

Industrial power demand forecasting based on big data technology orienting to energy internet: A case study of Hunan Province

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Abstract. Making energy carry information is the major research direction of achieving Energy Internet. Besides, electric energy has incomparable advantages in energy transmission efficiency. Therefore, the future of Energy Internet is the Power Internet. Then, accurately predicting the consumption of power becomes the foundation of Energy Internet. Depending on the extraction, transformation, loading (ETL), Hadoop, Oracle and OLAP technologies. This paper establishes energy, electricity, economy forecasting and warning system. By considering the data of energy, electricity and economy together, a new economic power transmission model is established. The traditional econometric methods, such as OLS, AR, MA, ARMA and X11, are all employed during the estimated process. The estimating results demonstrate that the goodness of fits of the new models are all approximately equal to 0.998. The electricity consumption of industry is 1935224.28×10^4 kWh in the 3rd quarter and $2,846,897.0 \times 10^4$ kWh in the 4th in 2017, respectively.

1. Introduction

With the degradation of the environment and the aggravation of energy shortages, a remarkable amount of attention has been paid to the energy revolution. Meanwhile, the concept of Energy Internet (EI) was developed [1-4]. Energy Internet, first proposed by Jeremy Rifkin, is a new development form of energy system [5]. The main unit of Energy Internet is the renewable energy. Consuming renewable energy sources, such as wind, solar, hydro water, biomass, geothermal and marine energies, have been considered as alternatives for conventional energy resources in most developed and developing countries [6,7].

According to Ming Zeng *et al* [6], during the establishment of Energy Internet, technologies will be applied are as follows: interaction analysis technology for energy flow and information flow; coordinated optimization planning technique for wide area energy resources; coordinated scheduling technique for wide area integrated energy. Moreover, the key technology of Energy Internet is to utilize internet technology to combine energy flow with information flow at real-time, so as to achieve the goal of energy saving and emissions reduction [8-10]. In general, Energy Internet is characterized by openness, interconnection, reciprocity and sharing, exhibiting a multi-source collaborative optimization decision effect [11]. Technologies, such as Cyber-Physical System (CPS) technology,



Active Distribution Network (AND) technology and self-balancing of distributed resources, etc. primary discussed applying in Energy Internet, demonstrating that making energy carry information is the major research direction of achieving Energy Internet [12-17].

Owing electric energy has incomparable advantages in energy transmission efficiency, power acts as the core of secondary energy, playing an important role in transforming the renewable energy into the direct available energy [18]. Essentially, the future of the Energy Internet is the Power Internet. The dramatic increase of renewable energy generation brings some intermittent problems to the power distribution networks. Real-time optimal power flow may solve these intermittent problems [19-22]. However, how to accurately predict the consumption of power becomes another significant challenge of Energy Internet, with substantial renewable energy utilization. Fortunately, the applying of big data technology makes it possible to improve the accuracy of power forecasting.

However, the recent development of big data technology employed in energy researches are mainly the following ones: power marketing innovation, electricity customer value, and consumption habits of residents' electricity consumption [23-27]. As far as we are aware, there is no one that utilizes big data technology to forecast the consumption of electricity. This research gap forms the basis for this paper. In this novel analysis, there is a case study that highlights the implications of using big data technology to predict power consumption. This paper firstly demonstrates how economic statistics can be used to predict electricity consumption from a new perspective.

The remainder of the paper is organized as follows: Section 2 details the methodology utilized in this paper. Section 3 describes the data collection. Section 4 presents and discusses the results of the regression. Section 5 presents conclusions as usual.

2. Methodology

2.1. Analysis of the variables of interest

The ultimate aim of this study is to precisely forecast the demand of industrial electricity consumption, and makes it orient to Energy Internet based on the big data technology, focus on:

Electricity consumption of energy-intensive industries: a correlation analysis will be carried out to detect the influence of the microeconomic indicators on the power demand of power-intensive industries.

Climate variables: those variables that have a most significant influence on the electricity consumption will be detected.

