Research Article

Data-Driven Consumption Load Monitoring and Adjustment Strategy in Smart Grid

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The enhancement of the intelligent construction of the power grid and widespread popularity of smart meters enable large amounts of electrical energy consumption data to be collected and analyzed. Based on the data, the energy provider gives a guiding price in the future periods to users. It encourages users to be more economical and smarter in the process of using electricity. By applying the social welfare model to equate demand and supply in every time interval, we gain the optimal prices and generation capacity. Nevertheless, the truth is that there is a great gap between the consumers' booked electrical energy consumption and the optimal generation capacity, causing the power system overload and even outage. This article puts forward a novel automatic process control strategy in order to monitor the gap between the consumers' booked electrical energy consumption and optimal generation capacity by using statistical method to predict the future one. When the predicted value exceeds the boundary, the energy provider adopts the changeable electricity price to stimulate consumers to adjust their electrical energy demands so that it can have smoothly actual electrical energy consumption. Our adjustment method is data-driven exponential function-based adjustment. Case study results show that the strategy can obtain small adjustment times, stable actual consumption load, and controllable prediction errors. Different from the linear monitoring and adjustment strategy, our approach obtains almost the same adjustment frequency, less standard deviation of residuals, and higher total social welfare and energy provider profit.

1. Introduction

With the development of urbanization, human beings' material living quality has improved dramatically. However, some issues such as the environmental pollution also have emerged. In order to decrease the environmental pollution and avoid overconsumption of resources, words like peak carbon dioxide emissions and carbon neutrality have been hotly discussed. Mentioning energy consumption, human beings turn to some clean sustainable energy resources including hydropower and solar energy rather than restricting traditional coal fossil energy.

The limitation of traditional power grid's rigid construction, namely, the lack of flexibility for grid connection with new energy and the delays in the transmission of information due to the backward communication network and so on, may cause problems, for example, the supply-demand imbalance. Due to the defects of the previous generation of

grid and the emergence of mobile communication technology, smart grid was put forward by IBM (in America) in 2006, "next generation power grid" [1]. Not only America and EU countries but also China has picked up some cities as pilot ones for SG (smart grid) [2]. Compared with traditional grid, SG has the following advantages: timely reliable two-way communication among data on the network, the supply-demand balance on account of information interaction, simple and convenient storage of the distribution energy for security of the microgrid connection benefiting from the development of high capacity battery technology, and highly efficient calculating ability generated from the creative model and smart algorithm.

Smart meter develops rapidly with the gradually mature communication technology, which integrates the metering and data interaction functions of traditional one. So, users and energy providers can exchange data. Meanwhile, it also can analyze, forecast, and manage the consumption load.

Equipped with advanced sensor technology and reliable terminal equipment, real-time pricing (RTP) is booming. Different from traditional pricing structures, reasonable RTP can keep supply and demand in balance and keep the consumers' and suppliers' comfort maximized, because it has the flexible and intelligent characteristics.

The ultimate purpose of RTP research by domestic and foreign experts is to achieve maximized total social welfare [3, 4]. For this aim, a distributed dynamic pricing algorithm was developed to obtain peak-shaving and valley-filling [4]. Lately, this sort of RTP models has been advanced vigorously in terms of model improvement and stronger algorithm convergence. Chiu et al. [5] researched on an energy transaction billing system by using a dynamic pricing mechanism. Zhu et al. [6] got a better rate of convergence and a better operation effect by solving the model with ADMM algorithm.

RTP highlights the stable and reliable theoretical pricing policy and optimal generation capacity, but it is out of line with reality. The original intention is to guide users to make rational use of electric energy through changing electricity prices and balance the smart grid. Nevertheless, the truth is that the majority of consumers are unwilling to adjust their electricity demand with the ever-changing electricity price every hour. That causes the practical electrical energy consumption to lose control again and leads to the loss of the smart grid stability and reliability. Even in extreme cases, the fact that the energy provider offers the booked consumption to the users may cause blackouts at peak time. To solve the blackout, the electricity companies and power plants have to face the increasing energy cost, which is far more than the revenues. That is the least thing that the energy provider wants to have. In order to prevent this, we should work out a solution based on the operation of RTP model. It can not only make the power system have a limited changing price through the automatic monitoring but also have a smooth and steady practical electrical energy consumption. In other words, the users' practical electrical energy consumption is close to the optimal generation capacity from the RTP model. In the existing literature, there are many studies on how to manage the electrical energy consumption in smart grid. However, they rarely consider how to reduce the adjustment frequency of electricity price [7, 8].

The automatic process control (APC) strategy can make up for this shortcoming. It can offer effective process monitoring and adjustment. Box [9] applied APC method to product control. We will make an adjustment when the process is beyond the boundary set before. In this way, the adjustment frequency will decrease and the production quality will often be controlled in a certain range. The APC strategy is widely used in product, manufacture, and service fields. Hernández et al. [10] put forward a control tool to monitor variables. Yuan et al. [11] studied an APC chart to identify exceptions. To monitor the gap between the booked and optimal electrical energy consumptions, He et al. [12] researched a line function-based APC strategy. However, the APC strategy has not been widely used in SG [13–15].

