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Application of residual modification approach in seasonal ARIMA for electricity demand forecasting: A case study of China

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HIGHLIGHTS

- ▶ Three residual modification models are proposed to improve the precision of seasonal ARIMA.
- ▶ Accurate electricity demand forecast is helpful for a power production sector to come to a correct and reasonable decision.
- ▶ The results conclude that the residual modification approaches could enhance the prediction accuracy of seasonal ARIMA.
- ▶ The modification models could be applied to forecast electricity demand.

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ABSTRACT

Electricity demand forecasting could prove to be a useful policy tool for decision-makers; thus, accurate forecasting of electricity demand is valuable in allowing both power generators and consumers to make their plans. Although a seasonal ARIMA model is widely used in electricity demand analysis and is a high-precision approach for seasonal data forecasting, errors are unavoidable in the forecasting process. Consequently, a significant research goal is to further improve forecasting precision. To help people in the electricity sectors make more sensible decisions, this study proposes residual modification models to improve the precision of seasonal ARIMA for electricity demand forecasting. In this study, PSO optimal Fourier method, seasonal ARIMA model and combined models of PSO optimal Fourier method with seasonal ARIMA are applied in the Northwest electricity grid of China to correct the forecasting results of seasonal ARIMA. The modification models forecasting of the electricity demand appears to be more workable than that of the single seasonal ARIMA. The results indicate that the prediction accuracy of the three residual modification models is higher than the single seasonal ARIMA model and that the combined model is the most satisfactory of the three models.

1. Introduction

The electricity industry, which is gaining more attention from various countries, has become the most important factor impacting the development of socioeconomic status worldwide. Inaccurate demand forecasting raises the operating cost of a utility company, especially in a market environment, where accuracy means money (Sadeghi Keyno et al., 2009). For example, according to the research of Bunn and Farmer (1985), the operating cost will increase by 10 million pounds every year for every 1% increase in the forecasting error (Ying and Pan, 2008). Therefore, accurate forecasting of electricity demand is not only valuable for power generators, allowing them to schedule operation of their power stations to match generation capacity with demand, but is also a fundamental piece of information used for trading in the energy market (Nguyen and Nabney, 2010). Meanwhile, effective early warning of an increase in electricity demand is important to ensure the balance between supply and demand (González-Romera et al., 2008; Mu et al., 2010; Gareta et al., 2006). Consequently, electricity systems can be optimized by developing a scheduling algorithm for electricity demand. Because China's energy demand, electricity in particular, has increased dramatically in the last decade, the Chinese energy sector, as well as other energy sectors worldwide, must pay more attention to improvement of electricity demand forecasting.

There are other significant reasons that necessitate research on electricity demand. The first is global carbon dioxide emissions. Coal and coal-fired electricity are typical up- and downstream industries (Wang, 2007). The major energy source of thermal power is coal and the enormous environmental pressure resulting from coal consumption cannot be ignored. Thermal power

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accounts for approximately 40% of the total carbon dioxide emissions in China because of the high proportion in power generation. By the end of 2009, 74.6% of China's installed capacity was thermal power and 81.67% of power generation was thermal, resulting in large emissions of carbon dioxide and other pollutants. Therefore, accurate and timely electricity demand forecasting can provide a reliable basis for a reasonable plan for power generation and an adjustment of power policy and structures, which will decrease carbon dioxide emissions. Secondly, grid security affects national security. Grids in many countries fail frequently, causing widespread power outages that affect people's lives and cause huge economic losses. For example: (1) The Northeast Blackout of 2003, which was a widespread power outage that occurred throughout eight U.S. states and Ontario, Canada on August 14, 2003 at 4:11 P.M. Eastern Daylight Time (EDT), was the biggest blackout in North American history and resulted in the loss of 61,800 MW of power to over 50 million people (ieso (2003); Wikipedia, 2011a); (2) On May 25, 2005, Moscow's power supplies were at the center of a major incident, which resulted in an outage for several hours in many districts in the city of Moscow, as well as Moscow, Tula, Kaluga and Ryazan provinces. Some tens of thousands of people were trapped in elevators and in stranded underground trains in the Moscow Metro, railway signals were out of action and many commercial and governmental organizations were paralyzed (Wikipedia, 2011b); (3) The 2009 Brazil and Paraguay blackout, which occurred throughout much of Brazil and for a short time the entirety of Paraguay on Tuesday, November 10, 2009, at approximately 22:15 BST (Time in Brazil), was a power outage that affected an estimated 60 million people in Brazil and caused the complete loss of 14 GW of power and the shutdown of the Itaipu Dam for the first time in its 25-year history (Wikipediam, 2011c). Any overload of a power line, or under- or overload of a generator, can cause hard-to-repair and costly damage (Wikipedia, 2011a). Therefore, ensuring the security, stability and economic performance of a large-scale, interconnected power system is a significant and urgent issue. Given this fact, a sound forecasting technique is essential for accurate investment planning of energy production, generation and distribution (Bianco et al., 2009). However, electricity systems, together with power systems, the electricity market, and residents' lives, are affected by internal factors of power system and by the socio-economic environment, natural environment, law and policy, technical progress and population growth (Xu et al., 2009). The impact of these uncertainties increases the difficulty of forecasting electricity demand; moreover, the challenge is to develop forecasting techniques to establish a valid and feasible electricity demand estimate and forecast system for power sectors (Zhu, 1999; Kucukali and Baris, 2010).

In the past decades, due to the robust and sustained increase in electricity demand, which imposes a need for accurate planning to avoid electricity shortages and guarantee adequate infrastructures, many studies focused on the electricity demand forecasting using different techniques. Erdogdu (2007) used co-integration and ARIMA modeling to predict the electricity demand in Turkey. Moral-Carcedoa and Vicéns-Oterob (2005) analyzed and characterized the effect of temperatures on the variability of the daily electricity demand in Spain. Baxter and Calandri (1992) estimated changes in California's annual electricity demand using end-use energy models produced by each warming scenario. Amusa et al. (2009) applied the bounds testing method of co-integration within an autoregressive distributed lag framework to examine the total electricity in South Africa. Akay and Atak (2007) adopted the Grey prediction with the rolling mechanism (GPRM) approach to forecast Turkey's total and industrial electricity consumption. Taylor (2010) introduced the application of the triple seasonal methods in short-time electricity demand forecasting. Abraham and Nath (2001) used a neuro-fuzzy approach to model electricity demand in Victoria and concluded that the neuro-fuzzy system performed better than neural networks, ARIMA model and Victorian Power Exchange (VPX) forecasts. Amarawickrama and Hunt (2008) estimated electricity demand functions for Sri Lanka using six econometric techniques. Although these methods have successfully modeled electricity demand, weaknesses exist and the accuracy of some models is not quite satisfactory. Thus, different methods must be optimized to achieve enhanced results (Wang and Lan, 2007).

However, the general statistics forecasting methods are not workable for long term forecasting, especially for chaotic sequence, the forecasting step would be no more than 7. Among the statistics forecast methods, non-structural prediction methods only consider the changes of data rather than the structural changes in the system, and because of the complexity of systems, structural prediction method cannot achieve accurate predicting results in many situations. Therefore, using non-structural prediction models to forecast the complex systems may be a better choice.