Microeconomic indicators: added value of smelting and pressing of ferrous metals (SPFM), smelting and pressing of non-ferrous metals (SPNFM), manufacture of raw chemical materials and chemical products (RCCP) and manufacture of non-metallic mineral products industries (NMMP); steel production, investment in real estate, electrolytic aluminum output, production of cement, caustic soda production, the tertiary industry added value, urban disposable income.

2.2. The big data technology

With years of development, the information construction of power industry, such as electrical power dispatching SCADA system, power marketing SG186 system, power information collection system, ERP system, geographic information system (GIS) and other application systems, has achieved remarkable achievements. However, these systems have been running independently in the power enterprises, becoming an independent "information-island". Comprehensively considering the data from different systems has become virtually impossible [28], when predicting the power supply and demand data synthetically.

Owing the data of electricity is considerable in amount, complex in structure, the extraction, transformation, loading (ETL) technology is adopted in this article. The ETL technology has been widely used for big data system [29,30]. Meanwhile, Hadoop technology, a distributed file system with parallel execution environment, allows users to easily handle massive data over TB and above [31,32]. In this paper, Hadoop has been brought to store the immense electricity data, such as the

electricity consumption of day from the power information collection system, 24 or 96 load data, energy data, climate data, etc.

2.3. Electricity consumption forecasting models

As China faces a New Normal economic growth, traditional power demand forecasting methods seem like unsuitable for continued use [33]. Under the new normal economic growth setting, this paper divides the whole society power consumption into 8 parts, i.e. the power demand of four high energy-intensive industries (smelting and pressing of Ferrous Metals, smelting and pressing of Non-ferrous metals, manufacture of raw chemical materials and chemical products, manufacture of non-metallic mineral products industries), industrial electricity consumption, the tertiary industry, electricity consumption for urban residents and for rural residents. Considering the application of big data technology and the acquisition of detailed data for each industry, Hunan province is selected as a case in this article.

● Electricity consumption forecasting model for smelting and pressing of ferrous metals

Clearly, there is a need to discover ways of combining both “traditional” (grey prediction model, ARIMA model, multivariate regression models, and index decomposition analysis method) methods and “new” (big) data sources to harness the best attributes of both [34].

Traditionally, the growth rate of the added value of SPFM and that of the consumption of power are analyzed firstly. There exists a big deviation between them from the first quarter of 2012 (figure 1). As such, if we just utilize the added value to predict the demand of power based on traditional methods, there is no doubt that the power of SPFM will be overestimated. The short fluctuations between electricity consumption and the added value might be attributed to the output of ferroalloy, whose production is a power-intensive process. The amount of electricity consumption caused by ferroalloy production dropped sharply from 36.4% of the total consumption of SPFM in 2011 to 28.1% of that in the first quarter of 2012.

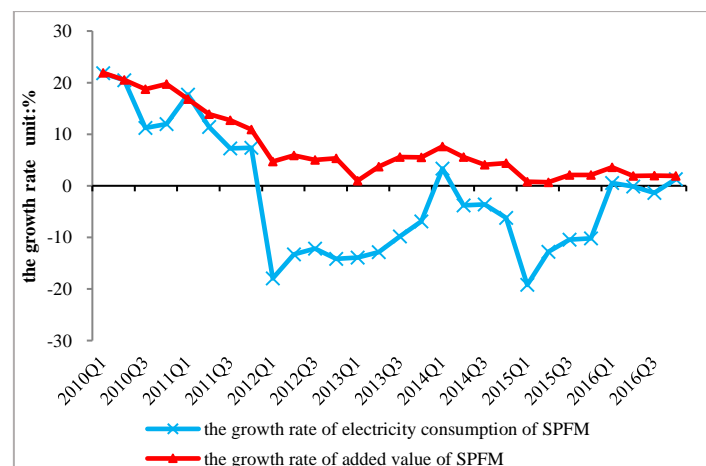


Figure 1. The growth rate of the added value of SPFM and that of electricity consumption of SPFM during 2010-2016.

