Applied Energy xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

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

Identifying regime shifts in the US electricity market based on price fluctuations ☆

Mei Sun *, Juan Li, Cuixia Gao, Dun Han

Center for Energy Development and Environmental Protection, Jiangsu University, Zhenjiang, Jiangsu 212013, PR China

HIGHLIGHTS

- Researching correlations evolution of the U.S. electricity market based on RMT.
- Identifying four regime shifts with five periods among the three departments.
- Analysing the characteristics of cluster evolution and verifying the existence of regime shifts.
- Studying the electricity price level influences regime shifts.

ARTICLE INFO

Article history:
Available online xxxx

Keywords:
U.S. electricity market
Electricity prices
Regime shifts
Cluster evolution

ABSTRACT

Electricity power is a basic industrial component which plays an important role in the economy of a nation. In this paper, the correlations evolution of electricity prices among 50 states and the District of Columbia are studied based on random matrix theory (RMT) Four regime shifts are identified from January 1990 to August 2014 in the U.S. residential, commercial and industrial electricity markets. Then, the genetic algorithm (GA) is applied to analyze the clusters of evolution. The results show that, the correlations of electricity prices increased continually in the three departments. However, it decreased in 2012 which further confirms its sensitivity to fuel market. Besides, four regime shifts exist in the three departments though the different times of occurrence caused by price level. And, the fluctuation of community evolution is consistent with four regime shifts. The final part is a summary of the research analyzed and results.

1. Introduction

Electricity industry [1–5] is the foundation of national economy, and electricity price affects expenditure in other fields as well as the living standard of residents directly or indirectly. In the 1980s, the reform of electricity industry overtook the world [6–9]. Western countries lost the regulations to restructure and establish a competitive electricity market, which has spread in the global electricity market. In the U.S., most of electricity industries are privatized [10,11]. Electricity industry reforms mainly means reducing regulation while increasing competition in spite of the programs of reform being different for regions. The purpose is to fuse market mechanism into electricity industry, to optimize and improve the allocation and efficiency of resources using competition and privatization.

In recent years, one of the most important commodities for national development and people's life is the electricity market, and policy makers and researchers are increasingly concerned about. It should be mentioned that related surveys on electricity market have been conducted by a few researchers and organizations. Torrent-Fontbona et al. [12] proposed a new method that, given the demanded power of close consumers for a time window (power profile), electricity costs were reduced by reallocating the demanded power among consumers in order to keep all of them below or equal to their contracted power. Cappers et al. [13] summarized the existing contribution of Demand Response resources in the U.S. electricity markets, and concluded that competition is critical to the development of electricity markets. A more recent update was accomplished by Castagneto-Gissey et al. [14] in 2014 on European electricity market. They analyzed the interactions of a representative sample of 13 European electricity spot prices during the period 2007–2012 based on complex network theory. Their model establishes a time-varying network describing the evolving influences among the European electricity prices, and detects important changes in market integration. Similar surveys have also been

☆ The short version of the paper was presented at CUE2015 on Nov. 15–17, Fuzhou, China. This paper is a substantial extension of the short version.

* Corresponding author.
E-mail address: sunm@ujs.edu.cn (M. Sun).

http://dx.doi.org/10.1016/j.apenergy.2016.04.032

conducted in other part of the world. For example, by using a fractional co-integration analysis, de Menezes Lilian et al. [15] showed that long memory for price shocks and co-integration exist only for a few markets, such as Germany, Netherlands and France. Subsequent survey, Pereira and Pronto [16] proposed a multistage stochastic optimization method for planning energy systems based on the approximation of the expected cost to go functions through the introduction of piecewise linear functions. Albadi and El-Saadany [17] applied an optimal power flow to economic dispatch including load forecast. The electricity prices for each period of the next day were calculated considering price elasticity. Ketter et al. [18] used an energy market simulator to study the dynamics of customer and retailer decision making. They introduced a coalition of customers and proposed a novel methodology to reduce electricity costs from the view of terminal consumer point. Wang and Li [19] reported a survey of Time-of-Use (TOU) pricing programs targeted industrial customers, and examined various industrial scenarios to predict electricity cost savings when customers were facing the transition from flat rates to TOU pricing.

The existing literatures has provided a solid empirical investigation and a good reference to understand the evolution of certain electricity markets around the world, but some studies of U.S. electricity market still needs to be further researched. The U.S. electricity market is one of the largest electricity markets in the world and the first country to reform. Two reasons supported the study of the U.S. electricity market. The first being its mature operation mechanism and supervision systems and the other are being the higher market competition. This paper researches the correlation coefficient of electricity price, and identifies the influencing factors whether they relate to policy, climate, geographical location, or distribution of coal resources. Our objective is to explore the principle of U.S. electricity market from the angle of electricity price and provide a reference for future research in the electricity market. We hope this research could be used to facilitate reforms in China's electricity market, as well as help energy investors to assess potential risk of the whole electricity market.

Motivated by these facts, this paper applies the RMT to the electricity market. First, the calculated parameters of electricity prices for 50 states and the District of Columbia are calculated by the method of RMT, with our focus on the correlations, eigenvalues and eigenvectors for the three departments. Secondly, we then proceed with the mechanisms of electricity market reform as well as the influencing factors. Then, the evolutionary characteristics of the electricity market are detected. Lastly, we identify and determine the important shift periods and some stylized facts of the actual electricity market the method of least-squares regression. This study reveals the main influencing factors in the regime shifts which are detected in the electricity market. Timely adjustment of policy in developing the electricity market would be given in accordance with the conclusions which are summarized from the analysis of the correlation between regime shifts and influencing factors.

The continuing parts of this paper is as follows: Section 2, the basic situation of the U.S. electricity market is introduced. Data sources and methods are showed in Section 3. In Section 4, the empirical study of the electricity prices for residential, commercial and industrial are presented. Section 5 provides concluding remarks.

2. Present situation of the U.S. electricity market

The U.S. has the largest and most advanced economies in the world with large total installed capacity and electricity consumption in the world. Coal-electricity is the main generating mode due to its rich coal resource. Therefore, the situation from the perspective of generation capacity, electric structure and electricity consumption is analyzed as follows.

2.1. Generation capacity and electricity structure

In the U.S., the generation capacity increased from 2000 to 2014. Data used in this part is downloaded from EIA [20]. In 2009, it decreased obviously as shown in Fig. 1(a and b). The electricity sources are mainly coal-electricity, gas-electricity and nuclear-electricity. However, the proportions of coal-electricity and gas-electricity have changed recently.

From the structure of generation capacity, the percentage of nuclear-electric varies between 19%–20%, while conventional hydroelectric is in the vicinity of 6–7%. However, the change in fuel oil-electricity is obvious declining from 3% to 0.7%, and will keep declining according to the national policy. Due to the adjustment in coal-electricity and gas-electricity in 2005, the percentage of coal-electricity declined from 52% to 38% while gas-electricity increased from 16% to 27%. However, coal-electricity has been recovering in 2012. In addition, conventional hydro-electricity and nuclear-electricity have remained in a stable level over a decade.