A new data-driven exponential function-based APC strategy is proposed in this paper. We use exponentially weighted moving average (EWMA) to monitor electrical energy consumption. After obtaining the dynamic pricing from energy providers, the users can book one day or more of electricity in advance through the smart meters. At that time, the energy providers can monitor users' booked consumption load and calculate the difference between the optimal generation capacity and it. Since then, it is the turn to use data-driven APC scheme to manage electrical energy consumption by changing the dynamic pricing. There is a long research history of the EWMA for scholars from home and abroad. Yang et al. [16] designed a Phase Two EWMA control model to monitor alterable dimension mean vector. In statistical applications, EWMA is often used to predict trends [17–19]. He et al. [20] studied an EWMA prediction model to monitor the process of electrical energy consumption. In this paper, EWMA is applied to predict the next interval gap between the optimal electrical energy generation capacity and the booked electrical energy consumption. When it exceeds the preset boundary, rising or reducing the price in some time interval is supposed to be adopted to stimulate the demand response. In this way, it can get a few adjustments and avoid the side effects on the users caused by the frequent price adjustments. The stable consumption load is finally achieved.

The research features and highlights of this article are listed as follows:

(1) This study comes up with an original data-driven exponential function-based automatic process control strategy to manage the gap between the consumers' booked electrical energy consumption and the optimal generation capacity

(2) A small adjustment number is obtained by the data-driven exponential function adjustment method, which can achieve a practical electrical energy consumption approaching the optimal generation capacity after adjustment

(3) This strategy can make up for the defects of the RTP algorithm and achieve effective peak carbon dioxide emissions effects

The remaining part of this article is arranged as follows: data-driven APC strategy is offered in Section 2. In Section 3, the algorithm is proposed. Case studies and result analysis are included in Section 4. The conclusions are drawn in Section 5.

2. Data-Driven APC (Automatic Process Control) Strategy

The structure of the SG system discussed in this article is as follows: a power plant, an energy provider, and a few users. The users have installed smart meters. The power plant transmits the power to an energy provider. The energy provider collects the power consumption data from users through smart meters. The energy providers apply the social welfare maximization model to calculate price of next time interval and transmit it to users. After receiving the price as p dollars/kWh, users reserve consumption load from the

energy provider (one day or even one week). Set the number of consumers as N, and assume that the time period of electrical energy operation is divided into T intervals. Suppose that set $\aleph = \{1, 2, \ldots, N\}$ represents consumers and set $\Gamma = \{1, 2, \ldots, T\}$ represents time intervals. The energy provider obtains each user i's $(i \in \aleph)$ valley and peak electrical energy consumption data in interval $t \in \Gamma$ according to the past data provided by the smart meter, namely, m_i^t and M_i^t. Denote x_i^t as user i's electrical energy consumption in interval t, and its range can be assumed as $m_i^t \le x_i^t \le M_i^t$. The detailed social welfare model is available in Appendix.

After we solve the optimization problem (C.1)–(C.3) (see Appendix), optimal price p_t^* and theoretical optimal generation capacity G_t^* in interval t can be gained. The electricity supplier obtains a smooth and steady electrical energy consumption based on G_t^*. But this is just an optimal situation. Most often, consumers' booked electrical energy consumption observed from smart meters is considerably different from optimal generation capacity G_t^*. Guiding the consumers to use electrical energy appropriately is the most effective way to prevent this kind of phenomenon.

Taking users' demand response mechanism to price into account, we calculate the gap between optimal generation capacity with the social welfare model and the booked consumption loads. Later, when it exceeds the boundary, we use the data-driven APC scheme to change the gap. The energy provider changes prices to make users adjust their actual consumption loads. In the end, the actual electrical energy consumption is near the optimal generation capacity. Moreover, we can obtain higher social welfare and the energy provider can get more profit with data-driven APC strategy than before. We first introduce the definition of the EWMA estimation [12, 20].

2.1. EWMA Estimation.
We suppose that the users book the electrical energy consumption of the next interval, and the reservation retains an important reference value for accurate adjustment.

In order to accurately obtain the extent of gap between booked electrical energy consumption x_t of users in time interval t and optimal generation capacity G_t^*, we set gap d_t as

$$d_t = x_t - G_t^*, \tag{1}$$

and we predict the next gap value d_{t+1} by the EWMA model from last adjusted gap value. The details of the calculation are as follows.

Set the initial gap value as d_τ, $\tau = t, t-1, \ldots$, and set the adjusted one as d_τ', $\tau = t, t-1, \ldots$. The EWMA $\overline{d}_{t+1}$ of gap value d_{t+1} in time interval $t+1$ is in the following formula:

$$\overline{d}_{t+1} = \theta \overline{d}_t + \mu d_t', \tag{2}$$

in which $\theta = 1 - \mu$ is the discount factor.

Similarly, EWMA $\overline{p}_{t+1}$ of price p_{t+1} in interval $t+1$ is

$$\overline{p}_{t+1} = \theta \overline{p}_t + \mu p_t', \tag{3}$$

in which p_t' is changed price in interval t.

In the process of adjustment, the changed EWMA value $\overline{p}_{t+1}'$ in interval $t+1$ is

$$\overline{p}_{t+1}' = \theta \overline{p}_t + \mu p_t'', \tag{4}$$

where p_t'' is readjusted price in interval t.