Further, the growth rate of power demand of SPFM, excluding ferroalloy industry, has great consistency with the growth rate of steel (figure 2). Historically, the prediction of production capacity based on the fixed assets investment is reasonable in theory. However, under the transition settings, investment in fixed assets are usually spent on improving the production technology, but not on expanding the production, especially for the overcapacity industry SPFM. Therefore, the estimation of the steel output is depended on its downstream industry (the growth rate of real estate industry). Therefore, the power consumption forecasting model (simultaneous equation model) for SPFM is established as follows:

$$\begin{aligned}
Q_{1mt} &= \alpha_0 + \alpha_1 \ln(I_{mt}) + AR(p_1) + MA(q_1) \\
\ln(E'_{1mt}) &= \beta_0 + \beta_1 \ln(Q_{1mt}) + AR(p_2) + MA(q_2) \\
\ln(E_{1mt}) &= \gamma_0 + \gamma_1 \ln(E'_{1mt}) + AR(p_3) + MA(q_3)
\end{aligned}
\quad (1)$$

where the dependent variable Q_{1mt} is the steel production in quarter m year t , I_{mt} is the investment of fixed assets in quarter m year t , E'_{1mt} is the consumption of electricity of SPFM without ferroalloy industry in quarter m year t , E_{1mt} is the electricity consumption of SPFM in quarter m year t . Variables $AR(p_i)$ and $MA(q_i)$ are indicated to the independent variables autoregressive model order and moving average model order.

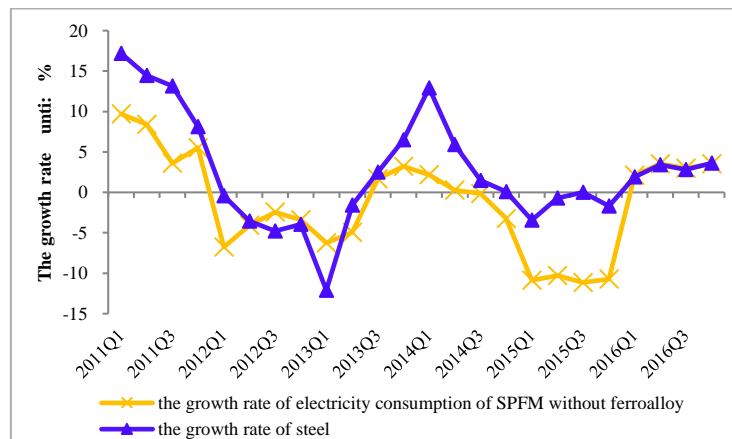


Figure 2. The growth rate of electricity consumption of SPFM without ferroalloy and the growth rate of steel during 2010-2016.

- Electricity consumption forecasting model for smelting and pressing of non-ferrous metals

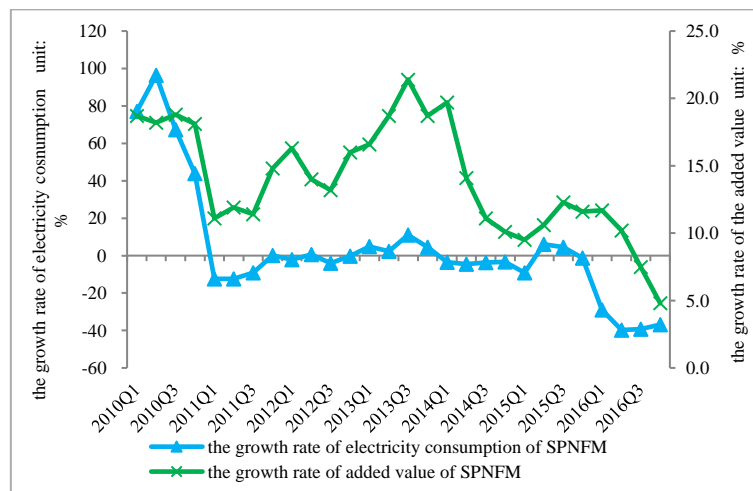


Figure 3. The growth rate of electricity consumption of SPNFM and that of the added value during 2010-2016 in Hunan China.

