Computers & Industrial Engineering 137 (2019) 106068

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Monitoring of power consumption requirement load process and price adjustment for smart grid

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ARTICLE INFO

Keywords:
Bounded adjustment
Engineering process control
Exponential weighted moving average
Power load monitoring
Smart grid

ABSTRACT

The recent development of smart meters and their incorporation into smart grid systems have allowed the analysis of household electricity consumption requirement in future. This development makes it possible to give a reasonable price in next time slots, which is a good tool to induce users to consume electricity more efficiently and wisely. We obtain the optimal consumption load and prices by establishing the real-time pricing model balancing supply and demand in every time slot. However, in reality, the user's reserved consumption requirement load is often different from the optimal load. In some time slots, the difference is large considerably, which may result in an overload power system. We propose a bounded adjustment strategy to monitor users' reserved consumption requirements. Using a price demand response mechanism, the power providers induce the users to adjust their reserved consumption requirements by the change of electricity price in response to variations in the difference between the users' optimal and reserved consumption requirement loads. An exponential weighted moving average model is used to forecast the load differences in the next time slots. The price is adjusted in the next time slots only when the load difference exceeds a given upper or lower boundary to reduce the frequency of adjustment as far as possible. Our method can ensure the stability of actual consumption loads after adjustment. Numerical results show that when the parameters are set appropriately, the proposed scheme can achieve superior performance characterized by the stable actual consumption load close to the optimal load and balanced energy provision.

1. Introduction

In recent years, energy and environmental issues have become more and more significant and people's consciousness of environmental protection is improving. More and more people are included to use electricity instead of using directly coal and petroleum having a high environment pollution because electricity can be generated by clean energy such as solar, wind and water. Many coal and petroleum installations are also being transferred as electrical installations such as electric vehicles, which potentially increase people's electrical demand. The increasing electricity demand will compel energy providers to supply more electricity. A limited generation capacity of electricity makes energy providers have to take measures to induce users to use electricity reasonably to ensure the security and reliability of electricity supply as well as stabilize the energy load within a certain range.

To solve the issue of lack of electricity, smart grids (SG) have been widely studied and implemented. For instance, both the European Union and America have selected some cities as pilot projects for SG (Nezamoddini & Wang, 2017). China is contemplating the transmission and distribution of SG and has carried out similar trials in Hangzhou, Beijing and Shanghai. SG can increase energy efficiency and reduce waste as it can induce users to use properly their electrical equipment in real time (Chiu, Shih, Pang, & Pai, 2017). With the rapid development of the advanced power industry and wireless communication technologies, smart meters occur. As a part of an SG system, smart meters make a real time interactive network connection among users, electricity companies and power facilities feasible. These data of smart meters can help us analyze, forecast and manage consumption load (Wang, Chen, Hong, & Kang, 2018).

The use of smart meter can also provide the chance of real-time pricing (RTP) and subsequently stimulate a price-based demand response (Mohsenianrad & Leongarcia, 2010; Samadi, Mohsenian-Rad, Schober, Wong, & Jatskevich, 2010). Comparing with other conventional pricing structures, i.e. critical peak load pricing and time of use

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https://doi.org/10.1016/j.cie.2019.106068
Received 19 November 2018; Accepted 14 September 2019
Available online 20 September 2019
0360-8352/

pricing, RTP can be more flexible and intelligent in using real-time information between users and the electricity companies. In recent literature, RTP has been adopted as an energy selling strategy to balance energy provision in an SG system. Samadi et al. (2010) proposed an optimal real-time pricing algorithm for demand response aimed at the maximization of the level of all users' satisfaction with energy consumption and the minimization of the power generation cost provided by energy providers. Chiu et al. (2017) put forward an energy sale and redemption pricing framework that exploits a time-dependent pricing strategy. Yang, Zhang, and Ma (2014) came up with an approach using real-time pricing and energy control, which helps to match consumer demand with the SG energy supply presuming a reasonable payment to maximize the consumer's comfort level. Real-time pricing strategy is developed from a series of methods, such as Markov chain model (Kobayashi & Hiraishi, 2015), Alternating Direction Method of Multipliers (Zhu, Gao, & Hou, 2018) and game theory, which help to manage energy consumption issues (Dai, Gao, Gao, & Zhu, 2017; Srinivasan, Rajgarhia, Radhakrishnan, Sharma, & Khincha, 2017; Yu & Hong, 2017). Real-time pricing (RTP) strategy is also used in smart home appliances (Zhu, Gao, Hou, & Tao, 2018). Data-based stackelberg game strategy is applied on a demand response distribution system (Lu, Wang, Wang, Ai, & Wang, 2018).

Applying real-time pricing (RTP) strategy, we can obtain an optimal price and the corresponding theoretical consumption load, which can often guide suppliers to give a reasonable supply. Hence, the theoretical consumption load is often stable and reliable. However, in real life, under the effect of many uncertain factors, the actual consumption load always changes radically, which may damage the stability of the grid. More seriously, the instability sometimes results in a large area of electricity interruption. Obviously, it is impractical to adjust the users' consumption behavior after abnormal electricity consumption load occurs.

To stabilize the actual consumption load, we want to design a strategy to beforehand induce the users' electricity behavior in order to make the actual consumption load be close to the theoretical consumption load as far as possible under the users' demand response. Smart appliances can help people plan their power usage by reserving function in future time slots while intelligent terminal equipment such as phone can also help people change their reservation plan of the power usage at any time via the network of linking the smart appliances with intelligent terminal equipment.

In this paper, an engineering process control (EPC) strategy (Box, 1992) is introduced to monitor and adjust the difference between the users' reserved consumption requirement load and the theoretical consumption load in future time slots so that the actual consumption load cannot drift away from the theoretical consumption load too far at last. One of the advantages of EPC is that the monitored process requires to be adjusted only when it is suggested as a necessity by the data. In other words, the adjustment is a "trend" instead of a "point". The EPC strategy can provide an effective monitoring and adjustment. EPC has been adopted in manufacturing and service process. For example, Li, Liu, Tsung, Huo, and Su (2016) proposed an EPC strategy in call centers to monitor the changes in the service level and adjust the relevant staff numbers. Runger, Lian, and Castillo (2010) proposed an optimal process control and adjustment system to minimize the adjustment cost.

Nowadays, there have been many methods to monitor the change of a process. Evora, Hernandez, and Hernandez (2015) gave a direct load control method based on multi-objective particle swarm optimization algorithm to manage loads on the demand side. Liu, Tsung, and Zhang (2014) provided a self-starting control chart to detect the location of parameter shifts by monitoring the process; Li, Tsung, and Zou (2013) proposed a detection and diagnostic method based on a log-linear model for process control; Ding, Tsung, and Li (2016) put forward a control chart indicating the diagnosed shift direction to monitor and diagnose mixed data types. They also described a control chart which monitored both the functional relationship and the random explanatory variables (Ding, Tsung, & Li, 2017). However, applying the EPC method to control the energy consumption load process is still a challenge and has never previously been investigated sufficiently in the literature.