2.2. Electricity price

The U.S. is a federal country, and its electricity regulatory system also complies with federal and state government. It is therefore

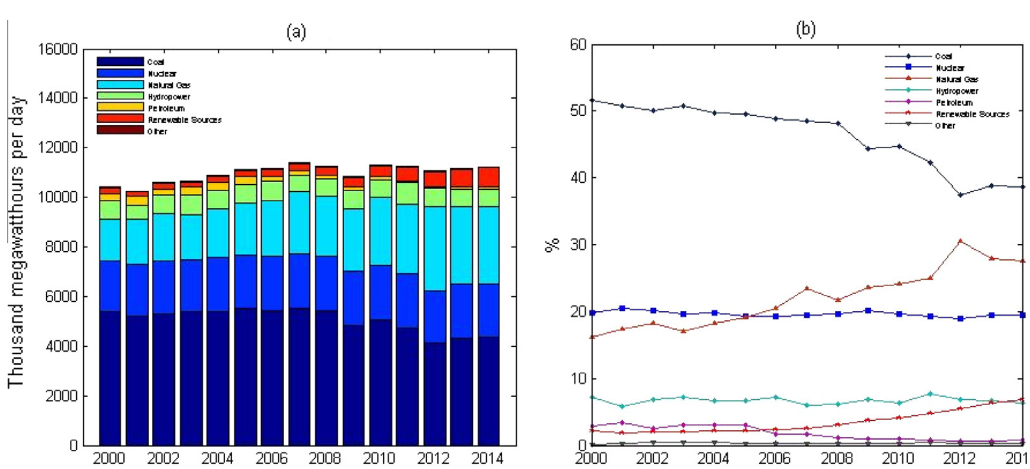

Fig. 1. Variation of electricity production in the U.S. *Note:* (a) Electricity production by energy resources. (b) Variation of electricity production percentage by energy resources.

obvious that the pricing of states would be different. Let us take the multi-step electricity pricing of residential as an example. In Virginia, the primary electricity need of a family is 800 kilowatt-hours (kW h) per month and if the electricity consumption exceeds 800 kW h, the family will pay extra electricity cost. In Vermont, the primary electricity of every family is 750 kW h and the second electricity quota of 1500 kW h per month. In Arizona, the primary electricity need of every family is 700 kW h in summer and the price is 10.6 cents/kW h within a range. The price is 12.4 cents/kW h when the electricity consumption exceeds 700 kW h any additional kW h up to 2000 kW h. However, if the consumption exceeds 2000 kW h, the family pays 16 cents/kW h. In the spring and autumn, the price of primary electricity is 10 cents/kW h, and the price in winter is cheaper. Thus, it can be seen that, there is large difference between the multi-step residential electricity pricing of 50 states and the District of Columbia.

The electricity prices in the U.S. are not unified due to different states having different policies and costs. In the U.S., every state takes its actual situation into consideration in the electricity pricing. For instance, Pennsylvania and Arizona consider seasonal factors into the electricity pricing.

3. Data and methods

In this section, we introduce our source of data and methodology. The purpose of our study is to investigate the transformation of electricity market development in the U.S.

3.1. Data

In this paper, the data of electricity prices are divided into three kinds: residential, commercial and industrial for 50 states and the District of Columbia and the U.S. electricity price. The data is recorded monthly from 1990M1 to 2014M8, given a total of 296 values [20].

The electricity consumption of U.S. shows an increasing trend for the last 15 years. Fig. 2 displays the electricity consumption in different departments in the U.S. In 2014, the proportion of residential, commercial and industrial consumption were 36.33%, 35.15%, and 24.74%, respectively. It can be observed that the proportion of industrial consumption shows a downward trend. While the commercial and residential consumption [21,22] keep the upward pattern.

3.2. Moving windows and correlation coefficient

We denote $P_i(t)$ the t-month electricity price of i-state ($i = 1, 2, 3 \dots 51$). Then, the logarithmic return at time t is defined as

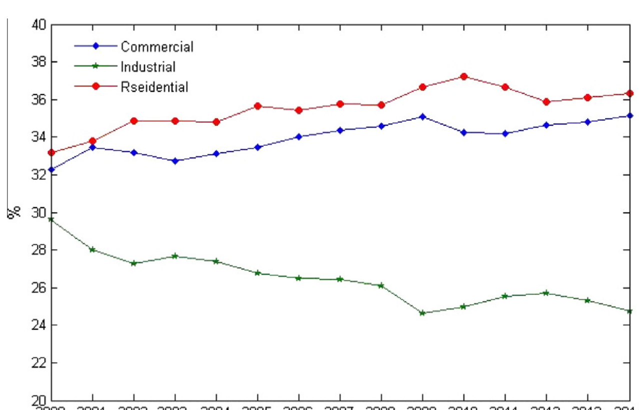

Fig. 2. Variation of electricity consumption percentage by main sectors in the U.S.

$$r_i(t) = \ln P_i(t) - \ln P_i(t-1) \tag{1}$$

For each moving window $[t - s + 1, t]$ at time t of size s, we compute the correlation matrix $C(t)$, whose element C_{ij} is the Pearson correlation coefficient [23] between the return time series of the U.S. states i and j.

$$C_{ij} = \frac{1}{\sigma_i \sigma_j} \sum_{t-s+1}^{t} [r_i(k) - u_i][r_j(k) - u_j] \tag{2}$$

where u_i is the sample means of the i-state in each moving window. σ_i and σ_j are the standard deviations of states i and j in each moving window, respectively.

To estimate the empirical correlation matrix and minimize the unavoidable statistical uncertainty, we use a large window containing a large number of data points [24].

Although large windows reduce our ability to investigate the fast dynamics in correlation studies, the correlation matrix is no longer invertible when the window size is smaller than the 51 time series in our study (50 states + District of Columbia) [25], implying $s_{\min} = 51$. We set the value at $s = 60$ months, giving us 237 moving windows for investigation.

3.3. Determining deviating eigenvalues

For each t larger or equal to $t = 1990/M1$, we calculate the correlation matrix $C(t)$ and compute its 51 eigenvalues $\{\lambda_n : n = 1, \dots, 51\}$. Then, we sort the eigenvalues $\{\lambda_n\}$ in descending order and calculate the corresponding eigenvectors $U_n(t) = [u_{n,1}(t), \dots, u_{n,51}(t)]^T$.