2.2. Data-Driven APC Electrical Energy Monitoring.
In this section, we discuss how to develop a data-driven APC electrical energy monitoring strategy in order to minimize the difference from the goal electrical energy gap E. We will change the price when the EWMA value is beyond the boundary as

$$\overline{d}_{t+1} \ge B_1$$
$$\text{or } \overline{d}_{t+1} \le B_2, \quad B_1 \ge 0, B_2 \le 0, \tag{5}$$

where B_1 is prestipulated upper limit and B_2 is prestipulated lower limit. In the process of monitoring, when $\overline{d}_{t+1}$ conforms to (5), the EWMA value $\overline{d}_{t+1}$ is out of the limits. The action of adjusting it to get nearer to the goal value will be taken. It is obvious in test results that, to achieve a stable subsequent adjustment, it is worthy of discussion to find a way to set parameters $E_1 \ge 0$ and $E_2 \le 0$ of the target process properly.

When monitoring users' booked consumption load, we obtain a series $\{\overline{d}_t\}_{t=1}^T$ of EWMA estimation. If $\overline{d}_{t+1}$ satisfies (5), the users' booking electrical energy consumption has been beyond the steady limit. For preventing the consumers' blind electricity utilization, the energy provider applies the users' price demand response. It guides the users to use power properly, which achieves smooth and steady electrical energy consumption.

2.3. Data-Driven APC Adjustment.
If the automatically calculated estimated value $\overline{d}_{t+1}$ exceeds the upper boundary B_1, it means the booked electrical energy consumption is beyond expectation. Meanwhile, the real-time price will be increased to induce consumers to reasonably reduce the booked electrical energy consumption. By the same token, if $\overline{d}_{t+1}$ is lower than the lower boundary B_2, it means scheduled electrical energy consumption is lower than expectation and the remaining power is sufficient. It is necessary to reduce the real-time price to encourage consumers to add more booked electrical energy consumption at that moment. Energy provider can even encourage users to store electricity in their own batteries to get through the period of rising prices. Through the above adjustments, users can be guided to reasonable electrical energy consumption. Therefore, a smooth and steady supply of electricity can be ensured from the energy supplier.

The strategy needs to be discussed in terms of the quantitative relation between price changes and the gap between users' booked electrical energy consumption and optimal generation capacity. The relationship can be tested by relevant data. In order to explain the adjustment strategy, we provide the following theorem.

Theorem 1. *Set the demand function as an exponential function. The gap EWMA estimation $\overline{d}_{t+1}$ is exponential to electricity price EWMA value $\overline{p}_{t+1}$, and the form is $\overline{d}_{t+1} = k_1 e^{k_2\overline{p}_{t+1}}$ or $\overline{d}_{t+1} = -k_1 e^{-k_2\overline{p}_{t+1}}$; $k_1 > 0$ and $k_2 < 0$ are constants. When the load gap satisfies $\overline{d}_{t+1} \geq B_1 > 0$, $\overline{d}_{t+1}$ is adjusted to $E_1 \in [0, B_1)$, and then the price variation is*

$$\delta_{t+1} = \frac{1}{\mu k_2}\left(\ln E_1 - \ln \overline{d}_{t+1}\right). \tag{6}$$

When $\overline{d}_{t+1} \leq B_2 < 0$, $\overline{d}_{t+1}$ is adjusted to $E_2 \in (B_2, 0]$, and then the price variation is

$$\delta_{t+1} = \frac{1}{-\mu k_2}\left(\ln|E_2| - \ln|\overline{d}_{t+1}|\right). \tag{7}$$

Proof. In interval $t + 1$, when $\overline{d}_{t+1} \geq B_1 > 0$, $\overline{d}_{t+1}$ has to adjust to $E_1 \in [0, B_1)$. Meanwhile, the EWMA price is shifted from $\overline{p}_{t+1}$ to $\overline{p}'_{t+1}$. Under the assumed condition, we have

$$\overline{d}_{t+1} = k_1 e^{k_2\overline{p}_{t+1}},$$
$$E_1 = k_1 e^{k_2\overline{p}'_{t+1}}, \tag{8}$$

which can be written as

$$\ln \overline{d}_{t+1} = \ln k_1 + k_2\overline{p}_{t+1},$$
$$\ln E_1 = \ln k_1 + k_2\overline{p}'_{t+1}, \tag{9}$$
$$\ln E_1 - \ln \overline{d}_{t+1} = k_2\left(\overline{p}'_{t+1} - \overline{p}_{t+1}\right).$$

According to (3), (4), (8), and (9), we have

$$\begin{aligned}\ln E_1 &- \ln \overline{d}_{t+1} \\ &= k_2\mu\left(p''_t - p'_t\right). \end{aligned} \tag{10}$$

Setting $\delta_{t+1} := p''_t - p'_t$ as change in price, we have

$$\delta_{t+1} = \frac{1}{\mu k_2}\left(\ln E_1 - \ln \overline{d}_{t+1}\right). \tag{11}$$

Similarly, when $\overline{d}_{t+1} \leq B_2 < 0$, we adjust $\overline{d}_{t+1}$ to $E_2 \in (B_2, 0]$; under the assumed condition, we have

$$\overline{d}_{t+1} = -k_1 e^{-k_2\overline{p}_{t+1}},$$
$$E_2 = -k_1 e^{-k_2\overline{p}'_{t+1}}, \tag{12}$$

so we obtain

$$\ln|\overline{d}_{t+1}| = \ln|-k_1| - k_2\overline{p}_{t+1},$$
$$\ln|E_2| = \ln|-k_1| - k_2\overline{p}'_{t+1}, \tag{13}$$
$$\ln|E_2| - \ln|\overline{d}_{t+1}| = -k_2\left(\overline{p}'_{t+1} - \overline{p}_{t+1}\right) = -\mu k_2\delta_{t+1}.$$