Our proposed EPC strategy is based on the users' demand response for electricity price. Under the strategy, by adjusting the price we can minimize the deviation of the difference between the users' reserved and theoretical consumption loads in each time slot. However, for an SG system, it would be unrealistic to adjust the price too frequently as it may result in the users' complaint and increase the energy providers' workload. To avoid the frequent price adjustment and estimate effectively the new values within next time intervals, the upper and lower boundaries are set. The strategy uses an exponentially weighted moving average (EWMA) for the difference of users' reserved electricity consumption requirement load resulting from the data of smart meters and the theoretical consumption load obtained by a RTP model to forecast their differences at the next time intervals (Liu, Xue, Zhang, & Zhao, 2013; Shen, Tsung, & Zou, 2014; Zhang, Tsung, & Zou, 2015). Observing the change of the EWMA values in next time slots, the energy providers induce the users to use electricity reasonably by adjusting the electricity price when the EWMA value exceeds the upper or lower bounds in some time slot. About the research of EWMA, many scholars have adopted EWMA to predict a new value at next time interval and generate control charts. He, Wang, Tsung, and Shang (2016) integrated a log-likelihood-ratio statistic into EWMA and proposed a control chart. Box (1992) and Box and Luceno (2009) applied EWMA to predict a next value with a discount factor, namely, smoothing constant. Different methods for EWMA control charts are proposed. Jiang, Wang, and Tsung (2012) proposed a variable-selection-based multivariate EWMA (VS-MEWMA) chart which used dimensionality reduction to monitor processes and diagnose faults. Nishimura, Matsuura, and Suzuki (2015) described a multivariate EWMA control chart based on a variable selection. Göb, Lurz, and Pievatolo (2013, 2015) explored the hourly estimation of electrical consumption based on EWMA with covariates. Li, Pu, Tsung, and Xiang (2017) integrated an EWMA charting scheme with a self-starting control chart based on forward variable selection. Yeong, Khoo, Tham, Teoh, and Rahim (2017) described an EWMA chart with variable sampling interval to monitor the coefficient of variation. Xu and Jeske (2018) proposed a weighted EWMA control chart for monitoring the Weibull scale parameter. Because the monitoring and adjustment process of EPC is an automatic feedback process by boundaries, the EPC strategy is often called boundary adjustment strategy or automatic process control technique (Akhmetsagirov & Nasibullin, 2016; Baldewijns, Luca, Nagels, Vanrumste, & Croonenborghs, 2015; Guo, Li, & Laverty, 2013; Lees, Ellen, & Brodie, 2014; Saif, 2015; Zhang, Qiu, Ruan, & Xiao, 2016).

The rest of this paper is organized as follows. Section 2 presents the real-time pricing model for solving the users' theoretical consumption load and optimal price. In Section 3, we give the detailed EPC strategy monitoring change of the differences between the reserved consumption requirement load and the theoretical consumption load within different time intervals. Section 4 offers some simulation results and analysis. In Section 5, we discuss the effect of the different boundaries and targets for the monitoring and adjustment process. The last is conclusion and observation.

2. Real-time pricing model

In the paper, we consider an SG system which is composed of an electricity company, some users who install smart meters and a regulatory authority. With an interaction infrastructure such as smart meters, the users and the energy provider can exchange pricing information in current time slot and next time slots and can obtain every user's minimum and maximum power requirement load in future time slots. The users can consume power reasonably according to the prices that smart meters show.

In our system, we divide the time period operating the users' electricity consumption requirement load into T time slots, where $T \triangleq |\mathbb{T}|$, and $\mathbb{T}$ is the set of all time slots, define N as the number of users and x_i^t as the amount of electricity consumed by every user $i \in \mathbb{N} = \{1, 2, \cdots, N\}$ in every time slot $t \in \mathbb{T}$. Since the consumed appliances are limited and some must be open like refrigerates, we assume that $m_i^t \leqslant x_i^t \leqslant M_i^t$, where m_i^t and M_i^t are the minimum and maximum consumption requirement loads of user i in time slot t respectively.

2.1. Users utility function

According to microeconomics, we adopt a utility function to represent the users' level of satisfaction with energy consumption and assume that the utility function increases as the users' electricity consumption increases and when the electricity demand reaches a certain level, it will be saturated. Thus, the utility function can be modeled as follows (Samadi et al., 2010).

$$U(x_i^t, \omega) = \begin{cases} \omega x_i^t - \alpha (x_i^t)^2/2, & \text{if } \ 0 \leqslant x_i^t \leqslant \omega/\alpha, \\ \omega^2/2\alpha, & \text{if } \ x_i^t \geqslant \omega/\alpha, \end{cases} \tag{1}$$

where $\omega > 0$ is a parameter representing the user's preference for energy consumption and $\alpha > 0$ is a pre-determined parameter.

Accordingly, the welfare function for each user is

$$W(x_i^t, \omega_i^t) = U(x_i^t, \omega_i^t) - p_t x_i^t, \tag{2}$$

where $W(x_i^t, \omega_i^t)$ is the user$i$'s welfare function in time slot t, p_t is the announced price in time slot t and $p_t x_i^t$ is the consumption cost of the user i in time slot t. Assume that each user tries to achieve maximum welfare, their utility functions will be maximized and their consumption cost will be minimized.

2.2. Cost function of the electricity company

We denote L_t as the generation capacity of the electricity company in time slot t and assume that the minimum generation capacity $L_t^{\min}$ and the maximum generation capacity $L_t^{\max}$ of the electricity company equal the total minimum and maximum electricity demands of all users, respectively, to prevent the power system being interrupted, i.e.,

$$L_t^{\min} \triangleq \sum_{i=1}^{N} m_i^t, \tag{3}$$

$$L_t^{\max} \triangleq \sum_{i=1}^{N} M_i^t. \tag{4}$$

We define $C(L_t)$ as the generation cost of the electricity company in time slot t, which is formulated as

$$C(L_t) \triangleq aL_t^2 + bL_t + c, \tag{5}$$

where $a > 0$, $b, c \geqslant 0$ are pre-determined cost parameters. Then, the profit function of the electricity company in time slot t is

$$P(L_t) = p_t L_t - C(L_t). \tag{6}$$

2.3. The real-time pricing model

We formulate the optimal problem that the welfare is maximized, that is to say, the sum of the users' utility functions is maximized and the generation cost of the electricity company is minimized. Obviously, the total energy consumption should not exceed the generation capacity of the electricity company at each time slot. Thus, in each time slot $t \in \mathbb{T}$, the model is depicted as

$$\max_{y} \sum_{i=1}^{N} U(x_i^t, \omega_i^t) - C(L_t), \tag{7}$$

$$s.\ t. \quad \sum_{i=1}^{N} x_i^t \leqslant L_t, \tag{8}$$

where y is represented as:

$$y = \{(x_i^t, L_t) | i \in \mathbb{N},\ t \in \mathbb{T},\ \mathrm{m}_i^t \leqslant \mathrm{x}_i^t \leqslant \mathrm{M}_i^t,\ \mathrm{L}_t^{\min} \leqslant \mathrm{L}_t \leqslant \mathrm{L}_t^{\max}\}, \tag{9}$$

and other variables are summarized in Table 1, which also contains the variables that other formulas require in this paper.

Table 1
Nomenclature.

Indices	
i	user unit
t	time slot
T	number of time slots
N	number of users
Sets	
$\mathbb{T}$	set of time slots, $\mathbb{T} = \{1,2,\cdots,T\}$
$\mathbb{N}$	set of users, $\mathbb{N} = \{1,2,\cdots,N\}$
Parameters	
λ	Lagrange multiplier
ω	the user's preference
α	predetermined utility parameter
a	predetermined cost parameter
b	predetermined cost parameter
c	predetermined cost parameter
m_i^t	minimum power requirement of user$i$ in time slot$t$
M_i^t	maximum power requirement of user$i$ in time slot$t$
Variables	
x_i^t	the amount of electricity consumed by user i in time slot$t$
L_t	generation capacity of the electricity company in time slot$t$
p_t	electricity price in time slot$t$
g_t	effect of price adjustment in time slot$t$
v_t	accumulated effect of price adjustment in time slot$t$

The objective function (7) is a concave function, the constraint (8) is linear and hence the feasible set is convex, so the model is a convex optimization problem. Although we can directly solve it using some convex programming methods such as the interior point method, the exact price information cannot be obtained, which is that we need to know in using the EPC monitoring strategy. However, when Problem (7)–(9) is transferred as the Lagrange dual problem, the optimal Lagrange multiplier is exactly the electricity price in that time slot (Samadi et al., 2010). Hence, we need use the Lagrange dual method to obtain the optimal price and theoretical power consumption load of the users in each time slot t, $t \in \mathbb{T}$ before passing on the EPC strategy.