If M is a $T \times N$ matrix with mean 0 and variance $\sigma^2 = 1$, we define $C = \frac{1}{T} M^T M$. In the limit $N \to \infty, T \to \infty$ where $Q = T/N \geqslant 1$ is fixed, the probability density $f_{RMT}(\lambda)$ of eigenvalues λ of matrix C is $f_{RMT}(\lambda) = \frac{Q}{2\pi}\sqrt{(\lambda_{\max} - \lambda)(\lambda - \lambda_{\min})/\lambda}$, where $\lambda \in [\lambda_{\min}, \lambda_{\max}]$ and $\lambda_{\min,\max} = 1 + 1/Q \pm 2\sqrt{1/Q}$. If an eigenvalue λ is greater than $\lambda_{\max}$ and thus deviates from the prediction of the RMT [24,26], its eigenvector frequently contains valuable information about market dynamics.

In real-world data, however, the limit conditions $N \to \infty$ and $T \to \infty$ are never fulfilled and some finite-size effect should be included in the RMT studies. In order to identify the deviating eigenvalues, we thus randomize the housing index time series to eliminate any temporal correlations. Then, we calculate a new correlation matrix C_{Rnd} from the randomized return time series, and compute the corresponding 51 eigenvalues. Although the density functions $f_{RMT}(\lambda)$ and $f_{Rnd}(\lambda)$ overlap to a great degree, they exhibit some differences in the right-hand tail. We find that $f_{Rnd}(\lambda)$ is not bounded by the maximum eigenvalue $\lambda_{\max}$ predicted by the RMT.

3.4. Least-squares regression

For each eigenvalue λ_n we construct its Eigen portfolio. The returns of which we calculate by

$$R_n(t') = U_n^T(t') \cdot r(t') \tag{3}$$

where $t' = t - s + 1, \dots, t$, and $r(t') = [r_1(t'), \dots, r_{51}(t')]^T$ is a vector whose components are state-level electricity price returns defined in Eq. (1). To evaluate the collective market information embedded in λ_n, we investigate the following linear regressive model between $R_n(t')$ and the return $R(t')$ of the U.S. electricity price

$$R_n(t') = k_n(t) R(t') + \varepsilon(t'). \tag{4}$$

where R is defined in Eq. (1) by the overall price index of residential, commercial and industrial in the U.S. respectively. R_n and R are normalized respectively to zero mean and unit variance [27], and $k_n(t)$

is the regression coefficient between R_n and R at time t'. If k_n differs significantly from 0, we assume the eigenvalue λ_n contains important information because the corresponding Eigen portfolio is correlated with the entire electricity market [27]. To estimate the value of k_n, we perform an ordinary least squares linear regression.

3.5. State clustering

It is considered widely for GA to study the clustering in 51 states. We represent states as nodes. l_{ij} means the edges between two states. Here, w_{ij} denote the correlation coefficient between states i and j. If $w_{ij} \geqslant V$, we set $l_{ij} = 1$, else $l_{ij} = 0$ $(w_{\min} < V < w_{\max})$ [28]. Data of one moving window form a single complex network. Therefore, there are 237 networks in time series in this study for residential, commercial and industrial, respectively. Then the evolution property of clusters (or community) [29–33] is analyzed based on GA.

To evaluate the quality of the partitions, we introduced the algorithm developed by Girvan and Newman [34]. The modularity [35] measures the density of links inside communities compared to links between communities, and can be used to evaluate the quality of the partitions obtained by a method. The modularity is defined as

$$M = \sum (e_{ii} - a_i^2) = tr(e) - \|e^2\| \tag{5}$$

where e_{ij} means the fraction of all edges in the network that link nodes in community i to nodes in community j. $tr(e) = \sum_i e_{ii}$ gives the fraction of all edges in the network that connect nodes in the same community. $a_i = \sum_j e_{ij}$ denote the fraction of edges that connect to nodes in community i.

4. Empirical analysis of the U.S. electricity market

In this section, the average correlation coefficients, eigenvalues and eigenvectors, evolvement of clusters and shift periods are analyzed in detail.

4.1. Correlation coefficient

The average correlation coefficients is analyzed first, then we analyze the eigenvalues and eigenvectors of electricity price in each department. This gives the average correlation coefficients with the time evolution in U.S. electricity market according to Section 3.2. Fig. 3 gives the average correlation coefficients calculated by Eq. (2) for each moving windows during the last two decades.

It is considered widely for cost plus method to regulate electricity price in spite of the different pricing mechanisms in the U.S. In addition, most of them adopt stepwise pricing. If the quantity of electricity that consumers used exceeds a certain limit, the unit price of electricity will be increased. However, the electricity prices of states are different due to the policy and cost of generation plants. Notably is California, for its success in energy-saving, is a typical example. The unit electricity price in California for residential are divided into five categories which is proportional to the amount of consumption. Residents have their preferential price options if their quantity of electricity consumption is within the baseline. California public utilities regulatory committee formulates the baseline with cognizance to location, seasons and the sources of household energy.

The average correlation coefficients increase rapidly in recent years as shown in Fig. 3. Thus, it indicates that the electricity price of 50 states and the District of Columbia (including residential, commercial, and industrial) become strongly correlated progressively with time. In 2000, the electricity structure was adjusted by the U.S. government. It increased the proportion of gas-electricity, and reduced the coal-electricity. Lesser capital, shorter construction period and taken full advantage of capacity are advantages of gas-electricity. However, cost associated with coal-electricity is transportation which depends on the distribution of coal deposits. As a result of adjustment, the correlation of electricity price became higher. With these changes, the correlation of the states' electricity prices is noticeable, although their pricing mechanism is independent.

In Fig. 3, the average correlation coefficients of the three departments have declined obviously in 2012 (see Fig. 1). This indicates that the electricity price of 50 states and the District of Columbia become less correlated because of the recovering of coal-electricity. Therefore, uneven distribution of coal resources lead to the various generating cost for states directly which has dropped the average correlation coefficients. However, the occurred time is different from each other in the three departments. It demonstrated that the occurrence of regime shifts is in proportion to price level. Moreover, the situation also illustrates that higher correlation coefficient can reflect the real market information. This is due to the largest correlation for residential electricity market.