To our knowledge, seasonal ARIMA is a high-precision non-structural model for cyclical data, specifically time series data. Therefore, it is introduced in this article and the residual errors are modified by three methods, namely Particle Swarm Optimization (PSO) optimal Fourier approach, the seasonal ARIMA model and the combined model, to enhance the prediction precision.

In this paper, we mainly focus on electricity and energy policy assessment and prediction based on the results of an analysis of improved forecasting. Although much work has been performed combining other models with S-ARIMA, such as Tseng et al. (2002) and Tseng and Tzeng (2002), the method in this paper is innovative. This paper is organized as follows: Section 2 provides current policy in China; Sections 3–6 introduce the aforementioned algorithms in this article; the forecasting results and analysis are stated in Section 7.

2. Current energy status and policy in China

With the rapid development of the national economy, China's energy demand, for electricity in particular, is increasing dramatically in the last decade. Since 2000, China's GDP has a rapid growth (shown in Fig. 1), and the total installed capacity also increased sharply. As shown in Fig. 2, the total installed capacity reached 300 GW in April 2000, 400 GW in May 2004 and 500 GW in December 2005 (Zhou et al., 2010). By the end of the year 2009, the total installed capacity exceeded 874 GW, at a 10.23% increase over the previous year. Although, the country's electric industry has a prosperous development, thermal power still accounts for the largest proportion of the existing methods of power generation. In 2008, thermal power accounted for 75.87% of installed capacity and 80.95% of power generation. Additionally, thermal power industries in the world accounts for approximately 24% of the global carbon dioxide emissions. Therefore, the state grid of China should lower the use of thermal power.

Following the past 10 years of strong growth in China's economy, there have been several power shortages in the country. An increase in coal price leads to rising electricity prices; in response to the fear of inflation, the government tried to drive down the contracted price of coal electricity and again tried to delay the price adjustment. Such price interventions weaken the power generation impetus of power plants. These factors raise the need for smarter and more effective electricity system operation.

At present, despite the growth of installed power generation capacity in China, it cannot meet the increasing demand. There are still some provinces, such as Zhejiang, Jiangxi, Anhui, Hainan,

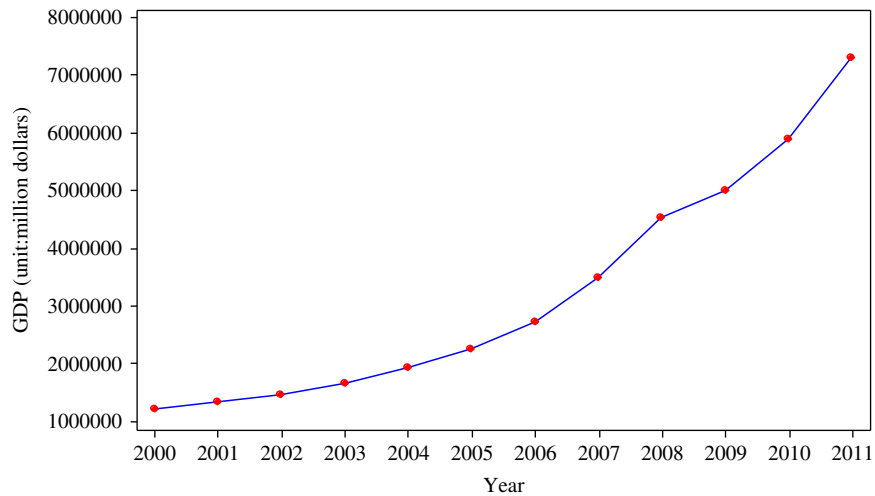

Fig. 1. The total GDP of China from 2000 to 2011 (the data original from China Statistical Yearbook, 2011).

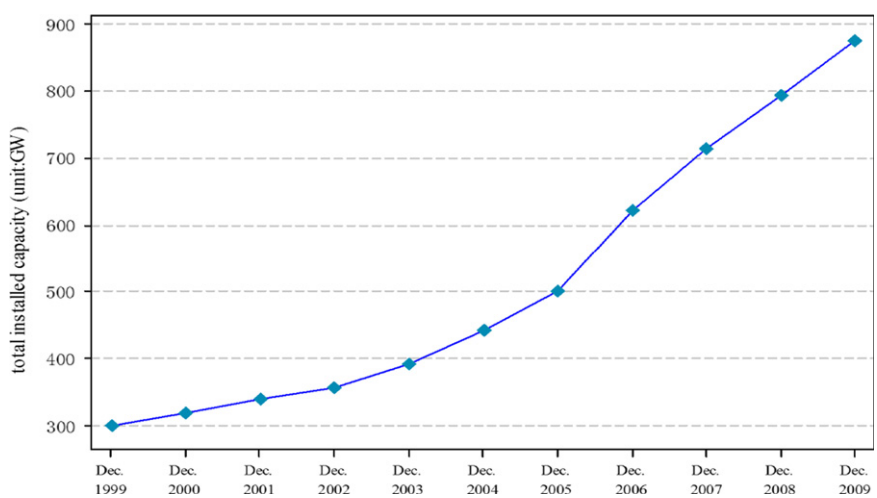

Fig. 2. The total installed capacity in China from 1999 to 2009.

and Fujian, reporting power shortages in 2011. Simultaneously, the data from the China Electricity Council show that thermal power enterprises in the six provinces of the central region are commonly in a deficit, which means power plants are motivated to reduce the loss by limiting electricity generation. The opposition between electricity deficit and power generation waste in different regions reflects the fact that policy is not entirely based on actual situations (Wang, 2011).

The data from the National Energy Board (Table 1) show that from January to February of 2011, the electricity consumption of China totaled 702.5 TWh, an increase of 12.32% compared with the same period of last year. In February, March and April of 2011, the electricity consumption in China totaled 313.6, 388.8 and 376.8 TWh, respectively, which is an increase of 15.82%, 13.41% and 11.2%, respectively, compared to the same period of the previous year. Electricity consumption in the first quarter by the primary, secondary and tertiary industries totaled 19.5, 802.5 and 123.6 TWh, respectively, an increase of 3.16%, 12.31% and 15.51%, respectively, which is also consistent with the results shown in Fig. 3. According to the analysis of Shu Yinbiao (Xinhua Finance, 2011), the vice president of the State Grid Corporation of China, electricity demand in China will continue to increase over the next 10 years. The current installed electricity generation capacity in China totals 960 GW and electricity demand totals approximately 4200 TWh. The installed electricity generation capacity will reach 1760 GW in 2020, and electricity demand will reach 7800 TWh. The large increase of consumption and power generation can never be ignored (Wang, 2011).

Table 1
Comparison of total electricity consumption in China between the first four months in 2010 and 2011 (unit: TWh).