2.4. Lagrange dual method

Problem (7)–(9) is regarded as a primal problem. Now we give its Lagrange dual form. In time slot $t \in \mathbb{T}$, the Lagrange function is written as

$$Z(y, \lambda_t) = \sum_{i=1}^{N} U(x_i^t, \omega_i^t) - C(L_t) - \lambda_t \left(\sum_{i=1}^{N} x_i^t - L_t \right), \tag{10}$$

where λ_t is a Lagrange multiplier. We can rewrite (10) as

$$Z(y, \lambda_t) = \sum_{i=1}^{N} (U(x_i^t, \omega_i^t) - \lambda_t x_i^t) + (\lambda_t L_t - C(L_t)). \tag{11}$$

Then, we maximize the Lagrange function

$$\Phi(\lambda_t) = \max_{y} Z(y, \lambda_t), \tag{12}$$

Thus, the Lagrange dual problem is

$$\Gamma(\lambda_t) = \min_{\lambda_t > 0} \Phi(\lambda_t). \tag{13}$$

Due to the strong duality property, the solution of the primary optimization problem (7)–(9) is the same as that of the dual problem (13).

Because users are independent, we reformulated (12) as

$$\Phi(\lambda_t) = \sum_{i=1}^{N} \max_{\lambda_t}(U(x_i^t, \omega_i^t) - \lambda_t x_i^t) + \max_{\lambda_t}(\lambda_t L_t - C(L_t)) = \sum_{i=1}^{N} f_i(\lambda_t) + g(\lambda_t), \tag{14}$$

where

$$f_i(\lambda_t) = \max_{m_i^t \leqslant x_i^t \leqslant M_i^t} (U(x_i^t, \omega_i^t) - \lambda_t x_i^t), \tag{15}$$

and

$$g(\lambda_t) = \max_{L_t^{\min} \leqslant L_t \leqslant L_t^{\max}} \lambda_t L_t - C(L_t). \tag{16}$$

Note that the first term of (14) can be resolved into N users' problems with (15), and the second term of (14) is a power company problem in the form of (16). We note that Problem (15) is identical to the user's welfare function (2) and also Problem (16) to the company profit function (6) if we set the price value $p_t = \lambda_t^*$, where λ_t^* is the optimal Lagrange multiplier in time slot t. Thus, by solving Problem (13) we can obtain an optimal electricity price $p_t^* = \lambda_t^*$ and the theoretically optimal consumption load $x_t^* = \sum_{i=1}^{N} x_i^t$ in time slot $t \in \mathbb{T}$. The optimal electricity price p_t^* is sometimes called as shadow price, which reflects the scarce degree of electricity resource and hence is a key reference standard that the energy providers make the electricity price.

3. EPC adjustment strategy

By solving the dual problem (13) of the real-time pricing model, we obtain the users' optimal price p_t^* and theoretical energy consumption load x_t^* in time slot t. x_t^* can guide the power supplier to provide a reasonable electricity. Thus, the consumption load will become stable and reliable if the users use electricity according to the theoretical consumption load in each time slot $t \in \mathbb{T}$. Obviously, it is an ideal state. In reality, the users' reserved consumption requirement load feeding back to the power company through smart meters will not be completely same as the theoretical consumption load x_t^*. Hence, the energy providers either adjust the theoretical consumption load to meet the users' actual electricity consumption requirement or induce the users to adjust their reserved power consumption requirements. However, the limited capacity generating electricity compels the energy providers to have to make the second choice in next time slots in order to keep the load reliable and stable.

For this, we give an EPC adjustment strategy to induce the users' electricity consumption behavior by using power price incentive mechanism based on users' demand response so that at last the users' actual consumption load x_t can be close to the theoretical value x_t^* as far as possible.

For this, we give an EPC adjustment strategy to induce the users' electricity consumption behavior by using price incentive mechanism based on users' demand response for the electricity price so that x_t is close to x_t^* as far as possible.

3.1. EWMA estimation

In via of smart meters we can obtain these data about the reserved electricity consumption requirement loads of the users in the next time slots, which offer a good information for adjusting the consumption requirement load exactly and making a reasonable price.

For measuring the deviation degree of the users' reserved consumption requirement load x_t and the theoretical consumption load x_t^* in time slot t, we define the difference y_t between them as follows,

$$y_t = x_t - x_t^* \tag{17}$$

For doing a good forecast of the difference y_{t+1} in next time slot $t + 1$, we use an EWMA of past adjusted difference values to estimate the difference. The EWMA process for the forecast estimate of the difference y_{t+1} is as follows.

Let y_ℓ'be an adjusted difference value of the initial difference y_ℓ, $\ell = t, t-1, \cdots$. Then the EWMA estimate value $\bar{y}_{t+1}$ for the difference y_{t+1} in next time slot $t + 1$ is:

$$\bar{y}_{t+1} = \mu(y_t' + \theta y_{t-1}' + \theta^2 y_{t-2}' + \cdots), \quad 0 \leqslant \theta \leqslant 1 \tag{18}$$

where the constant $\mu = 1 - \theta$ is called the instability parameter and θ is the smoothing constant. Simplifying (18), we get

$$\bar{y}_{t+1} = \mu y_t' + \theta \bar{y}_t. \tag{19}$$

Table 2
The original data of SG.

NO.	The optimal consumption load x_t^*	The reserved consumption load x_t	The original load difference $y_t = x_t$-x_t^*	The original (optimal) price$p_t = p_t^*$
1	34.62	26.00	−8.62	0.692
2	41.98	37.50	−4.48	0.840
3	33.73	29.50	−4.23	0.675
4	39.55	35.50	−4.05	0.791
5	36.16	38.50	2.34	0.723
6	36.22	39.50	3.28	0.724
7	37.16	40.50	3.34	0.743
8	37.27	45.00	7.73	0.746
9	37.17	49.50	12.33	0.743
10	45.40	56.50	11.10	0.908
11	35.07	48.00	12.93	0.701
12	42.57	51.50	8.93	0.851
13	43.51	48.00	4.49	0.870
14	44.03	44.50	0.47	0.881
15	37.02	40.50	3.48	0.741
16	34.04	39.50	5.46	0.681
17	40.92	36.00	−4.92	0.818
18	35.74	35.00	−0.74	0.715
19	31.36	31.00	−0.36	0.627
20	35.63	32.50	−3.13	0.713
21	34.04	25.50	−8.54	0.681
22	32.44	23.50	−8.94	0.649
23	32.82	22.00	−10.82	0.657
24	31.52	22.00	−9.52	0.630
25	33.93	27.50	−6.43	0.679
26	38.03	35.00	−3.03	0.761
27	31.12	29.00	−2.12	0.623
28	37.19	33.50	−3.69	0.744
29	34.99	34.50	−0.49	0.700
30	40.22	37.50	−2.72	0.804
31	34.04	42.00	7.96	0.681
32	37.17	44.00	6.83	0.743
33	42.29	52.00	9.71	0.846
34	45.50	59.00	13.50	0.910
35	37.81	51.00	13.19	0.756
36	44.67	54.00	9.33	0.894
37	39.48	47.50	8.02	0.789
38	41.11	44.50	3.39	0.821
39	39.33	42.50	3.17	0.786
40	36.73	38.00	1.27	0.735
41	38.45	36.50	−1.95	0.769
42	31.87	35.00	3.13	0.637
43	29.79	31.00	1.21	0.596
44	33.23	33.50	0.27	0.665
45	32.92	28.50	−4.42	0.658
46	32.06	28.50	−3.56	0.642
47	32.54	26.50	−6.04	0.651
48	32.30	27.50	−4.80	0.645