4.2. Eigenvalues and eigenvectors

The eigenvalues and eigenvectors are analyzed with the algorithm in Section 3.3 and the results are shown in Figs. 4 and 5. The eigenvalues of residential is the largest in the three departments. The size of eigenvalue is positive proportional to

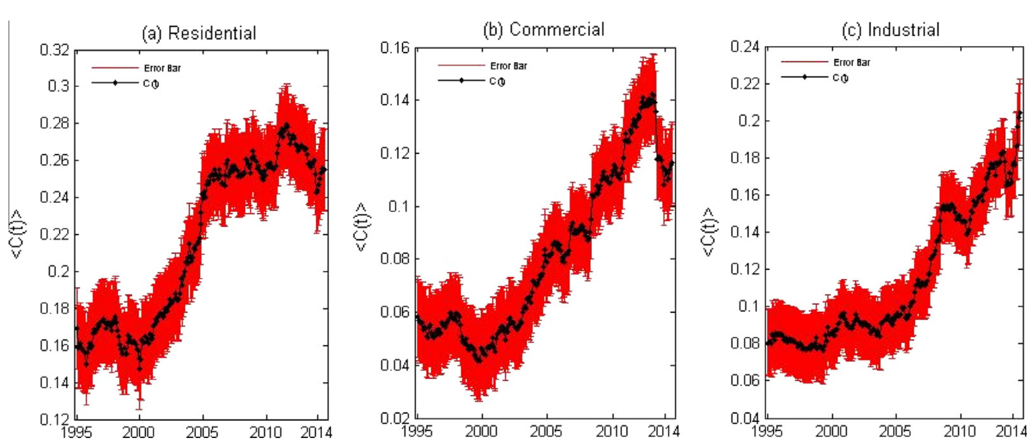

Fig. 3. Evolution of average correlation coefficients for electricity prices. *Note:* The error bar is the standard deviation of the PDF (Probability Distribution Function) for each time t.

Please cite this article in press as: Sun M et al. Identifying regime shifts in the US electricity market based on price fluctuations. Appl Energy (2016), http://dx.doi.org/10.1016/j.apenergy.2016.04.032

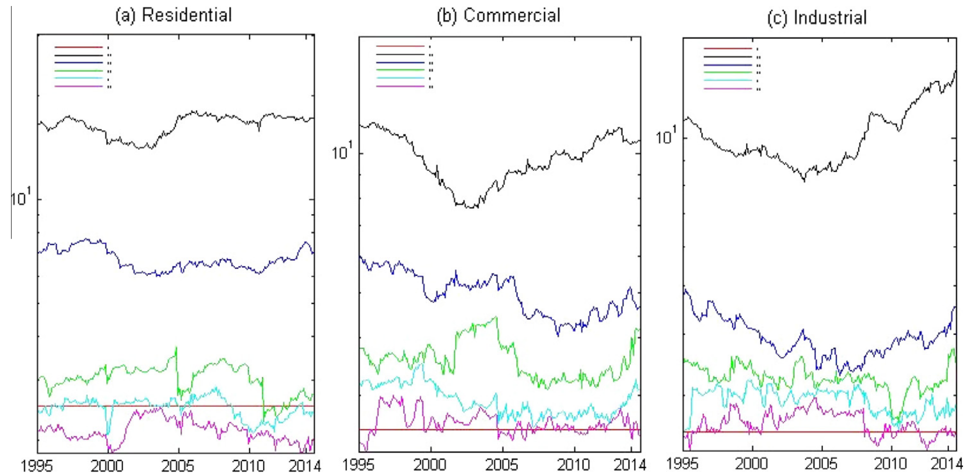

Fig. 4. Evolution of the top five largest eigenvalues λ_n of $C(t)$ with $n = 1, 2, 3, 4, 5$. *Note:* The horizontal dot-dashed red line is the maximum eigenvalue $\lambda_{\max}$ predicted by the RMT. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the amount of information which it contains. Fig. 4 shows that the largest eigenvalue λ_1 of $C(t)$ is larger than the maximum eigenvalue $\lambda_{\max}$ predicted by the RMT. For the second largest eigenvalue λ_2, we find $\lambda_2 > \lambda_{\max}$ for all $C(t)$ matrices. We also find that the third largest eigenvalue λ_3 is slightly larger than $\lambda_{\max}$. In contrast, the fourth largest eigenvalue λ_4 and the fifth largest eigenvalue λ_5 fall well within the range of $f_{RMT}(\lambda)$ and $f_{Rnd}(\lambda)$ (see Fig. 4). The eigenvalues λ_1, λ_2 and λ_3 thus contain information about nontrivial spatiotemporal properties of the U.S. electricity market dynamics. In this paper, we removed the eigenvalue λ_3 in our investigation. The reason is that the eigenvalue λ_3 of residential electricity price is less than $\lambda_{\max}$ at some time.

Fig. 5 presents the eigenvectors of the three departments. Most of the components of the eigenvectors were positive and a few negative for the 50 states and the District of Columbia for some period of time in the residential electricity market. The components also exhibited sudden fluctuations during 2000–2005, which led to the sudden transformation in electricity market. In the U.S. electricity market, the eigenvectors of the largest eigenvalues contain much richer information. The existence of five regimes is observed and the eigenvector components persist in each regime.

Starting with the first eigenvector U1 of residential electricity market, we study its components over time for different regimes. In regime R1, the components are almost positive. It means that the electricity pricing of states shows some general character in some extent. In contrast, Fig. 5(a) clearly shows that, after 1999M11 and during the second regime, many components of the first eigenvector U1 turn from positive to negative. Before 2000, the electricity mainly comes from coal-electricity. After 2000, the U.S. has adjusted the structure of the electricity generation, increasing the natural gas-electricity generations and reducing coal-electricity generations. This led to most states carrying out electricity reform which diversified the electricity pricing of each state. During the period from 1990M1 to 1999M11, negative components of U1 are approximately corresponding to the North Eastern region of the U.S. which means the largest eigenvector U1 partitions the states into two groups. The states with negative components are predominantly the states with low electricity price and situated in the North Eastern region of the U.S with rich coal resource and convenient transportation. For the eigenvector U2 of residential electricity market we find a comparable number of negligible positive and negative components, and it is not completely clear what information they carried in the U.S. states electricity market.

In Fig. 5, unlike the residential electricity, the information contained in commercial and industrial is sparse. This phenomenon is also reflected in Section 4.1. Low correlation coefficient cannot reflect the real market information and the details are presented in Section 4.3. The correlation coefficient of commercial is the minimum as compared to the residential and industrial.

4.3. Shift periods

To investigate the possible collective market information embedded in the deviating eigenvalues, we compare the returns of the Eigen portfolio with the U.S. electricity price returns. In this part, the least-squares regression results obtained for the electricity market are reported. To identify the different shift periods, we locate sudden transformation in the evolution of different variables using qualitative and quantitative methods. Then, the coefficients of regression are analyzed according to the method described in Section 3.4. The first class of variables is the degree of commonality quantified by $k_n(t)$ for the deviating eigenvalues as shown in Fig. 6. If the absolute change $|k_n(t+1) - k_n(t)|$ is significantly greater than the average of the absolute changes around t, t is identified as a possible regime shift point. For the evolution of eigenvectors in Fig. 5, if there appears to be significantly less similarity between two successive eigenvectors $U_n(t)$ and $U_n(t+1)$, t is a possible regime shift point. The regime shifts depends on the union of K_1 and K_2. Comparing the results from different variables can thus serve as a method of cross-validation. Thus to design a reliable method of period identification, we clearly need to construct mathematical models that include the kind of regime shift seen in the U. S. electricity market.