SPNFM is an energy-intensive industry like SPFM. Hence, the deviation between the growth rate of the added value of SPNFM and that of electricity consumption also exists (figure 3). The output of electrolytic aluminium makes a big difference in the power demand of SPNFM (figure 4). It is easily found that the deviation exists steadily during 2012-2015 (figure 4). The discontinued production of Chuangyuan aluminium industry makes the 300000 tons of electrolytic aluminium production capacity

almost all shut down in Hunan in January 2016, which expanded the deviation in the first quarter of 2016 (figure 4). Moreover, the growth rate of nine non-ferrous metal products has a close correlation with the growth rate of industry electricity either. Considering the rich kinds and widely use of SPNFM in products, it is difficult to predict the prosperity just depend on the downstream enterprises. While the investment in fixed assets of SPNFM in China reflects the prosperity of the whole industry to a certain extent. Thus, the power consumption forecasting model for SPNFM is established as follows:

$$\begin{aligned} Q_{2mt} &= \alpha_0 + \alpha_1 D_{mt} + AR(p_4) + MA(q_4) \\ \ln(E_{2mt}) &= \beta_0 + \beta_1 (\ln Q_{2mt}) + AR(p_5) + MA(q_5) \end{aligned} \quad (2)$$

where Q_{2mt} is the nine non-ferrous metal products, Q_{2mt} is indicated to the products of electrolytic aluminum, D_{mt} is indicated to the investments of fixed assets. Variables $AR(p_i)$ and $MA(q_i)$ are indicated to the independent variables autoregressive model order and moving average model order.

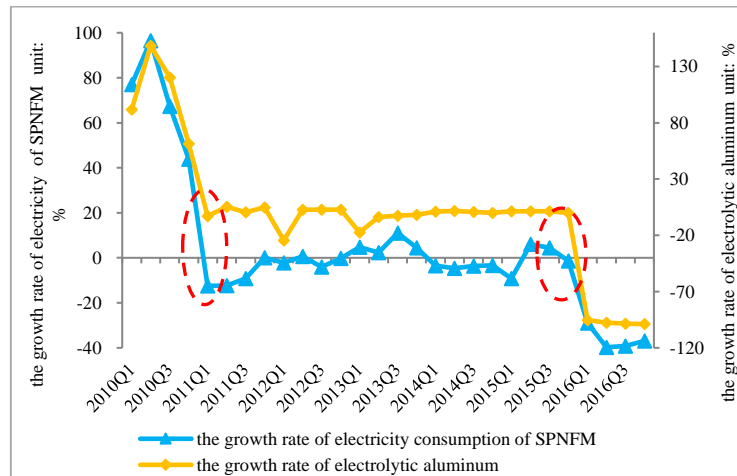


Figure 4. The growth rate of electricity consumption of SPNFM and that of electrolytic aluminium during 2010-2016 in Hunan.

- The electricity consumption forecasting model for the manufacture of non-metallic mineral products industries

As the same with SPNFM and SPFM, the deviation also exists between the growth rate of the added value of NMMP and that of the consumption of electricity of NMMP (figure 5). The cumulative growth rate of cement output and the growth rate of industry electricity consumption is not consistent in individual quarters, the general trend is the same, though. Thus, the electricity consumption of NMMP is depended on cement output. The cement outputs relies on its downstream industry (real estate industry) (figure 6). Thus, the power consumption forecasting model for SPNFM is established as follows:

$$\begin{aligned} Q_{3mt} &= \alpha_0 + \alpha_1 D_{mt} + AR(p_6) + MA(q_6) \\ \ln(E_{3mt}) &= \beta_0 + \beta_1 (\ln Q_{3mt}) + AR(p_7) + MA(q_7) \end{aligned} \quad (3)$$

where the dependent variable Q_{3mt} is the cement production in quarter m year t, I_{mt} is the investment of fixed assets in quarter m year t, E_{3mt} is the consumption of electricity of NMMP; Variables $AR(p_i)$ and $MA(q_i)$ are indicated to the independent variables autoregressive model order and moving average model order.