3.2. Adjustment policy

Now we consider the EPC adjustment strategy to minimize the deviation from a target of the load differences. The strategy is that the price will be adjusted in time slot$t + 1$ if

$$\bar{y}_{t+1} \geqslant B \text{ or } \bar{y}_{t+1} \leqslant D, \tag{20}$$

where $B \geqslant 0$ and $D \leqslant 0$ are an upper boundary and a lower boundary,

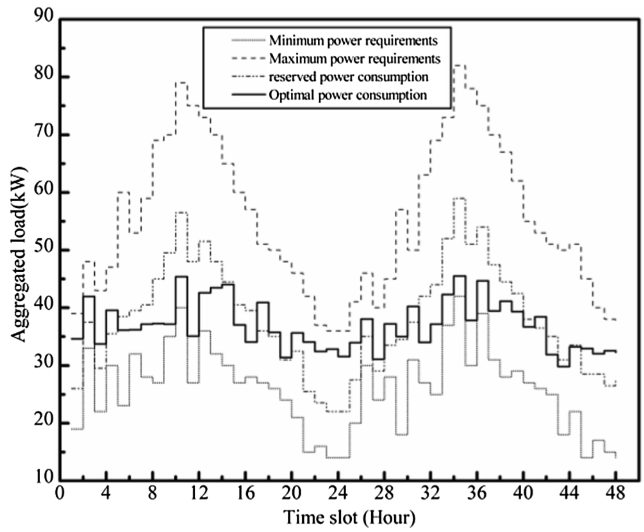

Fig. 1. Comparison of theoretically optimal and actually reserved power consumption.

respectively, which need to be set beforehand. In the monitoring process, if (20) holds, we need take action to adjust $\bar{y}_{t+1}$ to a target S we hope to arrive at. Although $\bar{y}_{t+1}$ can be adjusted to $S = 0$ when (20) is met in time slot $t+1$, the whole adjustment system is often unstable. Hence, in this case, it is necessary to choose proper targets $E \geqslant 0$ and $F \leqslant 0$. The chosen suitable value E or F will be discussed in Section 5.

By monitoring the whole consumption load process via (20), the power provider can induce the users to change their electricity consumption behavior according to a price demand response mechanism in time slot $t+1$ as follows.

In the process of monitoring the series $\{\bar{y}_t\}_{t=1}^{T}$, if $\bar{y}_{t+1}$ exceeds the upper boundary B, the power provider need raise the electricity price to induce the users to reduce their reserved electricity consumption requirements as far as possible in next time slots $t+1, t+2, \cdots$, while if $\bar{y}_{t+1}$ is below the lower boundary D, the power provider should decrease the electricity price to encourage the users to consume the electricity in next time slots $t+1, t+2, \cdots$. The following theorem give a demand response mechanism for the electricity price to make a power price adjustment.

Theorem 3.1. *Assume that users are sensitive to the change of the electricity prices and that the price demand response mechanism is that the change of the EWMA estimate difference value $\bar{y}_{t+1}$ is linearly proportional to the change of the corresponding EWMA price with a constant $-k$, $k \geqslant 0$. Then, if $\bar{y}_{t+1} \geqslant B \geqslant 0$ and $\bar{y}_{t+1}$ is adjusted to $E \in [0, B)$, the effect g_{t+1} of price adjustment is*

$$g_{t+1} = (\bar{y}_{t+1} - E)/(\mu k), \tag{21}$$

If $\bar{y}_{t+1} \leqslant D \leqslant 0$ and $\bar{y}_{t+1}$is adjusted to $F \in (D, 0]$, the effect g_{t+1} of price adjustment is

$$g_{t+1} = (\bar{y}_{t+1} - F)/(\mu k). \tag{22}$$

where μ is defined in (18).

Proof. According to the assumption of linear proportion, if $\bar{y}_{t+1} \geqslant B$ and $\bar{y}_{t+1}$ is adjusted to $E \in [0, B)$, we need adjust the EWMA price $\bar{p}_{t+1}$ to $\bar{p}'_{t+1}$ in time slot $t+1$, and we have that

$$E - \bar{y}_{t+1} = -k(\bar{p}'_{t+1} - \bar{p}_{t+1}), \tag{23}$$

where $\bar{p}_{t+1} = \mu p'_t + \theta \bar{p}_t$ is the EWMA forecast price estimate for the reserved price p_{t+1} in time slot $t+1$, p'_t is an adjusted price of the current price p_t in time slot t and $\bar{p}'_{t+1}$ is the adjusted value of $\bar{p}_{t+1}$ in time slot $t+1$. Hence,

$$\bar{p}'_{t+1} = (\bar{y}_{t+1} - E)/k + \bar{p}_{t+1}, \tag{24}$$

Meanwhile, from the EWMA definition of $\bar{p}'_{t+1}$, we have that

$$\bar{p}'_{t+1} = \mu p''_t + \theta \bar{p}_t. \tag{25}$$

where the price $\bar{p}''_t$ means that we must adjust to the price $\bar{p}''_t$ at time slot t if the adjusted price $\bar{p}'_{t+1}$ is taken at time slot $t+1$. Hence, from (24) and (25), we obtain that the effect g_{t+1} of price adjustment is

$$g_{t+1} := p''_t - p'_t = (\bar{y}_{t+1} - E)/(\mu k). \tag{26}$$

When $\bar{y}_{t+1} \leqslant D$ and $\bar{y}_{t+1}$ is adjusted to $F \in (D, 0]$, we obtain that (22) holds according to the same proof as the above. The proof is completed. □

By monitoring continuously the consumption load process, the accumulated effect of price adjustment will be

$$v_{t+1} = \sum_{i=1}^{t} g_i = v_t + g_{t+1}, \tag{27}$$

Thus, under the demand response mechanism for the power price, when $\bar{y}_{t+1}$ exceeds the boundary B or D, the users' reserved electricity consumption requirement load x'_{t+1} and the difference y'_{t+1} between the reserved and theoretical consumption loads at time slot $t+1$ will make adjustment as follows:

$$x'_{t+1} = x_{t+1} - kv_{t+1}, \tag{28}$$

$$y'_{t+1} = x'_{t+1} - x^*_{t+1}. \tag{29}$$

Now we give the algorithm of EPC load monitoring and price adjustment as follows.

Initialization: Given the original reserved consumption requirement load series $\{x_t\}_{t=1}^{T}$ analyzed from the data of smart meters and the original theoretical consumption load series $\{x^*_t\}_{t=1}^{T}$ and optimal price $\{p^*_t\}_{t=1}^{T}$ computed from (13), then the original consumption load difference series $\{y_t\}_{t=1}^{T}$ is computed according to (17). Let the initial adjusted load difference be $y'_1 = y_1$. Set the initial EWMA forecast load difference $\bar{y}_1 = S = 0$, and hence the initial estimation error $e_1 = y'_1 - \bar{y}_1 = y'_1$. Given the initial effect of price adjustment $g_1 = 0$, and hence the initial accumulated effect of price adjustment $v_1 = 0$ and the parameters $k > 0$, $E \in [0, B)$, $F \in (D, 0]$ and $\mu \in [0, 1]$. We adjust the prices and load differences as Algorithm 1 for each time slot t, $t = 1, 2, \cdots, T-1$.

Algorithm 1 (*EPC Adjustment Strategy*).