4.3.1. Results obtained from residential electricity market

Fig. 6(a) shows that the regression coefficient k_1 between $R(t')$ and $R1(t')$ is larger for the first five years, and then drops from 0.8236 (1999M11) to 0.5695 (1999M12). Then, K_1 decreased from 0.2518 (2005M3) to 0.4605 (2005M4) gradually. Subsequently, K_1 declined from 0.2029 (2007M9) to 0.1405 (2007M10). This behavior for λ_1 over time indicates that, we can approximately identify three regime shifts for four time periods: [1990M1, 1999M11], [1999M12, 2005M3], [2005M4, 2007M9] and [2007M10, 2014M8]. We find that the three regime shifts in Fig. 6(a) virtually overlap with the three local minima in the time dependence of λ_1 in Fig. 4(a). Therefore, this suggests that the three regime shifts are more credible. Then, Fig. 6(b) shows two regime shifts: [1990M1, 2010M8] and [2010M9, 2014M8] which, surprisingly, are identical to those we found for λ_1. Using the four regime

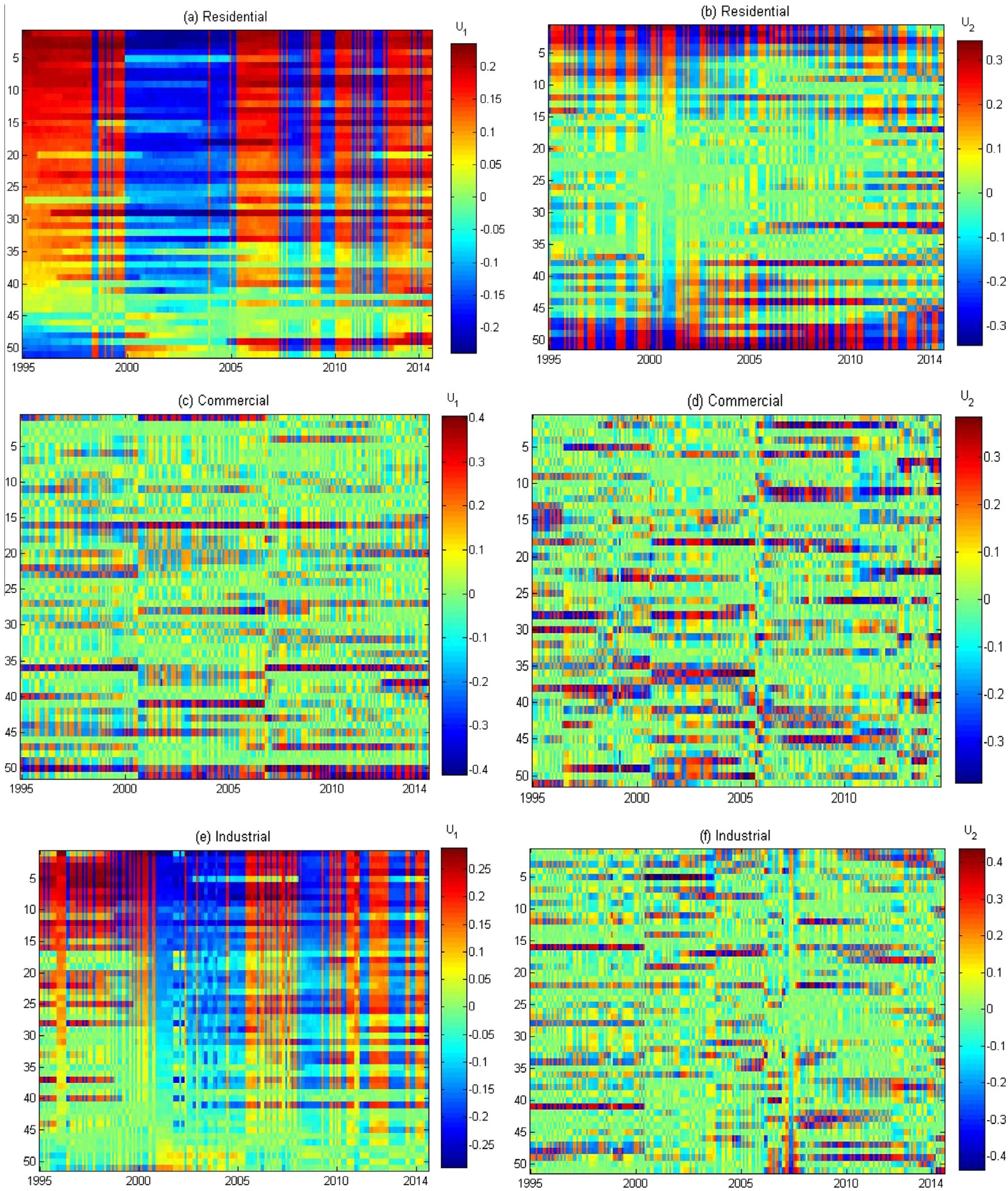

Fig. 5. Eigenvectors of the top 2 largest eigenvalues.

shifts in Fig. 6(a) and (b), we identify five periods: $R1$ = [1990M1, 1999M11], $R2$ = [1999M12, 2005M3], $R3$ = [2005M4, 2007M9], $R4$ = [2007M10, 2010M8] and $R5$ = [2010M9, 2014M8].

4.3.2. Results obtained from commercial electricity market

Fig. 6(c) shows that the regression coefficient K_1 is larger for the first five years and remains close to 1. It drops from 0.8836 (2000M6) to 0.6195 (2000M7). K_1 further drops rapidly from 0.2118 (2005M5) to 0.1505 (2005M6) but it rises from 0.2629 (2010M6) to 0.1605 (2010M7) slowly. We can approximately identify four periods: [1990M1, 2000M6], [2000M7, 2005M5], [2005M6, 2010M6] and [2010M7, 2014M8]. Similarly, the three regime shifts in Fig. 6(c) virtually overlap with the three local minima in the time dependence of λ_1 in Fig. 4(b). This is a highly

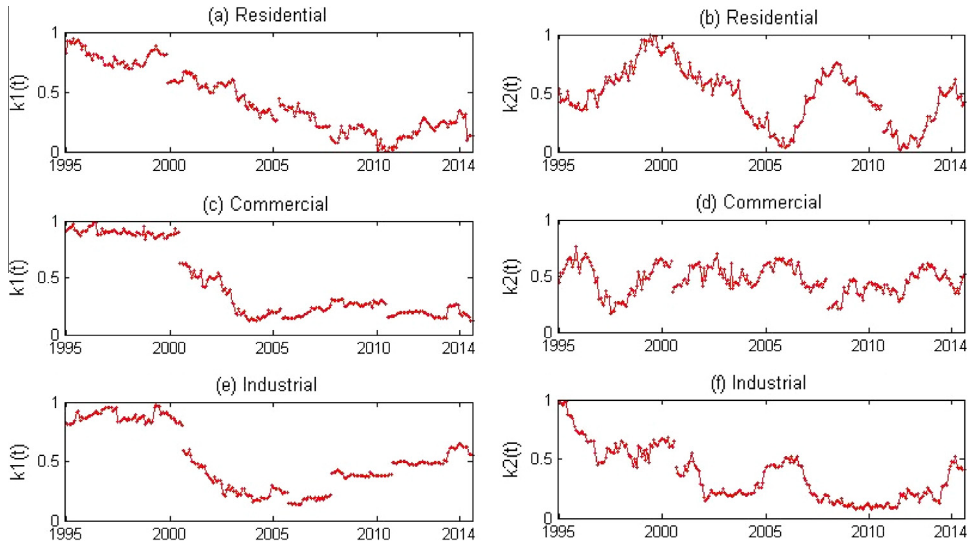

Fig. 6. Evolution of the correlation coefficient $k_n(t)$ between R_n and R in each moving window.