Hence, from above, formula (7) is established. □

3. Algorithm

According to Theorem 1, the adjusted electrical energy consumption in interval $t + 1$ is

$$x'_{t+1} = \begin{cases} x_{t+1} - k_1 e^{k_2\delta_{t+1}}, & \delta_{t+1} > 0, \\ x_{t+1}, & \delta_{t+1} = 0, \\ x_{t+1} + k_1 e^{k_2\delta_{t+1}}, & \delta_{t+1} < 0. \end{cases} \tag{14}$$

Then we have

$$\begin{aligned} d'_{t+1} &= d_{t+1} + x'_{t+1} - x_{t+1} \\ &= \begin{cases} d_{t+1} - k_1 e^{k_2\delta_{t+1}}, & \delta_{t+1} > 0, \\ d_{t+1}, & \delta_{t+1} = 0, \\ d_{t+1} + k_1 e^{k_2\delta_{t+1}}, & \delta_{t+1} < 0. \end{cases} \end{aligned} \tag{15}$$

We get optimal solution $\{p_t^*\}_{t=1}^T$ and $\{G_t^*\}_{t=1}^T$ by applying Lagrange dual method to solve the social welfare maximization problem (C.1)–(C.3) (see Appendix). Smart meters feed users' booked electrical energy consumption series $\{x_t\}_{t=1}^T$ back to the energy supplier. According to (1), we calculate the series $\{d_t\}_{t=1}^T$ of gap between booked electrical energy consumption x_t of users in interval t and optimal generation capacity G_t^*. Let the initial adjusted consumption load gap $d'_1 = d_1$, $p'_1 = p_1^*$, and $\overline{d}_1 = 0$, so that the initial predicted error is $e_1 = d'_1 - \overline{d}_1 = d'_1$. Set the initial price adjustment as $\delta_1 = 0$. Suppose that the parameters $k_1 > 0$ and $k_2 < 0$, $0 \leq E_1 < B_1$, $B_2 < E_2 \leq 0$, and $\mu \in [0, 1], \omega \in [1, 4]$. In interval $t \in \Gamma$, applying data-driven APC strategy, the monitoring and adjustment algorithm is summarized as Algorithm 1.

4. Case Analysis

The operation effect of data-driven exponential function-based APC monitoring and adjustment strategy is analyzed through Singapore's power market data [21] in this part.

4.1. Power Load. We select RTP data from Mar 5, 2017, to Mar 6, 2017, and electrical energy consumption data from Mar 3, 2017, to Mar 6, 2017, for simulation. In Algorithm 1, we set the RTP data as the initial booked sequences $\{p_t^*\}_{t=1}^T$. In equation (1), we set the electrical energy consumption data from Mar 5, 2017, to Mar 6, 2017, as booked electrical energy consumption $\{x_t\}_{t=1}^T$. Past electrical energy data at the corresponding time from Mar 3, 2017, to Mar 4, 2017, is regarded as optimal generation capacity $\{L_t^*\}_{t=1}^T$ in equation (1). The original power loads are shown in Figure 1.

As illustrated in Figure 1, the users' booked consumption power load runs far away from the optimal generation capacity. In order to encourage users to reasonably consume power, the data-driven APC strategy needs to be adopted. This means that the adjustment of electricity prices is set by suppliers. Then it will guide consumers to adjust real electrical energy consumption.

4.2. Numerical Analysis for APC Adjustment. Let $\overline{p}_1 = 75$, and see Section 3 for the other initial arguments. Set the parameters in Algorithm 1 as follows: $k_1 = 20, k_2 = -1$, $\mu = 0.3$, $B_1 = 800, B_2 = -800$, $E_1 = B_1/2$, and $E_2 = B_2/2$. Assume that the arguments a, b, c in equation (B.3) are

Step 1: calculate $\overline{d}_{t+1}$ according to (2). If (5) holds, turn to Step 4. Otherwise, $\delta_{t+1} = 0$, turn to Step 2.
Step 2: calculate x'_{t+1} according to (14), d'_{t+1} according to (15), $e_{t+1} = d'_{t+1} - \overline{d}_{t+1}$.
Step 3: repeat Step 1.
Step 4: when $\overline{d}_{t+1} \geq B_1 > 0$, let $\delta_{t+1} = (1/\mu k_2)(\ln E_1 - \ln \overline{d}_{t+1})$, when $\overline{d}_{t+1} \leq B_2 < 0$, let $\delta_{t+1} = (1/-\mu k_2)(\ln|E_2| - \ln|\overline{d}_{t+1}|)$, then turn to Step 2.