Time	Electricity consumption	Time	Electricity consumption	Growth rate (%)
Jan. 2011	388.9	Jan. 2010	354.680	9.65
Feb. 2011	313.6	Feb. 2010	270.765	15.82
Mar. 2011	388.8	Mar. 2010	343.645	13.14
Apr. 2011	376.8	Apr. 2010	338.849	11.2

We can summarize the importance of electricity demand forecasting into the following aspects. Firstly, an accurate forecast of electricity demand is helpful for reasonable production plan arrangements and electricity policy developments, as early prediction could provide an accurate estimate of the variation of electricity demand. Secondly, because coal based thermal power is the main power generation method in China, predicting the electricity demand could provide information for the evaluation of carbon emissions. China is facing increased international pressure to mitigate carbon emissions within the framework of

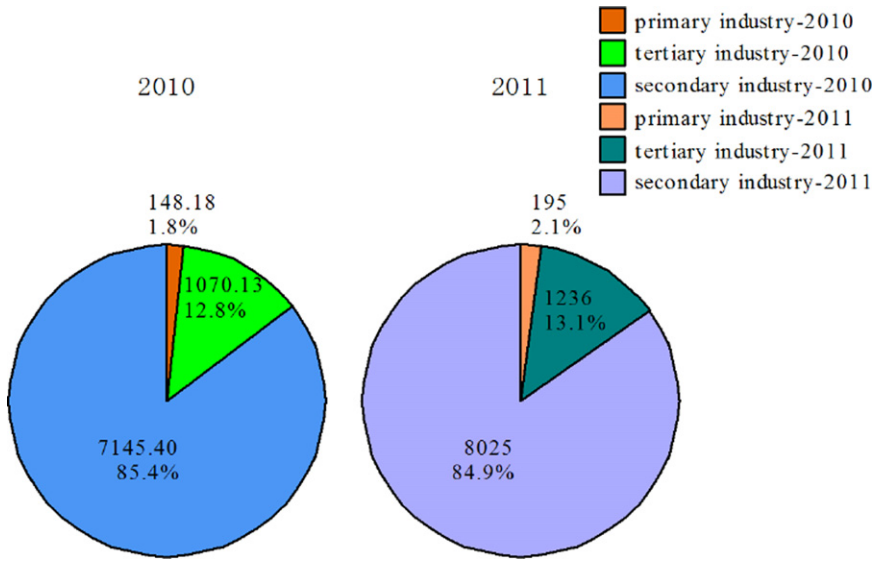

Fig. 3. Electricity consumption of the primary, secondary and tertiary industries in the first quarter of 2010 and 2011 (unit: 100 GWh).

global governance. Thirdly, with sufficient estimation of electricity demand, accidents such as energy waste, electricity shortage, blackouts and others caused by consumption and generation will be prevented. Finally, an accurate demand forecast is beneficial for development of a plan for rational use of energy and energy policy. Therefore, it is important and necessary to develop an accurate energy demand forecasting method. Based on the reasons above, this article simulates the historical electricity demand and predicts it to provide policy assessments and suggestions.

3. Review of the seasonal ARIMA model

In the real world, the environment is uncertain and changes rapidly, and many random series present as a periodic change. To adjust for these periodic non-stationary stochastic processes, we can sample the whole process according to periodic intervals to eliminate the effect of periodicity on forecasting results. If we assume that the period is T, then there is no periodicity in the observed series $\{y_t, y_{t-T}, y_{t-2T}, \ldots\}$, but the random series may be non-stationary. Seasonal ARIMA can eliminate the periodicity influence in a prediction process and thus is a widely applied model for forecasting seasonal time series. Seasonal ARIMA has resulted in great achievements in both academic research and industrial applications during the last three decades (Chen and Wang, 2007).

Seasonal ARIMA, which we denote as S-ARIMA$(p,d,q)(P,D,Q)_S$, is the product of the two polynomials generated by the (p,d,q) ARIMA model and the $(P,D,Q)_S$ ARIMA model. As mentioned previously (Tseng and Tzeng, 2002), it can be expressed as follows:

$$\theta_p(B)\Theta_P(B^S)(1-B)^d(1-B^S)^D y_t = w_q(B)W_Q(B^S)a_t \tag{1}$$

where B is the backward shift operator, and for a non-stationary time series y_t, $(1-B)^d y_t$ could come to a stationary series by using the difference operator $1-B$. B satisfies $By_t=y_{t-1}$ and $B^k y_t=y_{t-k}$. Additionally, p, d and q are integers. The equations

$$w_q(B) = 1-w_1B-w_2B^2-w_3B^3-\cdots-w_qB^q \tag{2}$$

$$\theta_p(B) = 1-\theta_1B-\theta_2B^2-\theta_3B^3-\cdots-\theta_pB^p \tag{3}$$

are polynomials in B of degrees q and p. The integer d is the number of regular differences, p is the order of $\theta_p(B)$, q is the order of $w_q(B)$, and a_t is a current interference with mean=0 and variance σ^2. Typically, we consider a_t as the estimated residual at time t. Meanwhile, a_t is also an independent and identically distributed normal random variable. The roots of $w_q(y)=0$ and $\theta_p(y)=0$ should all lie outside the unit circle (Box and Jenkins, 1976; Tseng et al., 2002; Koutroumanidis et al., 2006).

At the same time

$$\Theta_P(B^S) = 1-\Theta_1B^S-\Theta_2B^{2S}-\Theta_3B^{3S}-\cdots-\Theta_PB^{PS} \tag{4}$$

$$W_Q(B^S) = 1-W_1B^S-W_2B^{2S}-W_3B^{3S}-\cdots-W_QB^{QS} \tag{5}$$

are polynomials in B of degrees P and Q. D is the number of seasonal differences, P is the order of $\Theta_P(B^S)$, and Q is the order of $W_Q(B^S)$. y_t denotes the tth observed value of time series data. Furthermore, as suggested by Box and Jenkins (1976), at least 50 and preferably 100 or more observed data points are needed to establish the S-ARIMA model.

In addition, four-step iterative cycles are needed to fit an S-ARIMA model (Tseng and Tzeng, 2002; Chen and Wang, 2007) as follows:

(1) Identify the structure of the S-ARIMA$(p, d, q)(P, D, Q)_S$ model;
(2) Estimate unknown parameters;
(3) Perform goodness-of-fit tests on the estimated residuals;
(4) Forecast future outcomes based on the known data.

In the S-ARIMA $(p,d,q)(P,D,Q)_S$ model, p and P indicate non-seasonal AR and seasonal AR processes, respectively, q and Q indicate non-seasonal MA and seasonal MA processes, respectively, d signifies the integrated order of a non-seasonal component named regular difference and D signifies the integrated order of a seasonal component named seasonal difference (Sumer et al., 2009).

4. PSO optimized Fourier residual modification approach

Despite its good properties and extensive application in many areas, unavoidable errors exist in the seasonal ARIMA forecasting process and the prediction results may not be satisfactory. A significant research goal is to find an effective approach to improving the precision of forecasting. Here, we introduce a PSO-optimized Fourier approach to modifying the residual errors, which we will denote as F-S-ARIMA below. The approach is expected to enhance prediction accuracy.

We denote the residual series R_i as follows:

$$\{R_i\} = \{R_1, R_2, R_3, \ldots, R_n\} \tag{6}$$

where

$$R_i = y_i - \hat{y}_i \quad (i = 1,2,3,\ldots,n) \tag{7}$$

where $\{\hat{y}_i\} = \{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n\}$ is the output series of the S-ARIMA, and $\{y_i\} = \{y_1 \ldots y_n\}$ is original time series.

According to the definition of Fourier Series Expansions, as it has been mentioned by Zhou et al. (2006) and Hsu (2003), the residual series generalized by Fourier approach, which we denote as R_{Fi}, can be written as follows:

$$R_{Fi} = \frac{1}{2}a_0 + \sum_{k=1}^{\infty}\left[a_k \sin\left(\frac{2\pi k}{L}i\right) + b_k \cos\left(\frac{2\pi k}{L}i\right)\right], \quad i = 1,2,\ldots,n. \tag{8}$$

Here, L is a user-specified parameter that is related to the period of the main cyclic variations. We consider k as a parameter and it is clear that R_{Fi} is converging when $k=m$, $m \to \infty$, where m is integer number, $m=1,2,\ldots$.