reliable evidence. There are three periods: [1990M1, 2000M6], [2000M7, 2007M12] and [2008M1, 2014M8] in Fig. 4(d). According to the four regime shifts in Fig. 6(c)–(d), we examine five periods: $R1$ = [1990M1, 2000M6], $R2$ = [2000M7, 2005M5], $R3$ = [2005M6, 2007M12], $R4$ = [2008M1, 2010M6] and $R5$ = [2010M7, 2014M8].

4.3.3. Results obtained from industrial electricity market

Fig. 6(e) and (f) are the regressive results of the industrial electricity price. Fig. 6(e) shows that the regression coefficient K_1 is large for the first five years. K_1 then dropped from 0.7936 (2000M8) to 0.6915 (2000M9). Subsequently, the K_1 rapidly decline from 0.2108 (2005M9) to 0.1605 (2005M10). It also slightly rose from 0.2015 (2007M10) to 0.3905 (2007M11), then stabilized. It changed from 0.3890 (2010M9) to 0.4759 (2010M10). So it presents five periods: [1990M1, 2000M8], [2000M9, 2005M9], [2005M10, 2007M10], [2007M11, 2010M9] and [2010M10, 2014M8]. Moreover, Fig. 6(f) shows two periods: [1990M1, 2005M9], [2005M10, 2014M8]. These coincide with the periods shown in Fig. 6(e). Based on the above analysis, five periods are demonstrated: $R1$ = [1990M1, 2000M8], $R2$ = [2000M9, 2005M9], $R3$ = [2005M10, 2007M10], $R4$ = [2007M11, 2010M9] and $R5$ = [2010M10, 2014M8] according to Fig. 6(e)–(f).

The cross-validation of the four regime shifts in the six plots of Fig. 6 indicates that, our identification of the different periods is valid. We concluded that, the time of shift regimes occurred in residential, commercial and industrial are inconsistent. The time that regime shifts happened in residential are earliest, whereas that of commercial and industrial are later. For instance, the percentage of coal-electricity and gas-electricity achieve stability in 2005. However, the turning point of residential, commercial and industrial appear in 2005M3, 2005M5, and 2005M9, respectively. The electricity prices of the three departments are different accordingly. The electricity price level of residential is the highest, while the industrial is lowest. It is obvious that, the turning points is affected by the electricity price. We draw a novel conclusion from the analysis. The regime shifts in commercial and industrial markets exhibits hysteric patterns compared with residential which has the highest price level. It shows that the occurrence of regime shifts is in proportion to price level. Moreover, the situation also illustrates that higher correlation coefficient can reflect the real market information due to the largest correlation for residential electricity market.

$k_n(t)$ reflects the electricity market commonness $k_n(t)$ in U.S. electricity market when it is high, otherwise the electricity market diversified. Fig. 6 shows, the value of K_1 is high before 2000 in residential, commercial and industrial. In this period, coal-electricity is the main electricity source. Moreover, each state adopted the traditional electricity pricing. These two factors contribute to the commonness in 50 states and the District of Columbia. The value of K_1 declined gradually after 2000 indicating that, the electricity market of U.S. is being diversified. Reasons are as following: firstly, gas-electricity units increased gradually with coal-electric declining. In addition, the share of new energy electricity generation increased. Secondly, with the reforms in electricity market in the U.S., the electricity pricing of each state has been formed differently. We then analyze the five periods, in detail.

As show in Fig. 6(a), the value of K is larger in period $R1$, λ_1 which is market commonness–quantified by the regression coefficient K_1 between $R(t')$ and $R1(t')$. It means that the electricity market presents some commonness in the electricity pricing, and the oneness of electricity generation contributed to the commonness. Coal-electricity account for more than 50% of the electricity capacity and its proportion hardly fluctuations. Thus, the main influencing factor of electricity price is limited to coal cost and resource distribution. This is due to the oneness in electricity generation.

In period $R2$, the value of K_1 decreases gradually. The electricity market commonness becomes substantially weaker than that in period $R1$ which indicated that, the electricity market commonness is absent and the sources of electricity industry become diversified. The percentage of gas-electricity units gradually increased. On the contrary, the scale of coal-electricity units declined dramatically. Coal-electricity and gas-electricity have become the main options in electricity industry. It implies that, the electricity pricing of states also presents options and, the electricity market also being diversified gradually. It is consistent with Fig. 1. The proportion of gas-electricity units reached a steady state after the adjustment of $R2$. This status was kept in period $R3$ in the U.S. electricity market until 2007.

In period $R4$, the outbreak of subprime crisis and the financial crisis have greatly influenced the international order which caused credit crunch effect in financial markets. The recession in financial sector caused great negative impact on the fuel market, including coal and natural gas industry. This had a simultaneous effect on the electricity industry. The electricity market experienced fluctuation due to the influence of the financial crisis on energy sources. Period $R5$ is mainly influenced by the shale gas. Under the pressure of environmentally friendly energy, the exploitation of shale gas becomes popular by energy investors. The gas production reached