- Electricity consumption forecasting model for the manufacture of raw chemical materials and chemical products

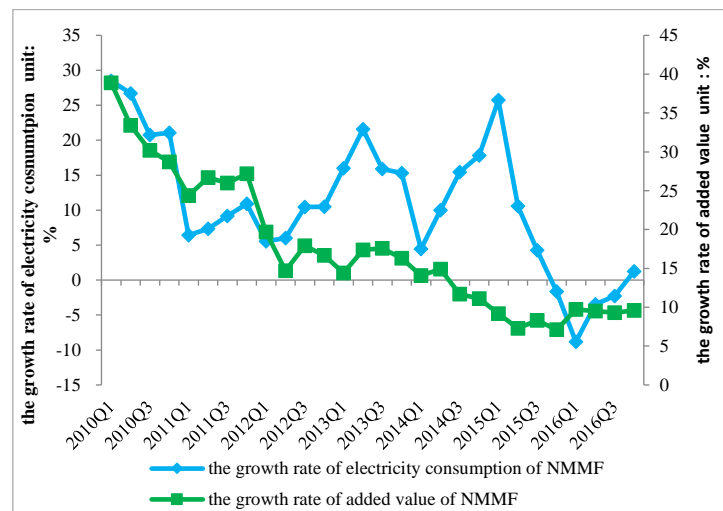


Figure 5. The growth rate of electricity consumption of NMMF and that of the added value during 2010-2016 in Hunan.

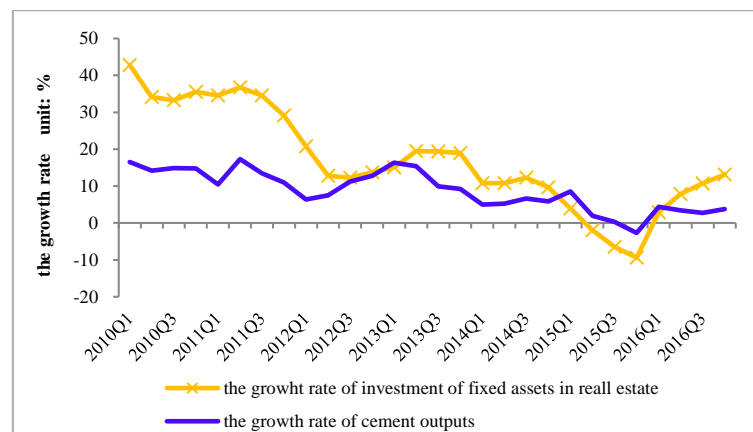


Figure 6. The growth rate of cement outputs and that of its downstream industry's investment in fixed assets.

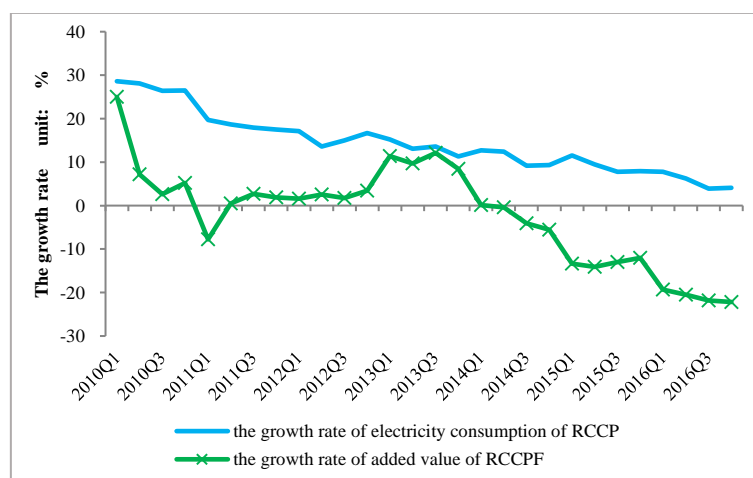


Figure 7. The growth rate of electricity consumption of RCCP and that of the added value during 2010-2016 in Hunan.

The deviation between the added value of RCCP and that of the consumption of electricity of RCCP is also the reason why we chose it to estimate independently (figure 7). The output of caustic soda can be considered as the prediction index of power consumption. The downstream products of caustic soda are as follows: alumina, paper- making, printing and dyeing, military project, etc. According to the national data depicting, alumina is the main downstream products, whose production contributes the highest rates, maintaining 23%-27%. Though the amount of the production of alumina is 0 in Hunan, caustic soda might be sold to other provinces to produce alumina. Based on the correction analysis, the correlation coefficient between the investments of fixed assets of SPNFM and the outputs of caustic soda is up to 0.8. Thus, the power consumption forecasting model for RCCP is established as follows:

$$\begin{aligned} Q_{4mt} &= \alpha_0 + \alpha_1 D_{mt} + AR(p_8) + MA(q_8) \\ \ln(E_{4mt}) &= \beta_0 + \beta_1 (\ln Q_{4mt}) + AR(p_9) + MA(q_9) \end{aligned} \quad (4)$$

where the dependent variable Q_{3mt} is the cement production in quarter m year t, I_{mt} is the investment of fixed assets in quarter m year t, E_{3mt} is the consumption of electricity of NMMP; Variables $AR(pi)$ and $MV(qi)$ are indicated to the independent variables autoregressive model order and moving average model order.