Then, Eq. (8) can be written as follows:

$$R = BA \tag{9}$$

where

$$B = \begin{Bmatrix} \frac{1}{2} & \sin\frac{2\pi}{L} & \cos\frac{2\pi}{L} & \sin\frac{2\pi 2}{L} & \cos\frac{2\pi 2}{L} & \cdots \\ \frac{1}{2} & \sin\left(2\frac{2\pi}{L}\right) & \cos\left(2\frac{2\pi}{L}\right) & \sin\left(2\frac{2\pi 2}{L}\right) & \cos\left(2\frac{2\pi 2}{L}\right) & \cdots \\ \frac{1}{2} & \sin\left(3\frac{2\pi}{L}\right) & \cos\left(3\frac{2\pi}{L}\right) & \sin\left(3\frac{2\pi 2}{L}\right) & \cos\left(3\frac{2\pi 2}{L}\right) & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{1}{2} & \sin\left(n\frac{2\pi}{L}\right) & \cos\left(n\frac{2\pi}{L}\right) & \sin\left(n\frac{2\pi 2}{L}\right) & \cos\left(n\frac{2\pi 2}{L}\right) & \cdots \end{Bmatrix}$$

$R = [R_{F1}, R_{F2}, R_{F3}, \ldots, R_{Fn}]^T$ and $A = [a_0, a_1, b_1, a_2, b_2, \ldots, a_m, b_m]$

When L is given and k is bounded, for example $k=5$ and $L=12$. Then, denoting the coefficient of Eq. (8) which are estimated by Ordinary Least Squares (OLS) as $\hat{A}$, we obtain the following equation:

$$\hat{A} = [\hat{a}_0, \hat{a}_1, \hat{b}_1, \ldots, \hat{a}_m, \hat{b}_m] = (B^T B)^{-1} B^T R \tag{10}$$

where $\hat{a}_0, \hat{a}_1, \hat{b}_1, \ldots, \hat{a}_m, \hat{b}_m$ is the estimated values of $a_0, a_1, b_1, \ldots, a_m, b_m$, respectively.

In this paper, with the given value of $k=5$and the unknown parameter L, the values of a_0, a_1, b_1, a_2, $b_2, \ldots, a_5$, b_5, L are designated by Nonlinear Least-Squares (NLS). The fundamental idea of NLS is to find parameters minimizing the sum of squares of R_i. Matlab is used to solve out the parameters.

However, in this paper, an innovative method is presented to confirm the parameters. Specifically, the parameters in Eq. (8) are recalculated using a particle swarm optimization algorithm (PSO) after preliminary estimation by Nonlinear Least Squares (NLS). Different from the tradition Fourier approach, PSO is applied to search for superior parameters by adding a proper disturbance to parameters calculated by NLS. The parameters are finally determined using PSO. With this method, better values of the parameters a_0, a_1, b_1, a_2, $b_2, \ldots$, a_5, b_5, L can be obtained to minimize the forecasting errors. The mean absolute percentage error (MAPE) is applied to control the selection of parameters. In other words, we must find parameters that minimize the value of MAPE. Simultaneously, the model is evaluated by relative error (RE), MAPE, root mean square error (RMSE), standard error of prediction (SEP), which can be expressed as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_{Fi} - y_i}{y_i} \times 100\%\right| \tag{11}$$

$$RE_i = \left|\frac{\hat{y}_{Fi} - y_i}{y_i}\right| \times 100\% \tag{12}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_{Fi})^2}{n}} \tag{13}$$

$$SEP = \frac{100}{\bar{X}}\sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_{Fi} - y_i)^2}{n}} \tag{14}$$

Then, we replace the values of a_0, a_1, b_1, a_2, $b_2, \ldots, a_5$, b_5, L in Eq. (8) with the respective PSO optimal parameters. Therefore, the PSO optimal Fourier residual modification model, which we denote as F-S-ARIMA, can be expressed as follows:

$$\hat{y}_{Fi} = \hat{y}_i + \hat{R}_{Fi}, \quad i = 1,2,3,\ldots,n, \tag{15}$$

where $\hat{y}_{Fi}$ denotes the values forecasted by PSO optimal Fourier residual modification model, $\{\hat{R}_{Fi}\} = \{\hat{R}_{F1}, \hat{R}_{F2}, \ldots, \hat{R}_{Fn}\}$ is residual series forecasted by PSO optimal Fourier approach.

5. Residual modification of S-ARIMA

We define the residual series R_i the same as in Eq. (6)

$$\{R_i\} = \{R_1, R_2, R_3, \ldots, R_n\}$$

Because the original data represents periodic change, the residual series takes on cyclical characteristics. Thus, we consider modifying the residual errors using S-ARIMA, which we will denote as S-S-ARIMA below, expecting to enhance forecasting accuracy. By the method introduced in Section 3, the residual series could be forecasted by S-ARIMA. The forecasting process consists of the following three specific steps:

Step 1: Structure the residual series by Eq. (6).
Step 2: Predict the residual series using the S-ARIMA approach generated in Section 3.
Step 3: Once the residual series is simulated, the predicted errors are added to the corresponding fitting values of S-ARIMA in Section 3. After the residual errors are modified by S-ARIMA, we obtain new forecasting values.

Table 2
Electricity demand of Northwest electricity grid in China from February 2006 to March 2010 (unit:100 GWh).

Time	Original data	Time	Original data
Feb. 2006	116.51	Mar. 2008	176.21
Mar. 2006	113.67	Apr. 2008	176.42
Apr. 2006	135.76	May. 2008	183.56
May. 2006	140.52	Jun. 2008	190.7
Jun. 2006	148.55	Jul. 2008	197.45
Jul. 2006	155.19	Aug. 2008	195.06
Aug. 2006	156.4	Sep. 2008	166.38
Sep. 2006	140.37	Oct. 2008	163.75
Oct. 2006	145.18	Nov. 2008	155.03
Nov. 2006	152.9	Dec. 2008	157.56
Dec. 2006	157.74	Jan. 2009	155.76
Jan. 2007	160.24	Feb. 2009	144.7
Feb. 2007	134.31	Mar. 2009	163.91
Mar. 2007	152.69	Apr. 2009	169.29
Apr. 2007	155.56	May. 2009	176.03
May. 2007	160	Jun. 2009	184.97
June 2007	162.86	Jul. 2009	202.83
Jul. 2007	165.68	Aug. 2009	198.99
Aug. 2007	168.69	Sep. 2009	188.41
Sep. 2007	157.29	Oct. 2009	196.56
Oct. 2007	164.64	Nov. 2009	213.61
Nov. 2007	173.04	Dec. 2009	225.67
Dec. 2007	178.98	Jan. 2010	230.73
Jan. 2008	180.06	Feb. 2010	193
Feb. 2008	158.26	Mar. 2010	220.72

We denote the values of residual errors predicted by S-ARIMA as follows:

$$\{R_{Si}\} = \{R_{S1}, R_{S2}, \ldots, R_{Sn}\}, \quad i = 1,2,\ldots,n. \tag{16}$$

Then, S-ARIMA modified values $\hat{y}_{Si}$ can be expressed as follows:

$$\hat{y}_{Si} = \hat{y}_i + R_{Si}, \quad i = 1,2,\ldots,n. \tag{17}$$

6. Combined Fourier and S-ARIMA residual modification model

A combined forecasting model is a significant method for enhancing forecasting precision. Here, we adopt it to modify the residual errors.

