, such as residential, industrial and commercial consumers. In the case of the same model and data, we adjust the fluctuation range of the RTP to 95% - 115% of the historical feed-in tariff (raised from 90% - 110%). The load curve is show in **Figure 11.** The profits of supply-side is increased about 0.03% and the electric expense of consumers is reduced about 0.06%. The simulation result achieves expected effect preliminarily, but the profits of both sides and the adjustment of load curve is relatively limited. The peak-shift of the load curve is not obvious as the RTP model set as 90% - 110%. The on-peak load is shifted about 0.9% and the off-peak load is increased about 0.75%. The prices data is shown in **Figure 12**.

4.2. The High Enough Elasticity Leads to Expected Result

Obviously, the higher price elasticity is better for the result of RTP simulation. Thus, if we choose a part of consumers to simulate RTP mechanism who get high elasticities means they respond to RTP more actively, it can achieve the expected result. When the elasticity is set about 0.4 - 0.45, the load curve is shown in **Figure 13**. The profits of supply-side are increased about 0.15% and the electricity expenses of consumers are reduced about 0.28%. The adjustment of the load curve is remarkable. The on-peak load is shifted about 2.12% and the off-peak load is increased about 3.03%. The prices data is shown in **Figure 14**.

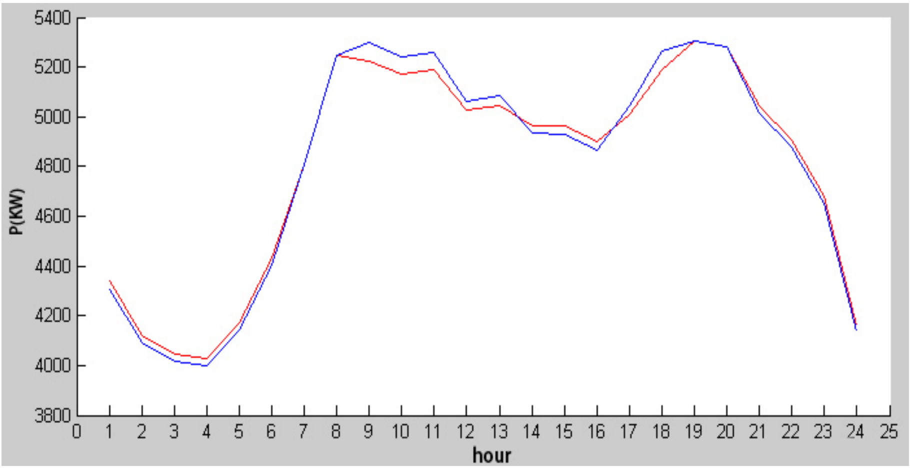

Figure 11. The load curve adjusted by the range of prices.

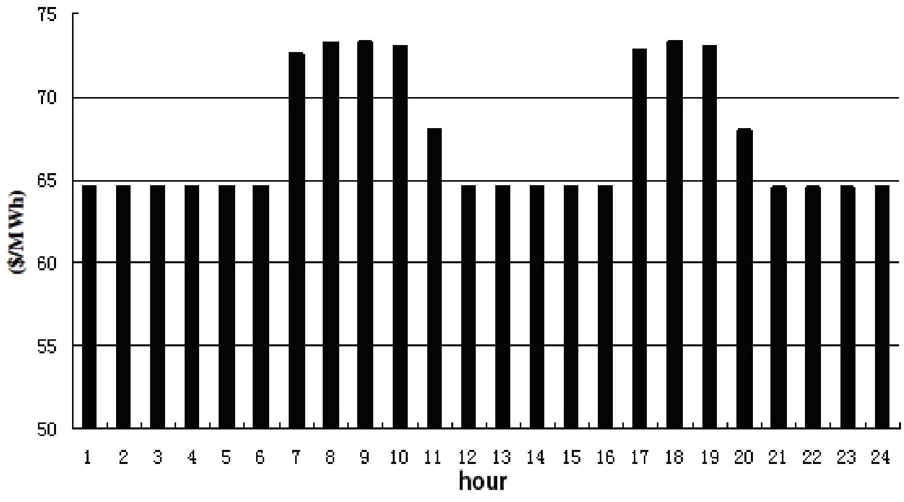

Figure 12. The real-times prices adjusted by the range of prices.