- The electricity consumption forecasting model for industrial electricity consumption

The proportion of electricity consumption of the four high energy consuming industries is relatively high, as high as 42.6% in 2016. Thus the electricity consumption of industry is established as follows:

$$\begin{aligned} E'_{mt} &= E_{1mt} + E_{2mt} + E_{3mt} + E_{4mt} \\ \ln(E_{mt}) &= \alpha_0 + \alpha_1 \ln(E'_{mt}) + AR(p_{10}) + MA(q_{10}) \end{aligned} \quad (5)$$

where E'_{mt} is indicated to the electricity demand of the four energy-intensive industries, E_{mt} is the power demand of the industry. Variables $AR(pi)$ and $MV(qi)$ are indicated to the independent variables autoregressive model order and moving average model order.

3. Data source

Electric power demand data used in this work was provided by State Grid Hunan Electric Power Company and gathered from the first quarter in 2010 to fourth quarter in 2016. The data includes day, month, year and aggregated electric load consumptions.

The meteorological data used in this study were collected from Hunan Provincial Bureau of Statistics and Chinese Bureau of Statistics, including the added value, the industry outputs, investment of fixed assets. These data were collected from the first quarter in 2010 to the fourth quarter in 2016.

The climate variables are precipitation (mm), air temperature ($^{\circ}\text{C}$), average wind speed (m/seg), average wind direction (sexagesimal degrees), relative humidity (%), pressure (hPa) and global solar radiation (W/m^2).

4. Result

4.1. Construction of the energy, electricity economy forecasting and warning system

Based on the ETL, Hadoop, Oracle, OLAP, etc. technologies, the economic, power, energy analysis systems are established (figure 8). The more accurately predicting of consumption of power lays a compacted foundation for achieving energy internet.



Figure 8. The energy, electricity, economy forecasting and warning system.

4.2. Description of scenarios

Based on the big data technology, a total of 3 scenarios are set to forecast the electricity consumption of the whole society in Hunan from 2017–2020. Different investment in real estate development growth rates, electrolytic aluminum output growth rates, investment in fixed assets of nonferrous metals in China, the growth rates of the added value of the territory industry, the growth rates of the income of urban residents. The details are as follows.

- Investment in real estate development growth rates in Hunan

The real estate development investment has experienced a gradual rebound after bottoming process (figure 9). By the end of the 4th quarter of 2016, the cumulative growth rate of Hunan's real estate development investment has rebounded to 13.1%. Regarding the truth of the commercial residential building sales in Hunan province, both the sales volume and the sales area of commercial housing have gone up again. Thus, this paper sets the growth rates of the investment of the real estate development still keep the stable recovery trend. The specific settings are shown in table 1.

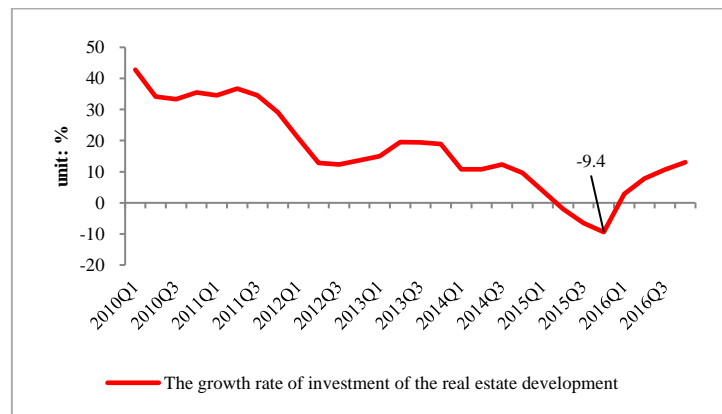


Figure 9. The growth rate of investment of the real estate development.