Step 0: Initialization. Set $t = 1$.
Step 1: Set $\bar{y}_{t+1} = \mu y'_t + (1-\mu)\bar{y}_t$. If (20) is not satisfied, $g_{t+1} = 0$, return Step 2. Otherwise, return Step 4.
Step 2: Set $v_{t+1} = v_t + g_{t+1}$, $x'_{t+1} = x_{t+1} - kv_{t+1}$, $y'_{t+1} = x'_{t+1} - x^*_{t+1}$, $e_{t+1} = y'_{t+1} - \bar{y}_{t+1}$.
Step 3: Replace t by $t+1$ and go back to Step 1.
Step 4: If $\bar{y}_{t+1} \geqslant B$, set $g_{t+1} = (\bar{y}_{t+1} - E)/(\mu k)$; If $\bar{y}_{t+1} \leqslant D$, set $g_{t+1} = (\bar{y}_{t+1} - F)/(\mu k)$,then return Step 2 .

4. Simulation results and analysis

In this section, we present simulation results and analyze the performance of the EPC monitoring and adjustment strategy. In the real-time pricing model, we assume that there are 10 users ($N = 10$). The entire time cycle we consider is two consecutive days, which is divided into $T = 48$ time slots (hours). The parameters $\omega \in [1, 4]$ in utility function (1) are selected randomly for each user and the values are fixed during the time cycle. The parameter α in (1) is assumed to be 0.5, and the parameters a, b and c in (5) are set to be 0.01, 0 and 0, respectively.

Table 3
Calculation of EPC adjustment strategy with $\mu = 0.3$, $B = -D = 5.5$, $E = -F = B/2$.

No.	Original load difference$y_t = x_t - x_t^*$	Adjusted load difference$y_t' = x_t' - x_t^*$	EWMA forecast for load difference$\bar{y}_{t+1}$	Adjusted consumption requirement Loadx_t'	Effect of price adjustment of g_t	Accumulated effect of price adjustment v_t	Forecasting error $e_t = y_t' - \bar{y}_t$
1	−8.62	−8.62	0	26.00	0.00	0.00	−8.62
2	−4.48	−4.48	−2.59	37.50	0.00	0.00	−1.90
3	−4.23	−4.23	−3.15	29.50	0.00	0.00	−1.08
4	−4.05	−4.05	−3.48	35.50	0.00	0.00	−0.57
5	2.34	2.34	−3.65	38.50	0.00	0.00	5.99
6	3.28	3.28	−1.85	39.50	0.00	0.00	5.13
7	3.34	3.34	−0.31	40.50	0.00	0.00	3.65
8	7.73	7.73	0.78	45.00	0.00	0.00	6.95
9	12.33	12.33	2.87	49.50	0.00	0.00	9.46
			[5.71]				
10	11.10	1.25	2.75	46.65	0.20	0.20	−1.50
11	12.93	3.08	2.30	38.15	0.00	0.20	0.78
12	8.93	−0.92	2.53	41.65	0.00	0.20	−3.46
13	4.49	−5.36	1.50	38.15	0.00	0.20	−6.86
14	0.47	−9.38	−0.56	34.65	0.00	0.20	−8.82
15	3.48	−6.37	−3.21	30.65	0.00	0.20	−3.16
16	5.46	−4.39	−4.16	29.65	0.00	0.20	−0.24
17	−4.92	−14.78	−4.23	26.15	0.00	0.20	−10.54
			[−7.39]				
18	−0.74	4.88	−2.75	40.62	−0.31	−0.11	7.63
19	−0.36	5.26	−0.46	36.62	0.00	−0.11	5.72
20	−3.13	2.49	1.26	38.12	0.00	−0.11	1.23
21	−8.54	−2.92	1.63	31.12	0.00	−0.11	−4.55
22	−8.94	−3.32	0.26	29.12	0.00	−0.11	−3.58
23	−10.82	−5.20	−0.81	27.62	0.00	−0.11	−4.39
24	−9.52	−3.90	−2.13	27.62	0.00	−0.11	−1.77
25	−6.43	−0.81	−2.66	33.12	0.00	−0.11	1.85
26	−3.03	2.59	−2.10	40.62	0.00	−0.11	4.70
27	−2.12	3.50	−0.70	34.62	0.00	−0.11	4.20
28	−3.69	1.93	0.56	39.12	0.00	−0.11	1.37
29	−0.49	5.13	0.97	40.12	0.00	−0.11	4.16
30	−2.72	2.90	2.22	43.12	0.00	−0.11	0.68
31	7.96	13.58	2.42	47.62	0.00	−0.11	11.16
			[5.77]				
32	6.83	2.38	2.75	39.55	0.20	0.09	−0.37
33	9.71	5.26	2.64	47.55	0.00	0.09	2.62
34	13.50	9.05	3.43	54.55	0.00	0.09	5.62
35	13.19	8.74	5.11	46.55	0.00	0.09	3.63
			[6.20]				−6.20
36	9.33	−6.62	2.75	38.05	0.23	0.32	−9.37
37	8.02	−7.93	−0.06	31.55	0.00	0.32	−7.87
38	3.39	−12.56	−2.42	28.55	0.00	0.32	−10.14
39	3.17	−12.78	−5.46	26.55	0.00	0.32	−7.32
			[−7.66]				7.66
40	1.27	1.68	−2.75	38.41	−0.33	−0.01	4.43
41	−1.95	−1.54	−1.42	36.91	0.00	−0.01	−0.12
42	3.13	3.54	−1.45	35.41	0.00	−0.01	5.00
43	1.21	1.62	0.05	31.41	0.00	−0.01	1.58
44	0.27	0.68	0.52	33.91	0.00	−0.01	0.17
45	−4.42	−4.01	0.57	28.91	0.00	−0.01	−4.57
46	−3.56	−3.15	−0.80	28.91	0.00	−0.01	−2.34
47	−6.04	−5.63	−1.51	26.91	0.00	−0.01	−4.12
48	−4.80	−4.39	−2.74	27.91	0.00	−0.01	−1.64

Notes: The value of square bracket indicates a point at which an adjustment is called for

4.1. Simulation results for real-time pricing model

By analyzing the data of smart meters we can give the reserved electricity consumption requirement load series $\{x_i^t\}_{t=1}^T$ and can analyze the minimum and maximum consumption requirement load series $\{m_i^t\}_{t=1}^T$ and $\{M_i^t\}_{t=1}^T$ of each user $i \in [1, N]$. Hence, we can obtain the total reserved consumption load requirement $x_t = \sum_{i=1}^N x_i^t$ (see Column 3 in Table 2) and the aggregated minimum and maximum consumption requirement loads $m_t = \sum_{i=1}^N m_i^t$ and $M_t = \sum_{i=1}^N M_i^t$(see Fig. 1). Now assume that the original reserved electricity forecast price p_t is the theoretical optimal price p_t^*, i.e., $p_t = p_t^*$ at every time slot $t \in [1, T]$.

The simulation results for the optimal problem (13) are shown in Table 2 and Fig. 1. In Table 2, the second and fifth columns contain, respectively, the theoretical optimal consumption loads $\{x_t^*\}_{t=1}^T$ and the theoretical optimal price $\{p_t^*\}_{t=1}^T$ calculated from model (13) by the given m_t, M_t and concerned parameters. The fourth column offers the original load difference $y_t = x_t - x_t^*$, which is calculated from Columns 2 and 3.

Fig. 1 shows the total theoretically optimal power consumption load and the actually reserved power consumption requirement load before adjustment in these time slots. As illustrated in Fig. 1, the theoretically optimal consumption load runs stably in the time slots, but the actual consumption requirement load has a large fluctuation. This shows that it is necessary to make an adjustment for the users' reserved consumption requirement load.