We denote $\{\hat{R}_{Fi} : i = 1,2,\ldots,n\}$ as the residual series generated by PSO optimal Fourier approach and $\{R_{Si}: i=1,2,\ldots,n\}$ as the residual series simulated by S-ARIMA. Then, the residual series is predicted by combining the PSO optimal Fourier approach with the S-ARIMA residual modification model. The combination forecasting model can be expressed as follows:

$$R_{Ci} = \alpha\hat{R}_{Fi} + (1-\alpha)R_{Si}, \quad i = 1,2,3,\ldots,n, \quad \alpha \in (0,1) \tag{18}$$

where R_{Ci} is the residual series forecasted by combined model.

Combining the PSO optimal Fourier approach with the S-ARIMA model yields the residual modification of S-ARIMA, which we name F-S-S-ARIMA. F-S-S-ARIMA modified values $\hat{y}_{Ci}$ can be expressed as follows:

$$\hat{y}_{Ci} = \hat{y}_i + R_{Ci}, \quad i = 1,2,3,\ldots,n. \tag{19}$$

7. Analysis results

The aim of forecasting is to analyze the development trend of system in the future by determining the relationships among already-known data. The developing trend of electricity demand in China can be regarded as a gradual increase because of rapid development of national economy. As is listed in Table 2, the total demand of northwest electricity grid in China has increased dramatically from 2006 to 2010. The total demand of northwest electricity grid was 11,651 GWh in February 2006 and reached 15,826 GWh in February 2008. By the end of March 2010, the total demand reached 22,072 GWh, at a 34.66% increase over the same period of last year. On the other hand, the development trend of electricity demand is cyclical. Consequently, a seasonal ARIMA (S-ARIMA) model can be used to build a forecasting model for electricity demand. Although, S-ARIMA is already a high precision model for periodic trend, more accurate prediction

Table 3
The verification of proposed models' forecasting ability (unit: 100 GWh).

Time	Original data	S-ARIMA		F-S-ARIMA		S-S-ARIMA		F-S-S-ARIMA	
		Forecasted value	RE (%)	Forecasted value	RE (%)	Forecasted value	RE (%)	Forecasted value	RE (%)
Modeling stage									
2007-3	152.69	161.8	5.97	156.03	2.19				
2007-4	155.56	147.14	5.41	152.39	2.04				
2007-5	160	160.22	0.14	156.11	2.43				
2007-6	162.86	167.04	2.57	163.53	0.41				
2007-7	165.68	172.13	3.89	170.45	2.88				
2007-8	168.69	163.81	2.89	167.58	0.66				
2007-9	157.29	145.5	7.50	146.33	6.96				
2007-10	164.64	158.5	3.73	158.66	3.63				
2007-11	173.04	163.36	5.59	159.69	7.72				
2007-12	178.98	179.43	0.25	180.63	0.92				
2008-1	180.06	177.33	1.51	173.26	3.78				
2008-2	158.26	166.46	5.18	163.1	3.06				
2008-3	176.21	170.23	3.39	174.85	0.77				
2008-4	176.42	184	4.30	178.79	1.34	171.67	2.69	175.23	0.67
2008-5	183.56	185.54	1.08	182.62	0.51	184.05	0.27	183.34	0.12
2008-6	190.7	191.51	0.43	190.58	0.06	193.07	1.24	191.83	0.59
2008-7	197.45	202.7	2.66	206.75	4.71	203.9	3.27	205.32	3.99
2008-8	195.06	195.13	0.03	195.32	0.13	189.91	2.64	192.61	1.26
2008-9	166.38	172.59	3.73	172.47	3.66	162.64	2.25	167.55	0.71
2008-10	163.75	169.14	3.29	165.35	0.98	162.44	0.80	163.89	0.09
2008-11	155.03	165.04	6.45	166.99	7.72	154.89	0.09	160.94	3.81
2008-12	157.56	163.14	3.54	157.04	0.33	159.76	1.40	158.4	0.54
2009-1	155.76	157.26	0.97	156.74	0.63	157.23	0.95	156.99	0.79
2009-2	144.7	138.6	4.22	141.6	2.14	138.22	4.48	139.91	3.31
2009-3	163.91	156.32	4.63	150.77	8.01	158.19	3.49	154.48	5.75
2009-4	169.29	173.35	2.40	170.8	0.89	174.85	3.29	172.82	2.09
2009-5	176.03	175.39	0.36	175.54	0.28	175.1	0.53	175.32	0.40
2009-6	184.97	181.37	1.95	185.16	0.10	181.54	1.85	183.35	0.88
2009-7	202.83	192.46	5.11	192.36	5.16	193.42	4.64	192.89	4.90
2009-8	198.99	203.2	2.11	202.44	1.73	205.81	3.43	204.12	2.58
2009-9	188.41	189.58	0.62	186.33	1.10	192.55	2.20	189.44	0.55
2009-10	196.56	195.97	0.30	197.82	0.64	197.67	0.57	197.75	0.6
2009-11	213.61	208.61	2.34	201.26	5.78	212.61	0.47	206.94	3.12
2009-12	225.67	221.23	1.97	223.42	1.00	222.67	1.33	223.04	1.16
2010-1	230.73	227.52	1.39	228.29	1.06	232.56	0.79	230.43	0.13
MAPE (%)			2.91		2.44		1.94		1.73
Verification stage									
2010-2	193	206.91	7.21	201.67	4.49	201.12	4.21	201.4	4.35
2010-3	220.72	220.85	0.06	218.48	1.01	224.78	1.84	221.63	0.41
MAPE (%)			3.63		2.75		3.02		2.38

models are expected in practice. Therefore, residual modification approaches are applied to enhance the accuracy of the prediction by reducing the error to a minimum. In this study, by applying PSO optimal Fourier approach, the S-ARIMA model and the combined model to residual modification of S-ARIMA model, four S-ARIMA model are presented to show that the three improved models (F-S-ARIMA, S-S-ARIMA, F-S-S-ARIMA) can improve the precision of S-ARIMA and overcome the restrictions of traditional methods.

To verify the effectiveness and feasibility of the methods presented in our research, the electricity demand of northwest electricity grid in China from February 2006 to March 2010 is used and is listed in Table 2. In order to analyze the forecasting capability of proposed models, the data from February 2006 to January 2010 is used for model verification to predict values from February 2010 to March 2010 (shown in Table 3). These original data stem from the website of the State Grid of China. Although it is unfortunate that the original data from May 2008 is absent, the average of the original data from April and June of 2008 is used to take its place. To our knowledge, the electricity demand changes by months, thus the seasonal cycle is 12. Using the statistical software Minitab, the S-ARIMA model is set up. We select $p=d=q=P=D=Q=1$, i.e., $S-ARIMA(1,1,1)(1,1,1)_{12}$ to simulate and forecast. In this paper, the PSO optimal Fourier approach and the S-ARIMA model are used to adjust the forecasting results by modifying the residual errors. When the S-ARIMA is applied to forecast the residual series, we select the seasonal cycle to be 12, so the data from 1 to 13 are absent. The results are listed in Table 4.