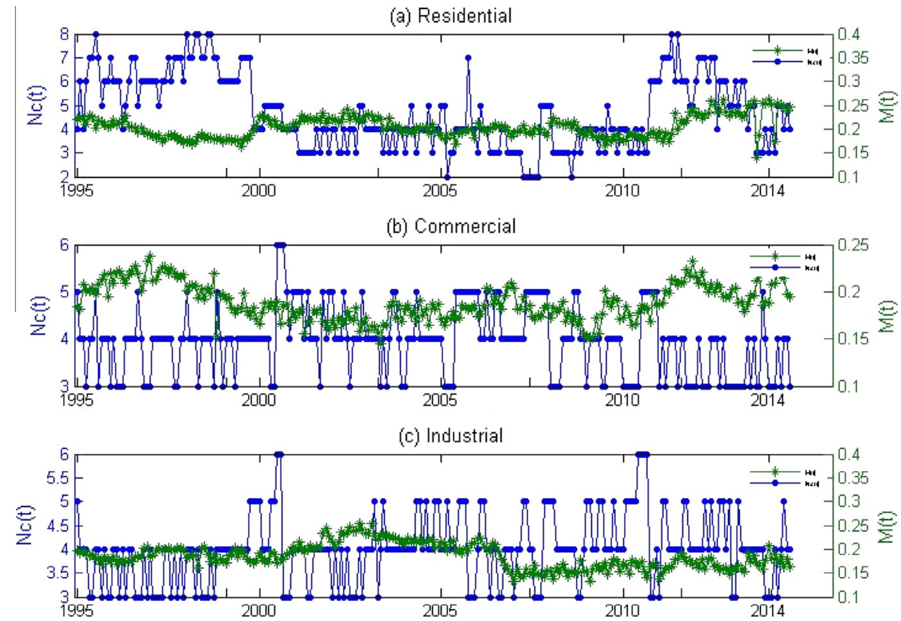

Fig. 7. Evolution of states clusters in residential, commercial and industrial. *Note:* The blue symbols Number of clusters $Nc(t)$, while the green ones are evolution of modularity $M(t)$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a historic peak in 2011 with the cost of gas-electricity generation being lower than coal-electricity. This transformation has a great impact on the electricity market of the U.S.

4.4. Evolvement of state clusters

To confirm the five periods and better understand the spatiotemporal dynamics of the U.S. electricity market at the state level, we partition the states into clusters for each time t. We analyze the cluster and the corresponding modularity of 51 state prices according to the method introduced in Section 3.5. Fig. 7 shows the evolution of states clusters and modularity of the three departments.

Modularity is one of the standards which measure the quality of the community division. The values of $M(t)$ are approximate to 0.2, and they fluctuate within the range ±0.05. This suggests that U.S. electricity market has a strong community structure and the clusters are reasonable. From Fig. 7, the points of sudden change are consistent with the four regime shifts of the three departments

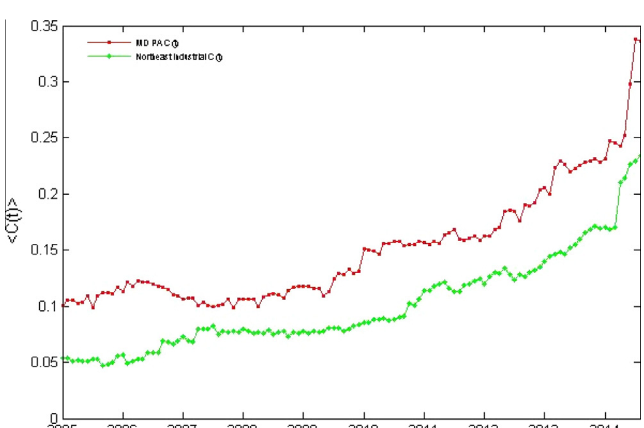

Fig. 8. Evolution of regional correlation coefficient. *Note:* The red symbols the evolution of the price correlation coefficient between the Maryland and Pennsylvania, while the green means the evolution of correlation coefficient of the northeast industrial district. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

we have discussed. For the residential electricity market, the clusters are unstable with a large number of states shifting between clusters in Fig. 7(a). Meanwhile Fig. 7(b) and (c) imply that the fluctuation of community evolution are relatively stable in the industrial and commercial departments. The clusters in three departments are relevant to diverse electricity prices. We draw an important conclusion that, the price level influences the evolution of community. In addition, the communities' fluctuations were caused by financial crisis in 2007. This mean that, factors influencing unstable clusters evolution is not uniquely diversity electricity price but also economic and generation distribution.

Fig. 8 shows the price correlation coefficient between the Maryland and Pennsylvania, and the evolution of correlation coefficient of the North Eastern industrial district. The North Eastern industrial district included Maine, Vermont, New Hampshire, Connecticut, New Jersey, Delaware, Wisconsin, Michigan, Illinois, Indiana, Ohio, Pennsylvania, Maryland, Kansas, and West Virginia. It can be found that the correlation coefficient between Maryland and Pennsylvania is larger than North Eastern industrial district. Two reasons explains this phenomenon. Firstly, Pennsylvania and Maryland have rich coal resource and convenient transportation. They are near to the great lakes. The great lakes forms the main part of their inland water transport It's the one of the important traffic line of coal which provides cheap transportation. Moreover, from the perspective of geography, Maryland is bordered by Pennsylvania. Secondly, Maryland and Pennsylvania belong to the PJM market. In the PJM market, market members send the bidding plans of next day to service center at 8:00–12:00 in every day. The service center of PJM evaluate the bidding plan of each member according to the system information which includes expected user demand, climate, transmission, etc. at 12:00–14:00 every day. The system then selects the most effective and economic operation mode. At 14:00–16:00 every day the service center of PJM sends the result of evaluation to members. The center of PJM also does some adjustments according to the requirement of reliability from the 16:00 to the next day 8:00. PJM market is a fluent and dynamic electricity market. Maryland and Pennsylvania are the members of the PJM market which contribute to the high correlation coefficient. In addition, in the evolution of community, Maryland and Pennsylvania are in the same community.

5. Conclusions

This paper studied the average correlations evolution of electricity price among 50 states and the District of Columbia in the U.S. residential, commercial and industrial electricity markets. The uncertain influence from fuel market is analyzed in detail based on eigenvalue and eigenvector of RMT. Four regime shifts with five periods are identified in the three departments by qualitative and quantitative methods simultaneously. Using empirical studies, we arrive at some useful conclusions and they are as follows;

First, the average correlation coefficients increased continuously in the three electricity markets which reflects the commonness of electricity market. This phenomenon is affected by the adjustment of the proportion for gas-electricity and coal-electricity directly. However, the average correlation coefficients decreased in 2012 due to the coal-electricity recovering, which explains its sensitivity to fuel market further.

Secondly, four regime shifts exist in the three departments even though there are different times of occurrence. The regime shifts in commercial and industrial markets have the hysteric pattern compare with residential which has the highest price level. It showed that the occurrence of regime shifts is in proportion to price level. The research on clusters evolution of 50 states and the District of Columbia in the three departments also verified the result.

The method used in this paper is verifiable, and it can be applied to electricity markets in other regions such as European Union, Japan and Korea. With this method, the regime shifts in the process of electricity market reform can be identified, and the hidden mechanism for the market can be revealed.

The process of electricity market reform in China is still slow, but the future directions are clear. Electricity price reform is regarded as one of the major policies to enhance the reform of electricity market in many developing and transitioning economies. Analyses of the barriers as well as drivers of the reform can provide references for policy makers. Thus, two policy suggestions are proposed from our results; first, the energy structure for generation must be optimized before the implementation of electricity market reforms. In China, the uneven distribution of energy resources results in the complexity of electricity structure. Grasping the development direction of electricity structure before proposing reforms in the electricity market is essential. Secondly, the higher electricity price for consumers, the more timely reflections when there are fluctuations in electricity market according to our results. In china, the industrial electricity price is the highest in all departments. Policy makers can adjust the reform plan of the whole electricity market according to industrial inputs to reduce the risk in the reform of the electricity market.