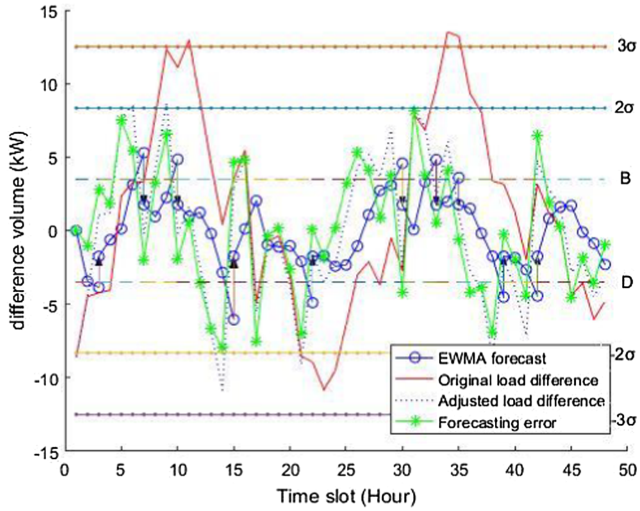

Fig. 2. Process of EPC monitoring and adjustment with $\mu = 0.4$, $B = 3.5$, $D = -3.5$, $E = B/2$ and $F = D/2$.

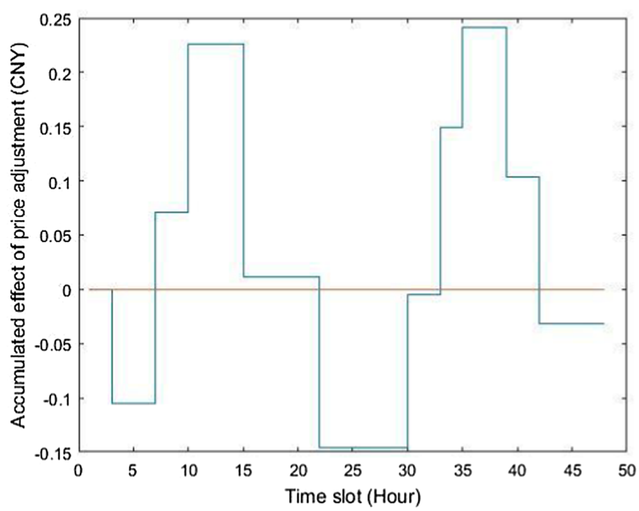

Fig. 3. Accumulated effect of price adjustment with $\mu = 0.4$, $B = 3.5$, $D = -3.5$, $E = B/2$and $F = D/2$.

4.2. Numerical analysis for EPC adjustment

Our purpose is to achieve peak load shifting and energy saving by EPC adjustment, and lead to a stable and feasible consumption load. We monitor the change of the load difference series $\{\bar{y}_t\}_{t=1}^{T}$ by calculating the EWMA estimate for the series $\{y_t'\}_{t=1}^{T}$ of the adjusted consumption load difference successively. When some EWMA $\bar{y}_{t+1}$ exceeds the given upper boundary B or the lower boundary D, it shows that the series $\{y_t'\}_{t=1}^{T}$ will become abnormal again in time slot $t + 1$. Hence, the next series $\{y_j'\}_{j=t+1}^{T}$of the adjusted load differences or the series $\{x_j'\}_{j=t+1}^{T}$ of the adjusted consumption requirements needs to be again adjusted to a normal level by changing the price inducing the users to update their consumption requirement based on the price demand response mechanism in Theorem 3.1. The price $p_t' = p_t + v_t$ after adjustment, $t = 1, 2, \cdots, T$, will be regarded as the actual operations price. In Algorithm 1, we suppose that the adjusted rate $k = 50$ and set parameters $\mu = 0.3$, $B = -D = 5.5$ and $E = -F = B/2$. The simulation results implementing Algorithm 1 in $T = 48$ time slots are shown in Table 3.

For each time slot $t \in [1, T]$, the second column of Table 3 shows the original load difference y_t. The third column provides the load difference y_t' after adjustment for y_t. The fourth column is the EWMA forecast

Table 4
Number of adjustments and SD (σ) for various $E(=-F)$ and $B(=-D)$ at $\mu = 0.3$.

$E(=-F)$	$B(=-D)$	Number of adjustments	SD(σ)
$B/2$	2	16	4.288
$B/2$	3	11	4.375
$B/2$	4	7	4.594
$B/2$	5	8	4.842
$B/2$	6	6	5.060
$B/2$	7	5	5.260
$B/2$	8	5	6.526
$B/2$	9	5	6.004
0	2	17	4.527
0	3	15	5.941
0	4	9	4.790
0	5	7	5.572
0	6	6	6.314
0	7	5	6.023
0	8	9	9.656
0	9	11	11.581
$9B/10$	2	19	4.133
$9B/10$	3	18	4.382
$9B/10$	4	11	4.947
$9B/10$	5	15	4.800
$9B/10$	6	10	4.870
$9B/10$	7	8	5.189
$9B/10$	8	7	5.435
$9B/10$	9	5	5.570

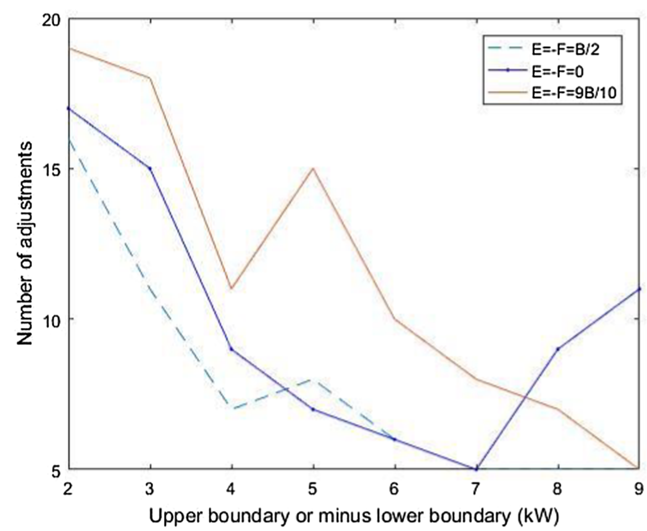

Fig. 4. Number of adjustments with different targets.

estimate $\bar{y}_{t+1}$ for the load difference y_{t+1} with $\mu = 0.3$, and the initial value $\bar{y}_1$ is set to zero. The fifth column gives the users' consumption requirement load x_t' after adjustment. The sixth and seventh columns are the effect g_t of the price adjustment and the accumulated effect v_t of the price adjustment, respectively. Notice that the values in the two columns are initially zero because the series are normal and unadjusted. The forecasting error $e_t = y_t' - \bar{y}_t$ is presented in the final column.

In this illustration, the EWMA forecast value $\bar{y}_{10}$ for the load difference y_{10} is 5.71 at time slot $t + 1 = 10$ and is the first value to exceed the upper boundary $B = 5.5$, which will be adjusted to $E = B/2 = 2.75$, a given target. Next, the effect of the price adjustment $g_{10} = 0.2$ and its accumulated effect $v_{10} = 0.2$ are calculated by (21) and (27) respectively, which means that the original price $p_{10} = 0.908$ will be adjusted to $p_{10}' = 1.108$. Then the adjusted consumption load x_{10}' is reduced to 46.65 resulting from (28) with $x_{10} = 56.5$ and hence the adjusted load difference$y_{10}'$is 1.25, which comes from (29) with $x_{10}' = 46.65$ and $x_{10}^{*} = 45.40$from Table 2. In Table 3, the second adjustment occurs at $t + 1 = 18$ when the EWMA forecast value $\bar{y}_{18}$is $-$ 7.39, which exceeds