Accuracy forecasting results for electricity demand is vital to policy decision. Therefore, due to accuracy issues in forecasting the development trend of electricity demand, the main work we do in this paper is to enhance the prediction accuracy by modifying residual errors. So the residual errors of the S-ARIMA are used as the original residual series in simulations with the PSO optimal Fourier approach, the S-ARIMA model and the combined model to adjust the original S-ARIMA forecast series. Table 3 shows the model verification results. The three proposed models in this paper present better performance than that of original S-ARIMA both in modeling stage and verification stage, the MAPE values of F-S-ARIMA, S-S-ARIMA and F-S-S-ARIMA in verification stage improves 24.24%, 16.8% and 34.44%, respectively. This proves that the drawbacks of original models can be mitigated in different degrees by modifying the residual. Therefore, we can conclude that the modified models have better performance than traditional models and can be applied for electricity demand forecasting. Then, data from February 2006 to March 2010 is used to forecast the demand from April 2010 to September 2010. Figs. 4–6 illustrate the residual series simulated by Fourier approach, S-ARIMA model and the combined model, respectively. The figures show that the trend of forecasting residual series is similar to the original error trend and that the residual series predicted by the combined model yields the best results compared to the other series. Specifically, the combined model forecasted residual series most closely resembles the original residual series. This outcome also coincides with the results listed in Table 5. In Figs. 5 and 6, a segment line is absent

Table 4
Comparisons of S-ARIMA, F-S-ARIMA, S-S-ARIMA and F-S-S-ARIMA (unit: 100 GWh).

Time	Original data	S-ARIMA		F-S-ARIMA		S-S-ARIMA		F-S-S-ARIMA	
		Forecasted value	RE (%)	Forecasted value	RE (%)	Forecasted value	RE (%)	Forecasted value	RE (%)
2007-3	152.69	165.51	8.39	159.74	4.62	–	–	–	–
2007-4	155.56	146.23	6	151.47	2.63	–	–	–	–
2007-5	160	156.19	2.38	152.09	4.95	–	–	–	–
2007-6	162.86	169.77	4.24	166.25	2.08	–	–	–	–
2007-7	165.68	173.38	4.65	171.7	3.63	–	–	–	–
2007-8	168.69	164.95	2.22	168.71	0.03	–	–	–	–
2007-9	157.29	142.98	9.1	143.82	8.56	–	–	–	–
2007-10	164.64	158.73	3.59	158.89	3.49	–	–	–	–
2007-11	173.04	161.94	6.41	158.27	8.53	–	–	–	–
2007-12	178.98	181.2	1.24	182.39	1.91	–	–	–	–
2008-1	180.06	176.41	2.03	172.33	4.29	–	–	–	–
2008-2	158.26	164.13	3.71	160.76	1.58	–	–	–	–
2008-3	176.21	172.96	1.84	177.58	0.78	–	–	–	–
2008-4	176.42	181.86	3.08	176.65	0.13	187.57	6.32	182.11	3.23
2008-5	183.56	187.57	2.18	184.66	0.6	186.69	1.7	185.67	1.15
2008-6	190.7	192.36	0.87	191.43	0.38	183.96	3.53	187.7	1.57
2008-7	197.45	205.6	4.13	209.65	6.18	186.24	5.86	197.95	0.25
2008-8	195.06	195.03	0.02	195.22	0.08	199.79	2.43	197.5	1.25
2008-9	166.38	169.69	1.99	169.57	1.92	177.63	6.76	173.6	4.34
2008-10	163.75	169.96	3.79	166.16	1.47	167.12	2.06	166.64	1.77
2008-11	155.03	163.77	5.64	165.73	6.9	159.56	2.92	162.64	4.91
2008-12	157.56	166.29	5.54	160.19	1.67	152.73	3.06	156.46	0.7
2009-1	155.76	156.12	0.23	155.6	0.1	153.49	1.46	154.54	0.78
2009-2	144.7	136.77	5.48	139.76	3.41	144.59	0.07	142.18	1.74
2009-3	163.91	155.83	4.93	150.28	8.31	154.98	5.45	152.63	6.88
2009-4	169.29	173.03	2.21	170.48	0.7	178.04	5.17	174.26	2.94
2009-5	176.03	175.82	0.12	175.96	0.04	178.63	1.47	177.29	0.72
2009-6	184.97	180.84	2.23	184.63	0.18	179.99	2.69	182.31	1.44
2009-7	202.83	193.16	4.77	193.05	4.82	194.43	4.14	193.74	4.48
2009-8	198.99	202.2	1.61	201.43	1.23	202.84	1.94	202.14	1.58
2009-9	188.41	192.58	2.21	189.32	0.49	197.3	4.72	193.31	2.6
2009-10	196.56	198.24	0.85	200.09	1.8	199.41	1.45	199.75	1.62
2009-11	213.61	211.4	1.04	204.05	4.48	217.37	1.76	210.71	1.36
2009-12	225.67	223.53	0.95	225.72	0.02	222.25	1.52	223.99	0.75
2010-1	230.73	226.56	1.81	227.33	1.47	229.28	0.63	228.31	1.05
2010-2	193	202.65	5	197.41	2.28	193.25	0.13	195.33	1.21
2010-3	220.72	210.01	4.85	207.64	5.39	214.83	2.67	211.23	4.3

because we chose the seasonal cycle to be 12 when the residual series is forecasted by S-ARIMA; thus the data from 1 to 13 are absent because of the seasonal difference.

As is listed in Table 5, the F-S-S-ARIAM model has the lowest MAPE among the four models. The MAPE of S-ARIMA, F-S-ARIMA, S-S-ARIMA and F-S-S-ARIMA are 3.28%, 2.75%, 2.91% and 2.19%, respectively. The three residual modification methods dramatically

Table 5
Comparative analysis of forecasting error MAPE, RMSE and SEP.

Models	S-ARIMA	F-S-ARIMA	S-S-ARIMA	F-S-S-ARIMA
MAPE (%)	3.28	2.75	2.91	2.19
RMSE	6.67	6.57	6.25	4.91
SEP (%)	3.74	3.68	3.37	2.65

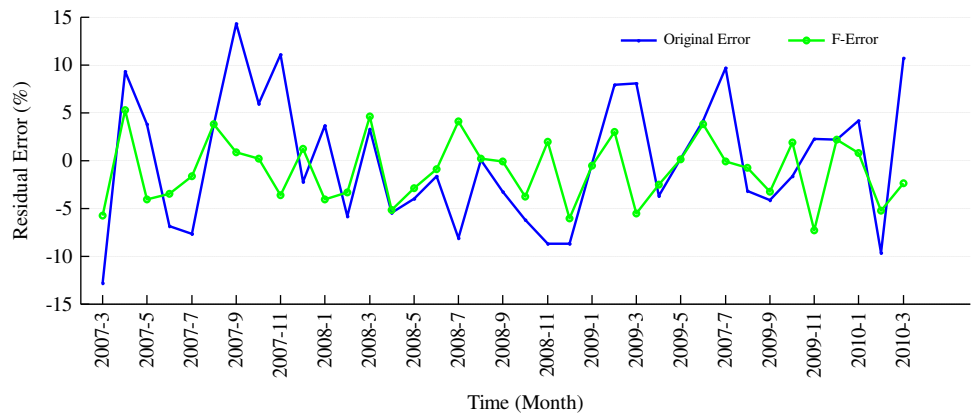

Fig. 4. Fourier approach simulated residual series compared with the original residual series.