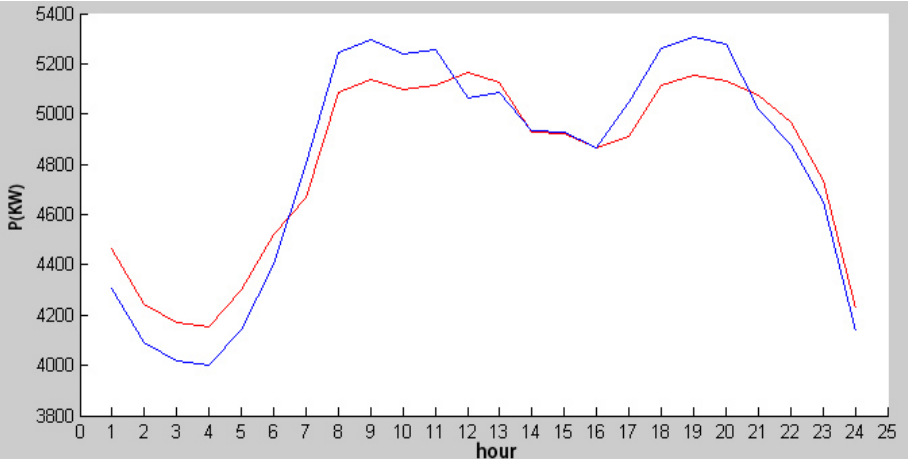

Figure 13. The load curve adjusted by elastics.

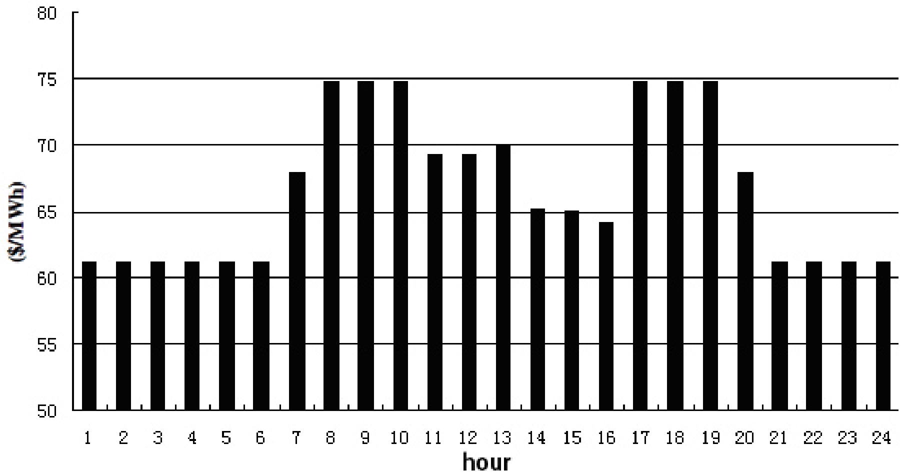

Figure 14. The real-times prices adjusted by elastics.

4.3. Suitable Day-Ahead Prices Ensure the Profits of Supply-Side

From the previous simulation result, the load curve and the profits of consumers can achieve the expected effect. But the revenue of the supply-side is difficult to be ensured. Therefore, the cost of supply-side is worth for further analysis. If the day-ahead market price fluctuates more extremely, it suits RTP better. With the same model and power system data, the on-peak prices and off-peak prices of day-ahead market is set about 2.7:1 (on-peak: off-peak). The profits of the supply side are increased about 0.17%, and the load curve and the profits of consumers can achieve the expected effect as before.

5. Conclusion

Under the background of real-time pricing model based on price electricity theory, the simulation by using real data shows RTP is competent in peak load shifting to adjust the load curve. Due to the demand response of consumers, electricity bills of the active consumers are reduced dramatically. But the profits of the supply-side cannot be ensured even with a risk of loss. Three cases are proposed to analyze in which situations RTP will achieve the expected result. 1) If we balance the profits of both sides, the supplier and consumers, the profits of both sides and the adjustment of load curve will be relatively limited. 2) If assuming the response of consumers to real-time prices is active enough, the RTP mechanism can achieve the expected effect. 3) If the cost of the power supplier (day-ahead prices) fluctuates dramatically, the profits of both sides can be ensured to achieve the expected result.

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