ALGORITHM 1: Data-driven APC algorithm.
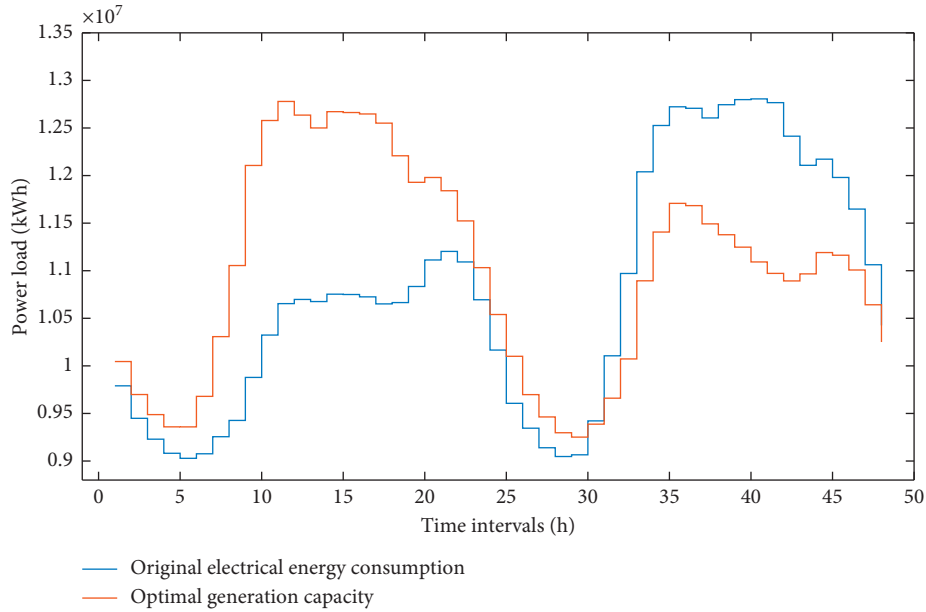
FIGURE 1: Comparison between optimal generation capacity and booked electrical energy consumption.

$0.01, 0, 0$. Figures 2–5 show the APC strategy simulation results.

Figure 2 depicts that electrical energy gap series are steadier than the ones without adjustment after 11 adjustments. By experience, the average adjustment interval is 47/11 = 4.3, and the standard deviation of residuals is $\sigma = \sqrt{(\sum_{t=1}^{T} e_t^2/(T-1))} = \sqrt{(\sum_{t=1}^{48} e_t^2/47)} = 734$. No points outside the range 3σ indicate that there is no sign of the abnormality.

As can be seen in Figure 3, adjusted electricity consumption is nearer optimal generation capacity than the one without adjustment, and expected effects can be achieved. Figure 4 shows that the electricity price has changed 11 times. The biggest change in price is -3.376×10^{-3} units. During these periods, we encourage the consumers to buy and use more electrical energy consumption. We apply equation (C.1) to calculate the total social welfare to get 6.34×10^8, and we apply equation (B.4) to calculate the profit to get 3.82×10^7. As can be seen from Figure 5 by running our strategy, we can obtain higher social welfare and profits than those without adjustment.

Besides improving energy provider's profit and total social welfare, the data-driven APC adjustment strategy helps to balance power supply and prevent SG outages.

4.3. Comparison between Two Different Demand Function Adjustments.
Reference [12] points out that there is a linear relationship between the EWMA predicted value $\overline{d}_{t+1}$ of consumption load gap and the EWMA predicted value $\overline{p}_{t+1}$ of price. This paper proposes that $\overline{d}_{t+1}$ and $\overline{p}_{t+1}$ are presented as an exponential function. The arguments are $k_1 = 120, k_2 = -1, k = 500, \mu = 0.5, B_1 = 1000, B_2 = -1000, E_1 = B_1/2$, and $E_2 = B_2/2$. The comparison of the electrical energy consumption results adjusted by these two methods is shown in Table 1 and Figures 6–8.

From Table 1 and Figure 6, we can learn that the adjustment frequency of the exponential adjustment is slightly higher than that of the linear one, but the standard deviation of the exponential adjustment is smaller than that of the linear adjustment.