Table 1. The settings of the scenarios.

indicators	Scenario	2017Q1	2017Q2	2017Q3	2017Q4
Investment in real estate development growth rates in Hunan	actual value	4.5	14.7		
	low scenario	4.5	14.7	15.7	15.9
	medium scenario	4.5	14.7	15.9	16.1
	high scenario	4.5	14.7	16.1	16.3
Investment of fixed assets of SPNFM in China	actual value	-3.5	-4.7	-4.2	
	low scenario	-3.5	-4.7	-4.2	-5.2

The products of electrolytic aluminum in Hunan	medium scenario	-3.5	-4.7	-4.2	-4.7
	high scenario	-3.5	-4.7	-4.2	-4.2
	actual value	0.1	0.1		
	low scenario	0.1	0.1	0.1	0.1
	medium scenario	0.1	0.1	0.1	0.1
	high scenario	0.1	0.1	0.1	0.1

- Investment of fixed assets of SPNFM in China

Affected by the rising prices of SPNFM, the investment of fixed assets of SPNFM will still keep increasing trend. The details are shown in table 1.

- The products of electrolytic aluminum in Hunan

As it analyzed in part 2, the discontinued production of Chuangyuan aluminium industry makes the 300000 tons of electrolytic aluminum production capacity almost all shut down in Hunan in January 2016, which expanded the deviation in the first quarter of 2016 (figure 4).

Under the constraints of energy-saving, emission reduction, reduction the production capacity and other policy factors, the probability of electrolytic aluminum output re-entering in Hunan province is small. Therefore, the output of electrolytic aluminum in Hunan province is set to be zero in 2017. The details are depicted in table 1.

4.3. Results

The estimated equation of power consumption forecasting model for SPFM are shown as follows:

$$Q_{1t} = -5160.15 + 837.27 * \log(I_t) + [AR(4) = 0.84, MA(1) = 0.93]$$

$$R^2 = 0.995, DW = 1.15$$

$$\log(E'_{1t}) = -2.9768 + 1.0059 * \log(Q_{1t}) + [AR(4) = 0.7230, MA(1) = 0.9403]$$

$$R^2 = 0.996, DW = 1.92$$

$$\log(E_{1t}) = -0.1108 + 1.1811 * E'_{1t} + [AR(4) = 0.7091, MA(4) = -0.9832]$$

$$R^2 = 0.999, DW = 1.34$$

The estimated equations of power consumption forecasting model for SPNFM are shown as follows:

$$\log(Q_{2t}) = 1.6631 + 0.9740 * \log(I_t) + [AR(4) = 0.3916, MA(3) = -0.8981]$$

$$R^2 = 0.999, DW = 0.87$$

$$\log(E_{2t}) = -4.4811 + 0.9773 * \log(Q_{2t}) + [AR(4) = 0.4231, MA(1) = 1.0000]$$

$$R^2 = 0.997, DW = 1.25$$

The estimated equations of power consumption forecasting model for NMMP are shown as follows:

$$\log(Q_{3t}) = -4.0137 + 0.7504 * \log(D_t) + [AR(4) = 0.9065, MA(1) = 1.0000]$$

$$R^2 = 0.987, DW = 0.83$$

$$\log(E_{3t}) = 0.2483 + 0.9787 * \log(Q_{3t}) + [MA(3) = 0.8507]$$

$$R^2 = 0.97, DW = 0.4$$

The estimated equations of power consumption forecasting model for RCCP are shown as follows:

$$Q'_{4t} = 23.7524 + 0.0323 * D_t + [AR(4) = 0.7776, MA(2) = 0.9241]$$

$$R^2 = 0.994, \quad DW = 1.14$$

$$\log(E_{4t}) = -0.6709 + 0.1134 * \log(q) + 0.872 * \log(Q'_{4t}) + [AR(1) = 0.6879]$$

$$R^2 = 0.99, \quad DW = 2.19$$

The estimated equations of power consumption forecasting model for RCCP are shown as follows:

$$E'_t = E_{1t} + E_{2t} + E_{3t} + E_{4t}$$

$$\log(E_t) = 3.3613 + 0.9673 * \log(E'_t) + [AR(1) = 0.9964, MA(2) = -0.9999]$$

$$R^2 = 0.99, \quad DW = 2.36$$

As the equations shown, the goodness of fits for the electricity forecasting models are all quite high. It demonstrates that the new view for forecasting the power demand is more suitable than the traditional models.