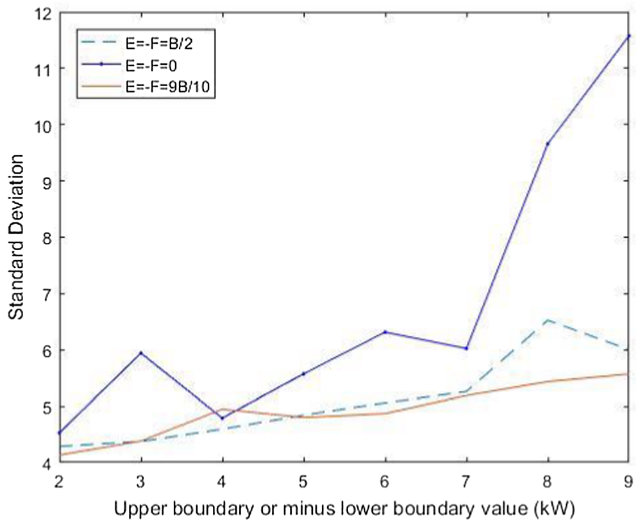

Fig. 5. Standard deviations with different targets.

the given lower boundary $D = -5.5$. This need to be adjusted to the target $F = -2.75$ that we hope to arrive at. The effect of the price adjustment will be $g_{18} = -0.31$ units from (22), which means that $p'_{18} = p_{18} + 0.20 - 0.31 = 0.605$. With the accumulated price adjustment $v_{18} = 0.20 - 0.31 = -0.11$ from (27), the original price $p_{18} = 0.715$ will be adjusted by -0.11 in fact. The adjusted consumption load x'_{18} is 40.62 by (28). The adjusted load difference is $y'_{18} = 4.88$ by (29).

We can discern and analyze from Table 3 that the number of adjustments in total is five.

The empirical average adjustment interval (AAI) is equal to $47/5 \approx 9$, which means that the adjustment process with $B = 5.5$ and $D = -5.5$ shows that only five minor changes were needed to generate a much more stable process with the empirical AAI 9. The standard deviation σ (SD(σ)) of residuals is calculated by

$$\sigma = \sqrt{\sum_{t=1}^{T} e_t^2/(T-1)} = \sqrt{\sum_{t=1}^{48} e_t^2/47} = 5.34$$

which shows all points are inside the 3σ boundary so there is no evidence of special causes.

For further learning about the parameter μ, the boundaries B and D and the target values E and F for the effect of the adjustment mechanism, we take again $\mu = 0.4$, $B = 3.5$, $D = -3.5$, $E = B/2$and $F = D/2$ in Algorithm 1. The results of the monitoring and adjustment are shown in Figs. 2 and 3.

From Fig. 2, we can see that the series of the load differences after adjustment are more stable than that of the original load differences, which can reach the desired effect. The adjustment chart shows that ten minor changes were needed to produce a much more stable process with an empirical AAI of $47/10 = 4.7$ and no points outside the 3σ limits show that there is also no evidence of special causes.

Fig. 3 is the accumulated effect of the price adjustment. From Fig. 3, we can learn about the fact that the accumulated effect can finally become close to zero in the whole adjust cycle, which is similar as Table 3. This shows that the adjustment is only to balance the load differences and achieve peak load shifting without increasing the price of the system.

5. Discussion

Considering the stability of the system in monitoring and adjustment, we have to concern the value E and F we hope to reach. Different E and F have different adjustment frequency of the price and load difference. We do not hope to adjust the system too frequently because adjustment too frequent will increase the workload of energy providers and users' complaint. So far, we still haven't found a strategy to compute the optimal E and F. Thus, we have to rely on the empirical E and F from Algorithm 1 instead of the optimal E and F. Because the optimal state is that the actual load requirement equals the theoretical load, the value (EWMA value after adjustment) should be theoretically set to 0 when we apply the EPC adjustment policy. Now we adopt the EPC adjustment strategy with parameters $\mu = 0.3$, different $E(=-F)$ and various $B = -D \in [2, 9]$ to discuss the effect of change.

The simulation results from the implement of Algorithm 1 over 48 time slots are shown in Table 4 and Fig. 4. Fig. 4 shows the number of adjustments for $E(=-F)$ values of 0, $B/2$ and $9B/10$. From Fig. 4, we can see that in the whole, the number of adjustments with $E = -F = 9B/10$ seems to be the greatest while that with $E = -F = B/2$ the smallest.

Next, the standard deviations (σ) of residuals about various E values are shown in Fig. 5. From Fig. 5, we can see that the standard deviations (σ) of residuals with $E = -F = 9B/10$ is the best among them in the whole.

Furthermore, from Figs. 4 and 5, we can also see that the adjustment series with $E = -F = 0$ is unstable. Hence, we discern that we can choose proper E and F by weighing the number of adjustments and standard deviation in reality.

6. Conclusion

The paper introduces an EPC monitoring and adjustment strategy to monitor the users' reserved electricity consumption requirement load and gives a price demand response mechanism to induce the users to use reasonably electricity. By setting an upper boundary and a lower boundary for the EWMA forecast of the difference between the theoretical consumption load computed from a given real-time pricing model in SG and the reserved consumption load requirement obtained by smart meters, the power providers can automatically monitor the change of the load differences in every time slot. Under the strategy and the price mechanism, if the forecast value exceeds the boundary in some time slot, the users will be induced to adjust their consumption requirement loads. Applying the strategy, energy providers can balance the consumption requirement load and power provision by avoiding frequently price adjustment. Therefore, the method provides an important reference for managing electricity load.

Acknowledgements

The authors thank the editor and the reviewers for their careful reading and helpful suggestions and comments. The work was sponsored by the National Natural Science Foundation of China, China (NSFC) (No. 71572113, 71432007, 71871144) and the matching project of NSFC, China (No. 1P16303003, 2019KJFZ048, 2018KJFZ035). The research of Prof. Tsung was supported by the Hong Kong RGC General Research Funds, Hong Kong, China (No. 16203917, 16201718).

References

Akhmetsagirov, R. I., & Nasibullin, R. T. (2016). *The Control parameters of automatic control system of the process of producing ferromagnetic powders by plasma erosion of a metallic anode. The 2nd international conference on industrial engineering, applications and manufacturing, Chelyabinsk, Russia*.

Baldewijns, G., Luca, S., Nagels, W., Vanrumste, B., & Croonenborghs, T. (2015). *Automatic detection of health changes using statistical process control techniques on measured transfer times of elderly. The 37th annual international conference of the IEEE engineering in medicine and biology society, Milan, Italy*.

Box, G. E. P. (1992). Process adjustment and quality control. *Total Quality Management, 4*(4), 215–228. https://doi.org/10.1080/09544129300000030.

Box, G., & Luceno, A. (2009). *Statistical control by monitoring and adjustment.* Hoboken, New Jersey: Wiley.

Chiu, T. C., Shih, Y. Y., Pang, A. C., & Pai, C. W. (2017). Optimized day-ahead pricing with renewable energy demand-side management for smart grids. *IEEE Internet Things*