Table 1 and Figure 7 illustrate that total social welfare and energy provider's profit of the exponential demand function are higher than those of the linear one. Figure 8 presents that price
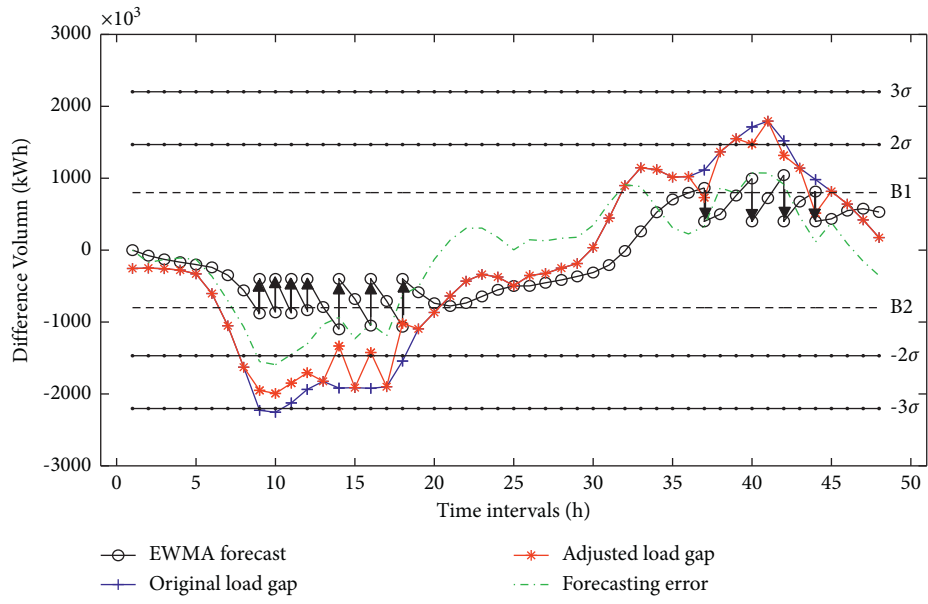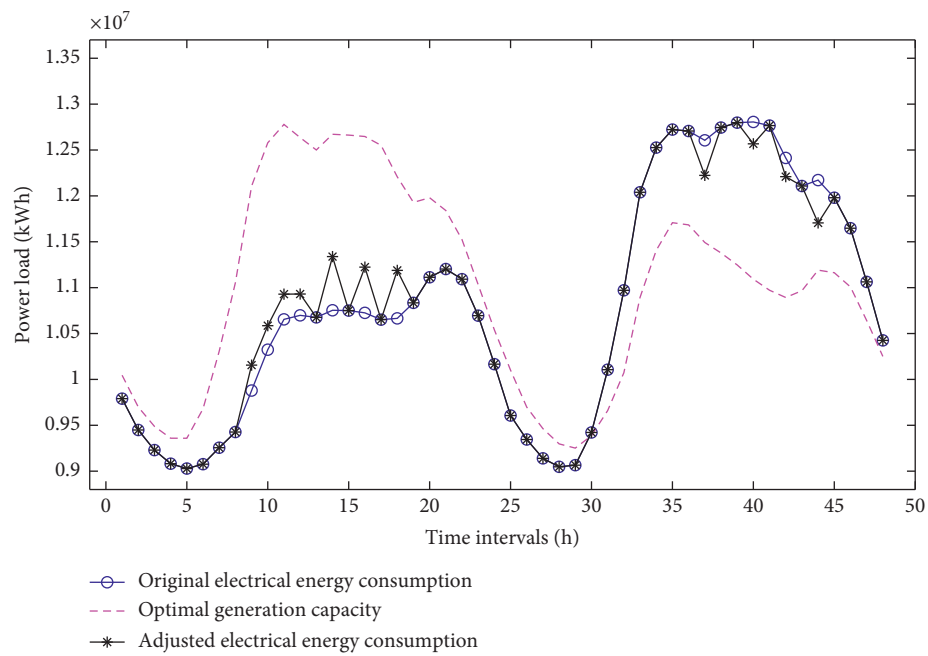
Figure 2: APC strategy process.

Figure 3: Electrical energies comparison.

adjustment effects of exponential demand function are better than those of the linear one. In particular, even the adjustment frequency with the exponential adjustment is slightly more than that in the linear one, and the standard deviation of residuals, total social welfare, and energy provider's profit with exponential demand function are better than those of the linear function adjustment.

From the observation results, we can conclude that, in general, the effect of exponential function adjustment is better than that of linear function adjustment.
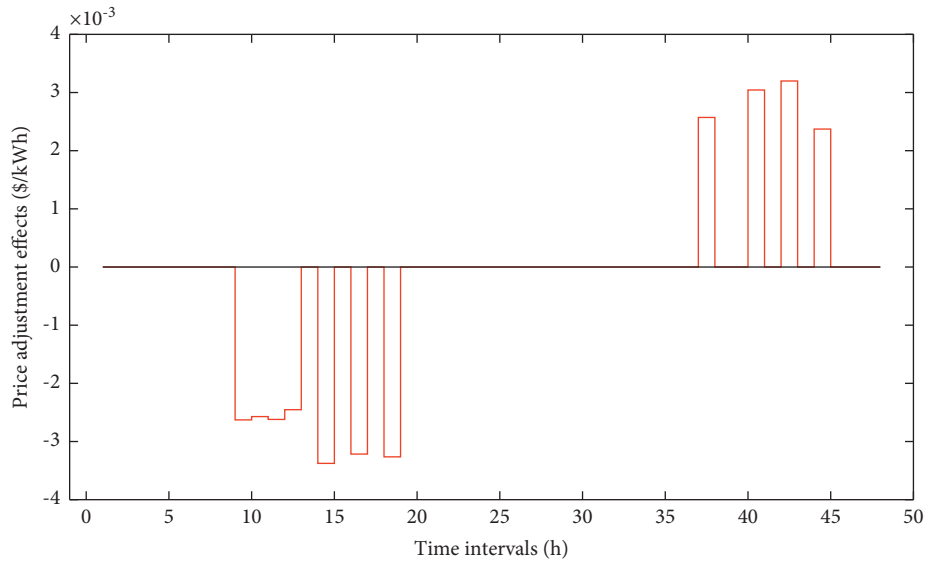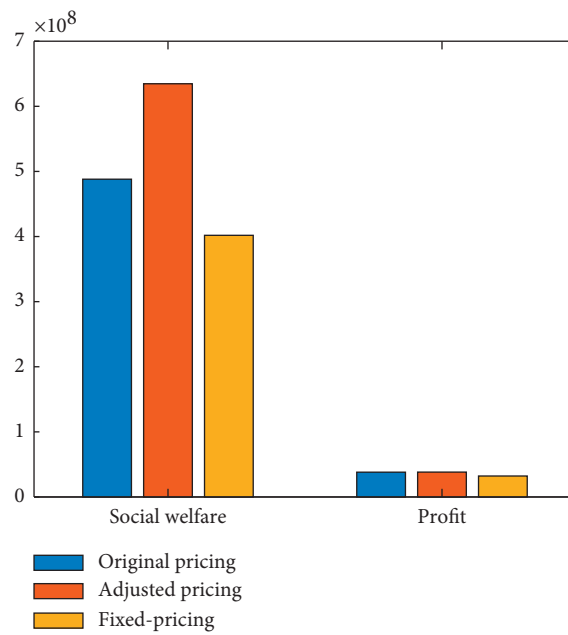
FIGURE 4: Price adjustment effects.