Finally, it is expected that electricity price reforms would be further promoted and to provide comprehensive suggestions for policy makers. Therefore, in order to make constructive suggestions for decision makers, researchers need to make further research on the drivers and barriers of electricity price reforms (such as energy structure for generation and the level of electricity price), and explore the feasible path of reform as well as complementary policies to reduce uncertainties.

Acknowledgements

This research was supported by National Nature Science Foundation of China (No. 71273119 and No. 71473108) and the Graduate Innovative Foundation of Jiangsu Province KYLX15_1076.

References

[1] Druce DJ. Modelling the transition from cost-based to bid-based pricing in a deregulated electricity-market. Appl Energ 2007;84(12):1210–25.
[2] Bahmani-Firouzi B, Sharifinia S, Azizipanah-Abarghooee R, Niknam T. Scenario-based optimal bidding strategies of GENCOs in the incomplete information electricity market using a new improved prey—predator optimization algorithm. IEEE Syst J 2015;9(5):1–11.
[3] Upton J, Murphy M, Shalloo L, Groot Koerkamp PWG, De Boer IJM. Assessing the impact of changes in the electricity price structure on dairy farm energy costs. Appl Energ 2015;137:1–8.
[4] Walawalkar Rahul, Blumsack Seth, Apt Jay, Fernands Stephen. An economic welfare analysis of demand response in the PJM electricity market. Energy Policy 2008;36(10):3692–702.
[5] Hung Ming-Feng, Huang Tai-Hsin. Dynamic demand for residential electricity in Taiwan under seasonality and increasing-block pricing. Energy Econ 2015;48:168–77.
[6] Wang Z, Zhang B, Zhang Y. Determinants of public acceptance of tiered electricity price reform in China: evidence from four urban cities. Appl Energ 2012;91(1):235–44.
[7] Joskow PL. Markets for Power in the US: an interim assessment. Energy J 2006;27(1):1–36.
[8] Sioshansi Fereidoon P, Pfaffenberger Wolfgang. Why restructure electricity markets. Electr Market Reform 2006:35–48.
[9] Zhao X, Lyon TP, Song C. Lurching towards markets for power: China's electricity policy 1985–2007. Appl Energ 2012;94:148–55.
[10] Coatalem Martin, Mazauric Vincent, Le Pape Claude, Maïzi Nadia. Optimal management of power generation assets: interaction with the electricity markets. Energy Procedia 2015;75:2575–80.
[11] Kai Wu, Nagurney Anna, Liu Zugang, Stranlund JohnK. Modeling generator power plant portfolios and pollution taxes in electric power supply chain networks: a transportation network equilibrium transformation. Transport Res D: Transp Environ 2006;11(3):171–90.
[12] Torrent-Fontbona F, López B. Power re-allocation for reducing contracted electric power costs. Energy Build 2015;89:112–22.
[13] Cappers Peter, Goldman Charles, Kathan David. Demand response in U.S. electricity markets: empirical evidence. Energy 2010;35(4):1526–35.
[14] Castagneto-Gissey G, Chavez M, De Vico Fallani F. Dynamic Granger-causal networks of electricity spot prices: a novel approach to market integration. Energy Econ 2014;44:422–32.
[15] de Menezes Lilian M, Houllier Melanie A. Reassessing the integration of European electricity markets: A fractional cointegration analysis. Energy Econ 2014;53:132–50.
[16] Pereira M, Pronto L. Multi-stage stochastic optimization applied to energy planning. Math Program 1991;52:59–75.
[17] Albadi MH, El-Saadany EF. A summary of demand response in electricity markets. Electric Power Syst Res 2008;78(11):1989–96.
[18] Ketter Wolfgang, Collins John, Reddy Prashant. Power TAC: a competitive economic simulation of the smart grid. Energy Econ 2013;39:262–70.
[19] Wang Y, Li L. Time-of-use electricity pricing for industrial customers: a survey of U.S. utilities. Appl Energ 2015;149:89–103.
[20] Energy Information Administration (EIA), <http://www.eia.gov/>.
[21] Du G, Lin W, Sun C, Zhang D. Residential electricity consumption after the reform of tiered pricing for household electricity in China. Appl Energ 2015;157:276–83.
[22] Herter Karen, Wayland Seth. Residential response to critical-peak pricing of electricity: California evidence. Energy 2010;35(4):1561–7.
[23] Sandoval Junior Leonidas, Franca Italo De Paula. Correlation of financial markets in times of crisis Original Research Article. Phys A: Stat Mech Appl 2012;391(1):187–208.
[24] Meng Hao, Xie Wen-Jie, Jiang Zhi-Qiang, Podobnik Boris, Zhou Wei-Xing. Systemic risk and spatiotemporal dynamics of the US housing market. Sci Rep 2014;4(3655). http://dx.doi.org/10.1038/srep03655.
[25] Billio Monica, Getmansky Mila, Lo Andrew W, Pelizzon Loriana. Econometric measures of systemic risk in the finance and insurance sectors. J Financ Econ 2012;104(3):535–59.
[26] Hua Han, Linyan Wu, Ningning Song. Financial Network model based on random matrix. Physics 2014;63(13):138901.
[27] Plerou V. Random matrix approach to cross correlations in financial data. Phys Rev E 2002;65:066–126.
[28] Qiu T, Zheng B, Guang C. Financial networks with static and dynamic thresholds. New J Phys 2010;12:043–57.
[29] Zhong Weiqiong, Ana Haizhong, Gao Xiangyun, Sun Xiaoqi. The evolution of communities in the international oil trade network. Phys A 2014;413 (1):42–52.
[30] Zeng An, Zhang Cheng-Jun. Ranking spreaders by decomposing complex networks. Phys Lett A 2013;377(14):1031–5.
[31] Mcloughlin F, Duffy A, Conlon M. A clustering approach to domestic electricity load profile characterisation using smart metering data. Appl Energ 2015;141:190–9.
[32] Rhodes JD, Cole WJ, Upshaw CR, Edgar TF, Webber ME. Clustering analysis of residential electricity demand profiles. Appl Energ 2014;135:461–71.
[33] Matteo Barigozzi, Giorgio Fagiolo, Giuseppe Mangioni. Identifying the community structure of the international-trade multi-network. Phys A 2011;390:2051–66.
[34] Newman MEJ, Girvan M. Mixing patterns and community structure in networks. In: Statistical mechanics of complex networks. Springer: Berlin Heidelberg; 2013. p. 66–87.
[35] Steinhaeuser Karsten, Chawla NiteshV. Identifying and evaluating community structure in complex networks. Pattern Recogn Lett 2010;31(5):413–21.