Fig. 5. S-ARIMA simulated residual series and original residual series.

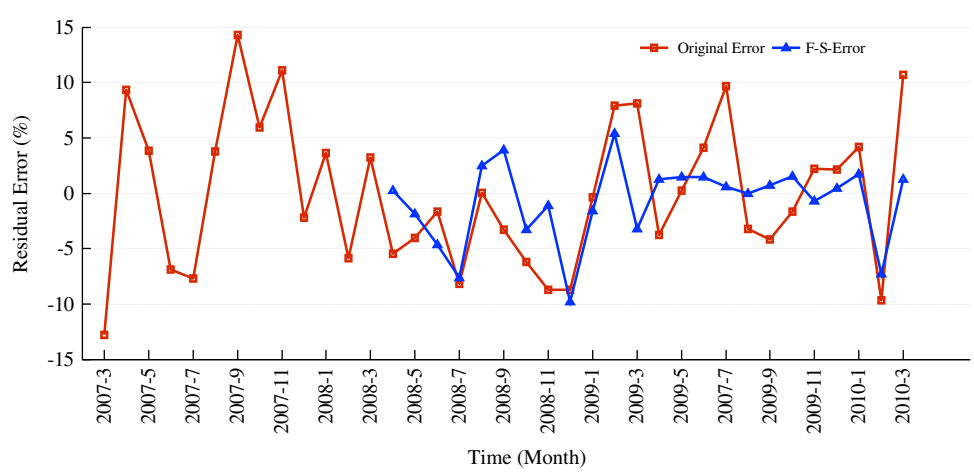

Fig. 6. Residual series simulated by the combined model.

enhanced the forecasting precision to different degrees, and after using the combined residual modification model, the MAPE has been lowered to 2.19%, which is a 1.09 percentage improvement compared with S-ARIMA. Moreover, in the case of other indices, such as RMSE and SEP the performances of the modified models are better than the corresponding original models. As listed in Table 5, the RMSE and SEP of modified models predicted series have obviously decreased, especially F-S-S-ARIMA model. The SEP of F-S-S-ARIMA forecasted values is 2.65%, dropping sharply compared with that of S-ARIMA forecasted values which is 3.74%. Therefore, a conclusion can be drawn that the three proposed models in our research are of well forecasting ability for electricity demand and the performance of F-S-S-ARIMA model is the best compared to other models, as well as the precision in predicting by F-S-ARIMA is better than that by S-S-ARIMA.

The results obtained from the modified S-ARIMA forecasting models agree with the original values exceptionally well. As shown in Fig. 7, it is clear that the curve of F-S-S-ARIMA more closely approaches the original curve. These results confirm that the F-S-S-ARIMA model can fit the electricity demand well and that this model is the best of these four models. Moreover, the demand development of Northwest electricity grid shows an increasing trend. The electricity generation in China is based on low-cost, plentiful domestic energy resources and locally made power generation technologies. Thermal power, which is the largest carbon dioxide emissions industries in the world, accounts for the largest proportion of the existing methods of power generation. Therefore, the state grid of China should lower the use of thermal power and develop renewable energy.

According to the above analysis, the proposed models have been employed to forecast electricity demand of Northwest electricity grid in China from April 2010 to September 2010 and the overall development trend of the next 2 years, which can help managers make strategic decisions. In Table 6, the electricity demand of the Northwest electricity grid in China from April 2010 to September 2010 forecasted by S-ARIMA, F-S-ARIMA, S-S-ARIMA and F-S-S-ARIMA is listed. The results of F-F-S-ARIMA indicate that the electricity demand of Northwest electricity grid in China would be 21,199 GWh in April 2010 and 20,072 GWh in September 2010. On the other hand, according to the outcome series of F-S-ARIMA, the total demand of Northwest electricity grid would be 22,097 GWh in April 2010 and 21,068 GWh in September 2010. However, compared with the same period of previous years, such as 2006, 2007, 2008 and 2009 (in Table 2), the general trend of electricity demand of Northwest electricity grid in China has a sharp increase. Then, Fig. 8 shows the forecasting results of the next 2 years by proposed algorithms. According to our predictions, the electricity demand in the next 2 years of Northwest electricity grid will be increasing continuously, even using the most conservative model. The minimum value of electricity demand in 2012 is almost equivalent to the maximum value in 2007. The future trend of Northwest electricity grid is also the same as overall trend in China according to Zhou's (Zhou et al. (2010)) view. It is necessary to note that the energy and electricity problems in China is problematic.

Finally, in order to provide a simple way for the users to understand the prediction process we put forward, Fig. 9 shows the forecasting framework for electricity demand, the forecasting framework for a time series y_t consists of four steps as follows:

Step 1: Establish a seasonal ARIMA model using the original time series y_t, and determine the forecasting value of primarily the original time series.
Step 2: Structure the original residual series, which is in fact the deduction of the original time series and forecasting values of the seasonal ARIMA.
Step 3: Use the PSO optimized Fourier approach, S-ARIMA model and combined model to simulate the original residual acquired in Step 2. Accordingly, we get the PSO-Fourier residual, S-ARIMA residual and combined residual.
Step 4: Determine the residual modification model of the seasonal ARIMA. Adding the simulated residual values to the forecasting values of the seasonal ARIMA model in Step 1 establishes three residual modification models, which are F-S-ARIMA, F-S-S-ARIMA and S-S-ARIMA.

Table 6
Forecasting results of electricity demand for Northwest electricity grid from April 2010 to September 2010 in China (unit: 100 GWh).

Time	S-ARIMA	F-S-ARIMA	S-S-ARIMA	F-S-S-ARIMA
Apr. 2010	219.57	220.97	203.01	211.99
Mar. 2010	229.39	232.46	216.83	224.64
Jun. 2010	231.71	231.62	226.33	228.98
Jul. 2010	234.01	232.32	223.96	228.14
Aug. 2010	234.87	232.75	223.73	228.24
Sep. 2010	209.88	210.68	190.76	200.72

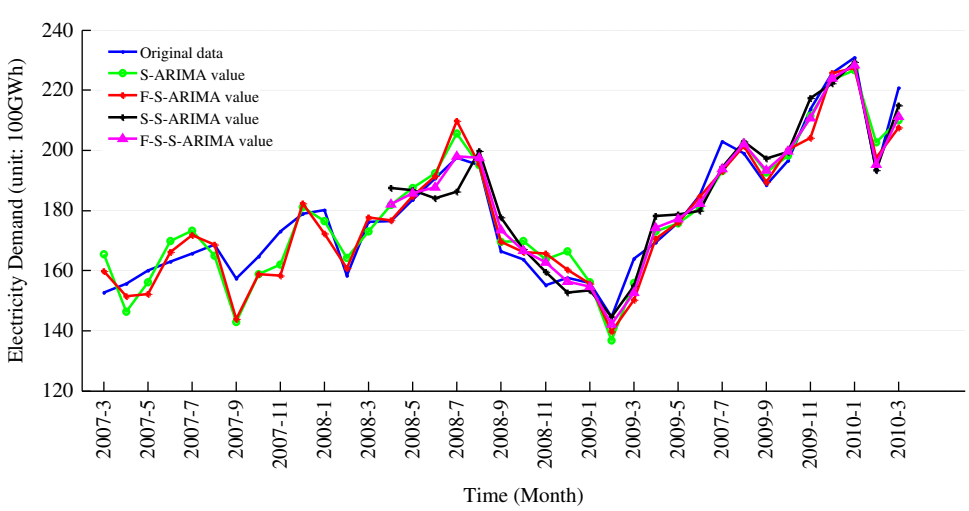

Fig. 7. Plot of original data and forecasted values.