FIGURE 5: Comparison of total social welfare and energy provider's profit, with original and adjusted pricing strategies.

TABLE 1: Comparison results.

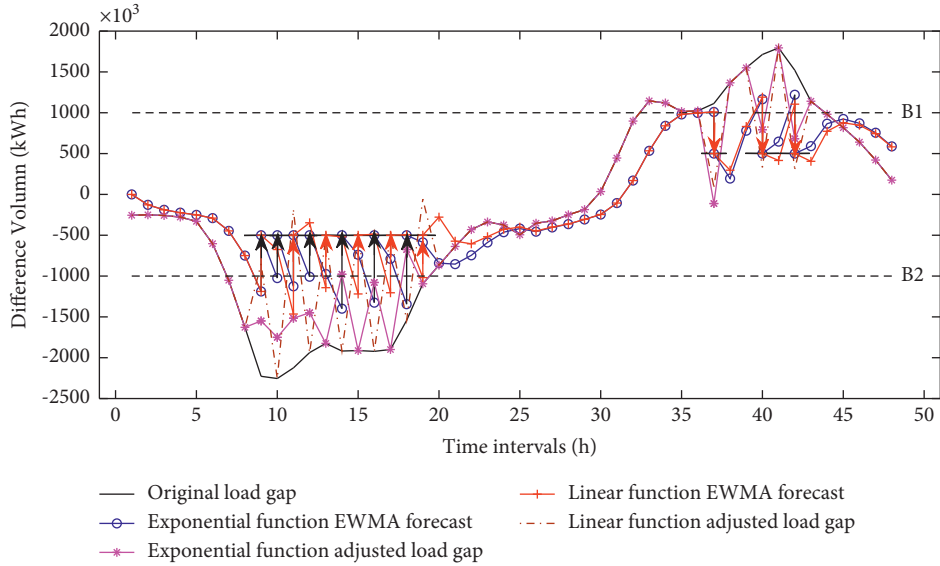|	Exponential adjustment	Linear adjustment
Adjustment frequency	10	9
Standard deviation	585	625
Social welfare	6.35×10^8	5.24×10^8
Profit	3.82×10^7	3.76×10^7

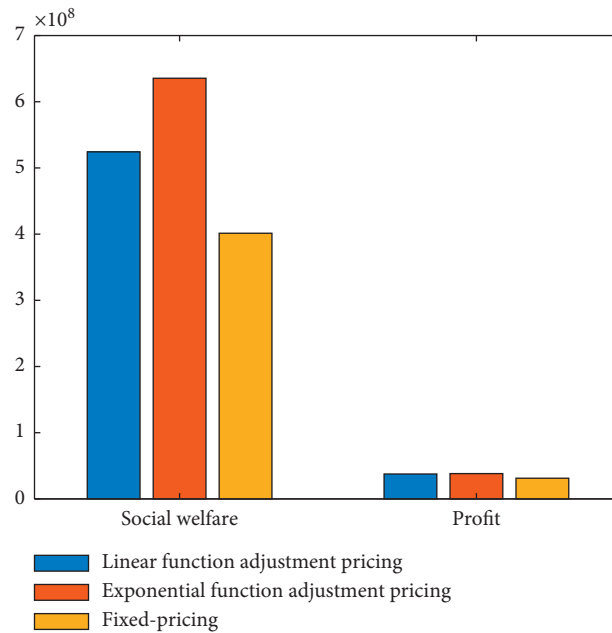FIGURE 6: Comparison of adjustments in different APC strategies.

FIGURE 7: Comparison of total social welfare and energy provider's profit, with linear and exponential adjustment pricing strategies.
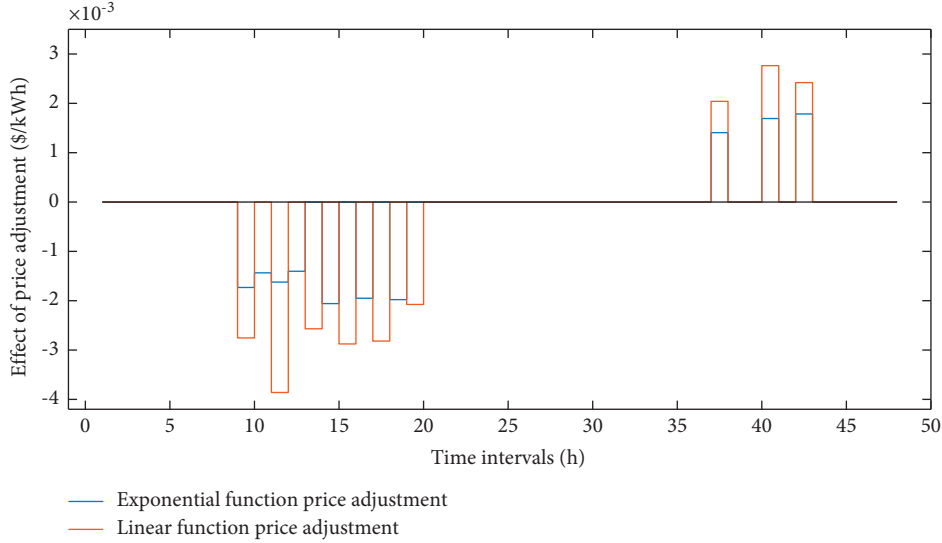
FIGURE 8: Comparison of price adjustment effects in different adjustment strategies.