Journal, 4(2), 374–383. https://doi.org/10.1109/JIOT. 2016. 2556 006.
Dai, Y., Gao, Y., Gao, H., & Zhu, H. (2017). Real-time pricing scheme based on Stackelberg game in smart grid with multiple power retailers. *Neurocomputing, 260*, 149–156. https://doi.org/10.1016/j.neucom. 2017. 04. 027.
Ding, D., Tsung, F., & Li, J. (2016). Directional control schemes for processes with mixed-type data. *International Journal of Production Research, 54*(6), 1594–1609. https://doi.org/10.1080/00207543.2015.1023402.
Ding, D., Tsung, F., & Li, J. (2017). Ordinal profile monitoring with random explanatory variables. *International Journal of Production Research, 55*(3), 736–749. https://doi.org/10.1080/00207543.2016.1204476.
Evora, J., Hernandez, J. J., & Hernandez, M. (2015). A MOPSO method for direct load control in smart grid. *Expert Systems with Applications, 42*, 7456–7465. https://doi.org/10.1016/j.eswa.2015.05.056.
Göb, R., Lurz, K., & Pievatolo, A. (2013). Rejoinder to the discussions of the paper on 'electrical load forecasting by exponential smoothing with covariates'. *Applied Stochastic Models in Business and Industry, 29*(6), 629–645. https://doi.org/10.1002/asmb.2008.
Göb, R., Lurz, K., & Pievatolo, A. (2015). More accurate prediction intervals for exponential smoothing with covariates with applications in electrical load forecasting and sales forecasting. *Quality and Reliability Engineering International, 31*(4), 669–682. https://doi.org/10.1002/qre.1625.
Guo, Y., Li, K., & Laverty, D. (2013). *A statistical process control approach for automatic anti-islanding detection using synchrophasors. 2013 IEEE Power Energy Society Generation Meeting, Vancouver, BC, Canada*.
He, Z., Wang, Z., Tsung, F., & Shang, Y. (2016). A control scheme for autocorrelated bivariate binomial data. *Computers and Industrial Engineering, 98*, 350–359. https://doi.org/10.1016/j.cie.2016.06.001.
Jiang, W., Wang, K., & Tsung, F. (2012). A variable- selection-based multivariate ewma chart for process monitoring and diagnosis. *Journal of Quality Technology, 44*(3), 209–230. https://doi.org/10.1080/00224065.2012.11917896.
Kobayashi, K., & Hiraishi, K. (2015). *Feberary). Algorithm for optimal real-time pricing based on switched Markov chain models. Innovative smart grid technologies conference, Washington, DC, USA*.
Lees, M., Ellen, R., & Brodie, P. (2014). *Challenges with performance management of automatic control loops in a large-scale batch processing environment. Australian control conference, Canberra, ACT, Australia*.
Li, J., Tsung, F., & Zou, C. (2013). Directional change point detection for process control with multivariate categorical data. *Naval Research Logistics, 60*(2), 160–173. https://doi.org/10.1002/nav.21525.
Li, W., Pu, X., Tsung, F., & Xiang, D. (2017). A robust self-starting spatial rank multivariate ewma chart based on forward variable selection. *Computers & Industrial Engineering, 103*, 116–130. https://doi.org/10.1016/j.cie.2016.11.024.
Li, J., Liu, Y., Tsung, F., Huo, J., & Su, Q. (2016). Statistical monitoring of service levels and staffing adjustments for call centers. *Quality & Reliability Engineering International, 32*(8), 2813–2821. https://doi.org/10.1002/qre.1966.
Liu, L., Xue, M. Z., Zhang, J., & Zhao, J. (2013). A sequential rank-based nonparametric adaptive ewma control chart. *Communications in Statistics - Simulation and Computation, 42*(4), 841–859. https://doi.org/10.1080/03610918.2012.655829.
Liu, L., Tsung, F., & Zhang, J. (2014). Adaptive nonparametric cusum scheme for detecting unknown shifts in location. *International Journal of Production Research, 52*(6), 1592–1606. https://doi.org/10.1080/00207543.2013.812260.
Lu, T., Wang, Z., Wang, J., Ai, Q., & Wang, C. (2018). A data-driven stackelberg market strategy for demand response-enabled distribution systems. *IEEE Transactions on Smart Grid*. https://doi.org/10.1109/TSG.2018.2795007.
Mohsenianrad, A. H., & Leongarcia, A. (2010). Optimal residential load control with price prediction in real-time electricity pricing environments. *IEEE Transactions on Smart Grid, 1*(2), 120–133. https://doi.org/10.1109/TSG.2010. 205 5903.
Nezamoddini, N., & Wang, Y. (2017). Real-time electricity pricing for industrial customers : Survey and case studies in the United States. *Applied Energy, 195*, 1023–1037. https://doi.org/10.1016/j.apenergy.2017.03.102.
Nishimura, K., Matsuura, S., & Suzuki, H. (2015). Multivariate ewma control chart based on a variable selection using aic for multivariate statistical process monitoring. *Statistics & Probability Letters, 104*, 7–13. https://doi.org/10.1016/j.spl.2015.05.003.
Runger, G., Lian, Z., & Castillo, E. (2010). Optimal multivariate bounded adjustment. *IIE Transactions, 42*(10), 746–752. https://doi.org/10.1080/07408171003670967.
Saif, A. W. A. (2015). *The need for integrating statistical process control and automatic process control. IEEE international conference on industrial engineering and engineering management. Bandar Sunway, Malaysia*.
Samadi, P., Mohsenian-Rad, A. H., Schober, R., Wong, V. W. S., & Jatskevich, J. (2010). Optimal Real-Time Pricing Algorithm Based on Utility Maximization for Smart Grid. *IEEE international conference on smart grid communications* (pp. 415–420). Gaithersburg, MD, USA.
Shen, X., Tsung, F., & Zou, C. (2014). A new multivariate ewma scheme for monitoring covariance matrices. *International Journal of Production Research, 52*(10), 2834–2850. https://doi.org/10.1080/00207543.2013.842019.
Srinivasan, D., Rajgarhia, S., Radhakrishnan, B. M., Sharma, A., & Khincha, H. P. (2017). Game-theory based dynamic pricing strategies for demand side management in smart grids. *Energy, 126*, 132–143. https://doi.org/10.1016/j.energy.2016.11.142.
Wang, Y., Chen, Q., Hong, T., & Kang, C. (2018). Review of smart meter data analytics: Applications, methodologies, and challenges. *IEEE Transactions on Smart Grid, 99*, 1–24. https://doi.org/10.1109/TSG.2018.2818167.
Xu, S., & Jeske, D. R. (2018). Weighted EWMA charts for monitoring type I censored Weibull lifetimes. *Journal of Quality Technology, 50*(2), 220–230. https://doi.org/10.1080/00224065. 2018. 1436830.
Yang, J., Zhang, G., & Ma, K. (2014). Matching supply with demand: a power control and real time pricing approach. *International Journal of Electrical Power and Energy Systems, 61*(61), 111–117. https://doi.org/10.1016/j.ijepes.2014.03.014.
Yeong, W. C., Khoo, M. B. C., Tham, L. K., Teoh, W. L., & Rahim, M. A. (2017). Monitoring the coefficient of variation using a variable sampling interval EWMA Chart. *Journal of Quality Technology, 49*(4), 380–401. https://doi.org/10.1080/00224065.2017.11918004.
Yu, M., & Hong, S. H. (2017). A real-time demand-response algorithm for smart grids: A stackelberg game approach. *IEEE Transactions on Smart Grid, 7*(2), 879–888. https://doi.org/10.1109/TSG.2015.2413813.
Zhang, C., Tsung, F., & Zou, C. (2015). A general framework for monitoring complex processes with both in-control and out-of-control information. *Computers and Industrial Engineering, 85*, 157–168. https://doi.org/10.1016/j.cie.2015.03.007.
Zhang, C., Qiu, Y., Ruan, F., Xiao, Pommerenke, W., & Yang, X. (2016). Automatic control process analysis of gas pressure in electrostatic discharge measurement system. In the Asia-Pacific Conference on Environmental Electromagnetics. Hangzhou, China.
Zhu, H., Gao, Y., & Hou, Y. (2018). Real-time pricing for demand response in smart grid based on alternating direction method of multipliers. *Mathematical Problems in Engineering, 2018*, 1–10. https://doi.org/10.1155/2018 /8760575.
Zhu, H., Gao, Y., Hou, Y., & Tao, L. (2018). Multi-time slots real-time pricing strategy with power fluctuation caused by operating continuity of smart home appliances. *Engineering Applications of Artificial Intelligence, 71*, 166–174. https://doi.org/10.1016/j.en gappai.2018.02.010.

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