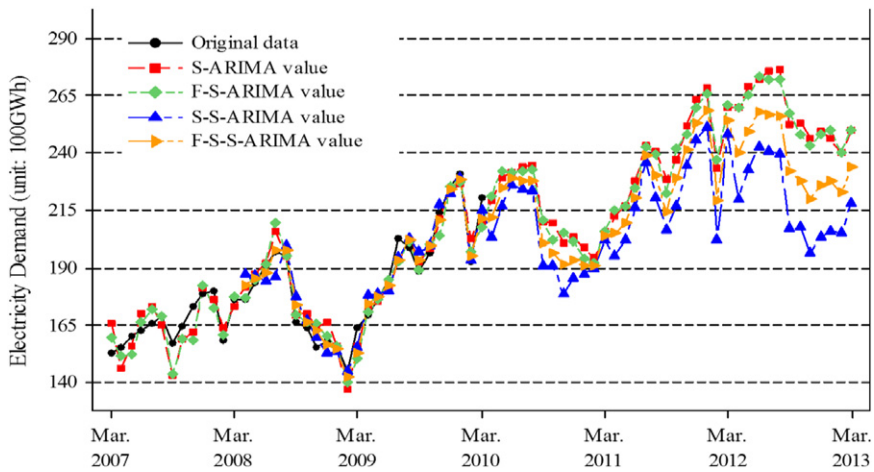

Fig. 8. Electricity demand forecasting in the next 2 years of Northwest electricity grid.

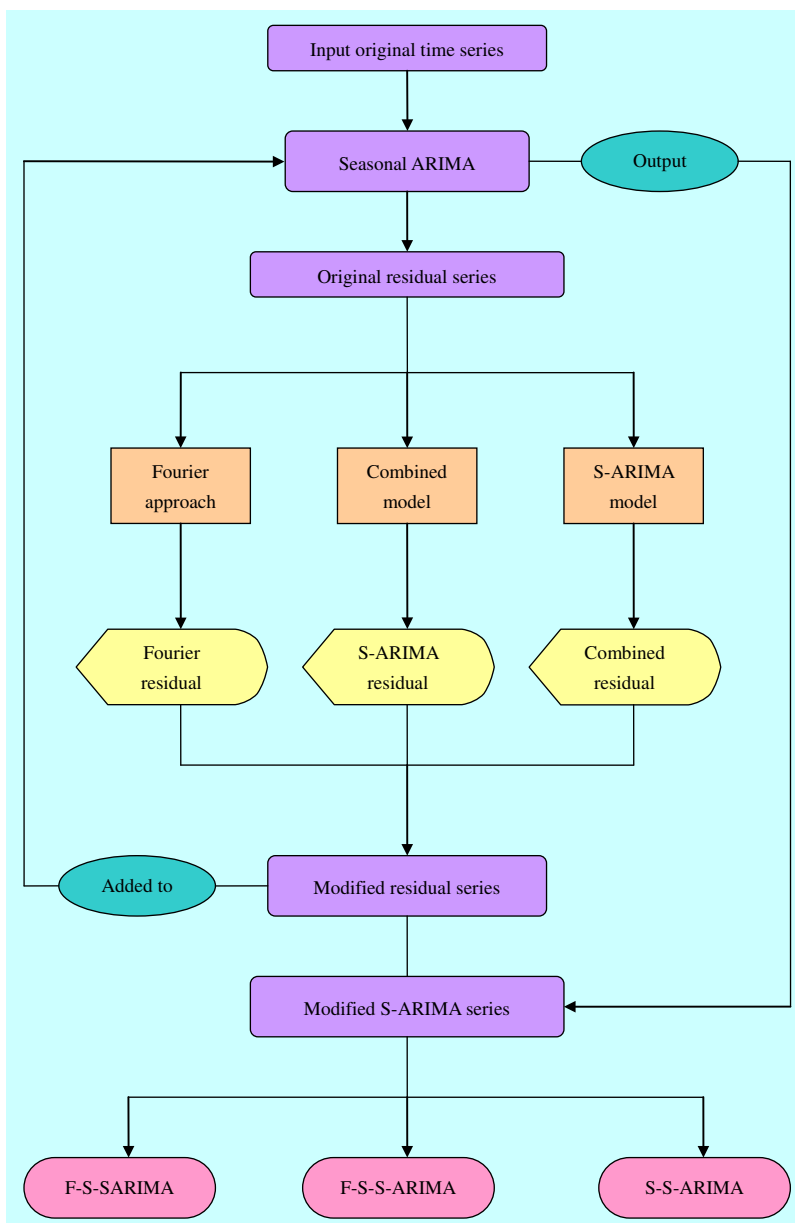

Fig. 9. Flow chart of forecasting process.

8. Conclusion

The purpose of this paper is to enhance the forecasting precision of S-ARIMA by modifying residual series based on the Fourier approach, the S-ARIMA model and the combined model. It is the first time the combined model has been applied to correct the residual series, and it is also innovative to use the Fourier approach and the S-ARIMA model to adjust the residual errors of S-ARIMA to enhance the precision. Although S-ARIMA has been a high precision model for electricity demand forecasting and it is difficult to further improve the accuracy, the results in the paper showed that the mentioned methods could enhance the prediction accuracy, especially the combined model.

Precision is an important evaluation standard of forecasting models. Much work has been performed on improving accuracy. From our experiment, we can see that it is a valid approach to enhance the forecasting precision by modifying the residual errors. S-ARIMA is adjusted by these three residual modification models in this paper and has been shown to be successful. Our results suggest that PSO is a perfect approach to optimize parameters and can be applied in many fields.

As a result of the versatility of the external environment, electricity demand is uncertain because of the changes in influencing factors. However, the general trend is increasing and it would be different according to the seasonal changes. The time series method needs little information and is a simple and feasible tool for data forecasting in a complex system like a power grid. Furthermore, S-ARIMA, as an excellent forecasting method for seasonal data, can be widely used to predict electricity demand. The residual modification models such as F-S-ARIMA, S-ARIMA and F-S-S-ARIMA, which have lower MAPE than S-ARIMA, are superior methods. Therefore, these models could be applied to forecast electricity demand, and provide an outstanding tool for power demand prediction. Meanwhile, it is helpful for a power production sector to come to a correct and reasonable decision.

Furthermore, China's electricity demand would continue to grow in the next few years and the attendant problems of electricity and energy could not be ignored. Therefore, facing this situation, we propose the following suggestions: (1) accelerate the development of a smart grid; (2) to change the burning of coal and develop clean coal technology; and (3) develop renewable energy.

Acknowledgments

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