5. Conclusions

In our smart grid system, users can book a day or more of electrical energy consumption according to dynamic pricing provided by the energy provider. This energy provider monitors the real-time booked consumption loads and obtains the stable consumption load through the price demand response mechanism. The automatic process control strategy put forward in the article is as follows. Manage power consumption process. That is to say, the energy supplier monitors the gap between the optimal generation capacity given by the social welfare maximization problem and consumers' booked electrical energy consumption. Then predict next time interval electrical energy consumption gap with statistical average model. It is only when predicted average number is beyond the presupposed boundary that price rises and cuts are used to change the price and to stimulate demand response. In this way, the adjustment frequency is not too great, and the users will change their initial consumption plan (i.e., reservation consumption) during the actual power consumption process. So the electrical energy consumption can become stable and the grid can run reliably and safely. The case analysis show that the network system of the energy provider automatically monitors and adjusts the price so as to get a small adjustment frequency, a stable actual electrical energy consumption, and a controllable residual standard deviation. After comparison, the exponential function adjustment method proposed in this paper is also shown to be more suitable than the linear one.

Appendix

The Social Welfare Model

A. Users' Utility Function.
Based on microeconomics, a utility function $U(x, \omega)$ can be chosen to show the users' satisfactory degree after power consumption. x means the consumption load, and ω gives consumers' electrical energy consumption wills, changing with intervals and consumers. Consider no electricity demand and no utility. We choose logarithmic functions as [20]

$$U\left(x_i^t, \omega\right) = \begin{cases} \omega \ln\left(x_i^t + 1\right), & \text{if } x_i^t \geq 0, \\ 0, & \text{if } x_i^t < 0. \end{cases} \quad (A.1)$$

px denotes the consumers' cost, and the benefit function of each user is

$$W\left(x_i^t, \omega_i^t\right) = U\left(x_i^t, \omega_i^t\right) - p_t x_i^t, \quad (A.2)$$

where $W(x_i^t, \omega_i^t)$ is the welfare function of consumer i in interval t. It is assumed that the goal of every consumer is getting the optimal benefit value; that is, the maximum utility function and the minimum power consumption cost are generated.

B. The Energy Provider Profit Function.
G_t denotes the energy provider's generation capacity in interval t. $G_t^{\max}$ and $G_t^{\min}$ denote peak and valley generation capacities, respectively. When consumers book electrical energy consumption several days ago, and the energy provider supplies power according to the booked electrical energy consumption, the energy system in this article will not have a blackout due to insufficient power supply. We assume $G_t^{\max}$ equals the amounts of maximum electrical energy demands of all users, and $G_t^{\min}$ equals those of minimum ones. $G_t^{\max}$ and $G_t^{\min}$ are expressed as follows [4]:

$$G_t^{\max} = \sum_{i=1}^{N} M_i^t, \quad (B.1)$$

$$G_t^{\min} = \sum_{i=1}^{N} m_i^t. \quad (B.2)$$

The power generation cost $C(G_t)$ in time interval t of the energy provider is [4]

$$C(G_t) = aG_t^2 + bG_t + c, \tag{B.3}$$

where $a > 0, b, c \geq 0$ are presupposed arguments. $p_t G_t$ is the energy provider's sales amount. Then the energy provider's profit in interval t is [4]

$$P(G_t) = p_t G_t - C(G_t). \tag{B.4}$$

C. The Social Welfare Maximization Problem. We discuss the optimization problem for the SG system in this article. The following formula shows the maximum total social welfare [4]:

$$\max_{x_i^t, G_t} \sum_{i=1}^{N} U(x_i^t, \omega_i^t) - C(G_t). \tag{C.1}$$

The constraint condition (C.2) displays that the consumption loads are less than the supply ones:

$$\text{s.t.} \sum_{i=1}^{N} x_i^t \leq G_t, \quad i \in \aleph, t \in \Gamma, \tag{C.2}$$

$$\begin{aligned} m_i^t \leq x_i^t &\leq M_i^t, \\ G_t^{\min} \leq G_t &\leq G_t^{\max}. \end{aligned} \tag{C.3}$$

Namely, under such a real-time electricity price mode, power failure caused by insufficient power supply can never happen. Because the objective function displayed in (C.1) is concave and the constraint condition (C.2) is linear, the model (C.1)–(C.3) is a convex programming problem. Therefore, not a few algorithms can solve the consumption load and generation capacity. For example, interior point algorithm can solve the problem. However, these algorithms cannot solve the exact RTP, a key point in controlling and managing the electrical energy consumption in the article. So the dual method is applied to solve problem (C.1)–(C.3).

Data Availability

The data used to support the findings of this study are included in the references within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

Acknowledgments

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