Based on the estimated results, the electricity consumption is shown in table 2. As displayed in table 2, in the 3rd quarter in 2017, the medium estimation results of electricity consumption of SPFM, SPNFM, NMMP, RCCP and Industry is 89.99×10^8 kWh, 41.6×10^8 kWh, 75.37×10^8 kWh, 35.29×10^8 kWh, 1386956.18×10^4 kWh, respectively. The electricity consumption of SPFM, SPNFM, NMMP, RCCP and Industry growth rate is 2.7%, -3.4%, -3.5%, -15.3% and 4.2% respectively. The decrease of the electricity consumption in energy-intensive industries might be attributed to the environmental supervision.

Table 2. The prediction results of energy-intensive industries and industry.

Indicators		2016Q1	2016Q2	2016Q3	2016Q4	2017Q1	2017Q2	2017Q3	2017Q4
SPFM	true value	26.20	56.50	87.65	120.63	31.15	61.30		
	high scenario	26.20	56.50	87.65	120.63	31.15	61.30	90.91	121.59
	medium scenario	26.20	56.50	87.65	120.63	31.15	61.30	89.99	120.35
	low scenario	26.20	56.50	87.65	120.63	31.15	61.30	89.07	119.10
	scenario								
SPNFM	true value	14.60	28.30	43.07	59.14	13.78	28.12		
	high scenario	14.60	28.30	43.07	59.14	13.78	28.12	42.28	58.07
	medium scenario	14.60	28.30	43.07	59.14	13.78	28.12	41.60	57.16
	low scenario	14.60	28.30	43.07	59.14	13.78	28.12	40.91	56.25
	scenario								
NMMP	true value	21.80	51.60	81.44	115.54	22.68	51.79		
	high scenario	21.80	51.60	81.44	115.54	22.68	51.79	76.62	108.26
	medium scenario	21.80	51.60	81.44	115.54	22.68	51.79	75.37	106.47
	low scenario	21.80	51.60	81.44	115.54	22.68	51.79	74.12	104.67
	scenario								
RCCP	true value	13.80	28.40	41.66	55.90	13.53	25.88		
	high scenario	13.80	28.40	41.66	55.90	13.53	25.88	35.79	47.94
	medium scenario	13.80	28.40	41.66	55.90	13.53	25.88	35.29	47.26
	low scenario	13.80	28.40	41.66	55.90	13.53	25.88	34.78	46.58
	scenario								
Industry	true	586,108	1,331,052	1,857,221	2,737,401	674,161	1,360,6		

value							95		
high scenario	586,108	1,331,052	1,857,221	2,737,401	674,161	1,360,6	1,968,654.	2,874,27	
medium scenario	586,108	1,331,052	1,857,221	2,737,401	674,161	1,360,6	1,935,224.	2,846,89	
low scenario	586,108	1,331,052	1,857,221	2,737,401	674,161	1,360,6	1,899,937.	2,819,52	
						95	08	3.0	

5. Conclusion

Based on the big data technology, a system about energy, electricity, economic forecasting and warning system is constructed, and a new predicting models of the industrial electricity consumption is established for orienting to Energy Internet. According to the estimates results, there are some conclusions:

- An integrated energy, electricity, economy forecasting and warning system is established, which might offer a more multivariate data to do more accurately predict.
- The new forecasting model is more suitable to predict the electricity consumption of the industry in the New Normal economic environment.
- The electricity consumption of the energy-intensive industries is 242.25×10^8 kWh, the growth rate of which is -4.6%. The decrease of the electricity consumption might be attribute to the strictly environmental supervision.
- Based on the more precisely electricity consumption prediction, overcoming the intermittent problem of renewable energy power generation would become much easier. Moreover, Energy Internet will become more stable.

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