Time Series Modeling of Power System

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Abstract. Europe hopes to wean itself off energy dependence by diversifying its energy supply, developing clean energy and conserving energy. There might be both opportunities and challenges in the future. It is worth studying the reasons and rules behind current situations and making contributions to sustainable energy development in China. We use Holt and ARIMA models to forecast annual and monthly data with small data volume, and LSTM neural network to forecast weekly and daily data with large data volume and stronger periodicity. We find that a total load of Europe will decrease in the next three years, but the clean energy power generation will increase. After the modeling work, we test the performance of the model through residual sequence test, proving the robustness and accuracy of the models. Finally, we end our research by giving a comprehensive conclusion.

Keywords: Power System, ARIMA, LSTM, Time Series Analysis

1 Introduction

1.1 Problem Background

European energy structure and supply are constantly trans- forming. It is worth studying the reasons behind this and making contributions to sustainable energy development. A data package covering the EU and some neighboring countries contains different kinds of time series data relevant to power system modelling from 2015 to 2020. The aim of this paper is to use these data to do some research and prediction.

1.2 Our Work

The whole modelling process is shown in the Figure 1. First, we pre-process the dataset with a large amount of data given by the problem, delete the invalid data, and fill in the missing values. Then, among many regions in Europe, we select Germany for a separate analysis of its energy indicators. Subsequently, we took different time resolutions with the corresponding models predicting energy consumption over time in the future. Finally, based on the perspective of sustainable development, we give some policy suggestions for China considering the current situation of China and other countries [1].

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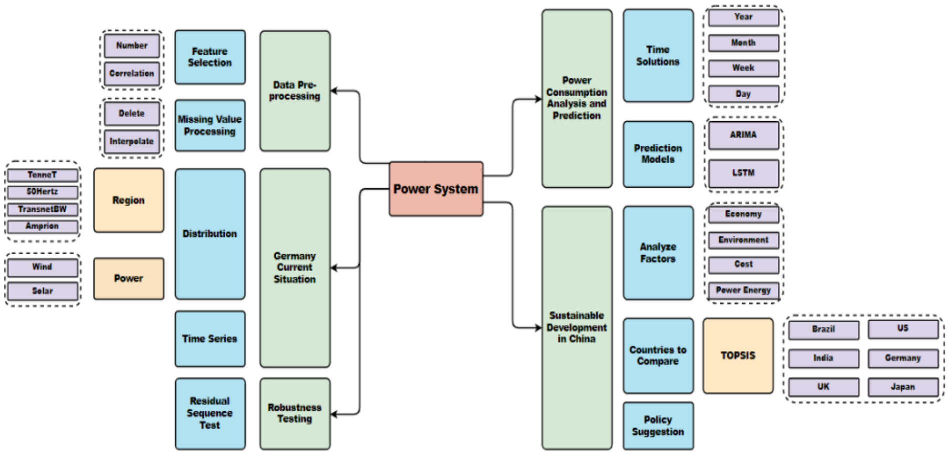


Fig.1 Whole modeling process of the paper

2 Assumptions and Notations

2.1 Assumptions

Assumption 1: The valid data provided by the problem is completely correct.
Justification: Our research will be meaningful only if the data are correct.

Assumption 2: There is no significant natural disasters, wars, diseases or new energy technologies breakthrough in the future.

Justification: These big events can lead to dramatic and disruptive changes in energy metrics, and our research will be meaningless in that case.

Assumption 3: We assume that the generating capacity of various energy sources can effectively approximate the load.

Justification: This problem lacks the key data for calculating the load, while other calculation items are relatively small compared with the power generation [2].

2.2 Notations

TABLE I lists the symbols used in this paper and their significance. If a symbol not listed in the table appears in the paper, it will be explained where the symbol appears.

Table 1. Symbol and Significance

Symbol	Significance
ξkt	Error term
ϕki	The coefficient

xt	Actual observation value of the issue t
lt	Estimated level of time t
bt	Forecast trend of time t
α	Smoothing parameters for horizontal
β	Smoothing parameters for trends
μx	Mean value of a sequence
h	The number of prediction overruns, also known as prediction step

3 Solution to Problem

3.1 Literature Review

In order to better analyze and evaluate various energy consumption, we consult a lot of data about Europe and come to the following conclusion: to achieve the purpose of energy conservation, Europe implements the summer time system, when the clock is usually set one hour faster, so that darkness comes at a later clock time [3]. Europe has recently made progress in decarbonizing electricity. coal power generation has dropped by more than one-third, most of which has been replaced by wind and solar energy Since 2015.

3.2 Time Series Analysis of Different Energy Sources

Because the data given in the title involves many regions, we average the features of all regions, so that the model can better represent the overall level of Europe. We have the data of two major clean energy generation capacity - wind energy and solar energy, among which wind energy is divided into offshore generation and onshore power [4].

Next, we want to get the total load. The calculation principle is shown in Fig. 2.

Considering the lack of key data for load calculation and other calculation items are relatively small compared with generation, we approximately evaluate the load through the generation of various energy sources. First, moving average is used to remove noise, so as to convert it into a waveform that is easier to observe. Then we draw the moving average time sequence diagram of offshore and onshore actual wind power generation, solar power generation and total load.

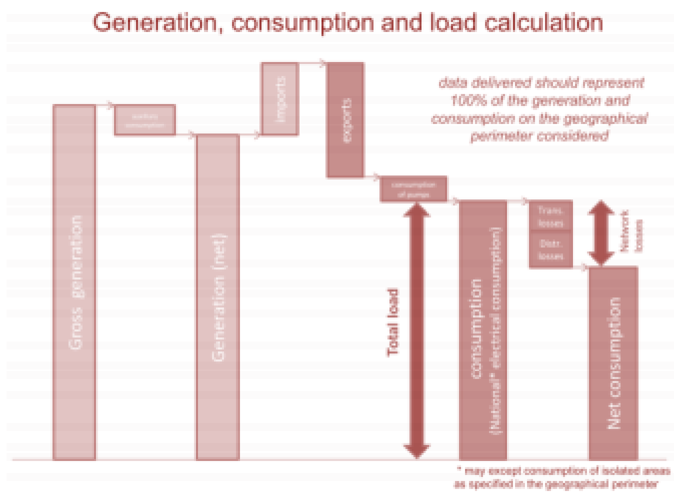


Fig.2 Generation, consumption and load calculation

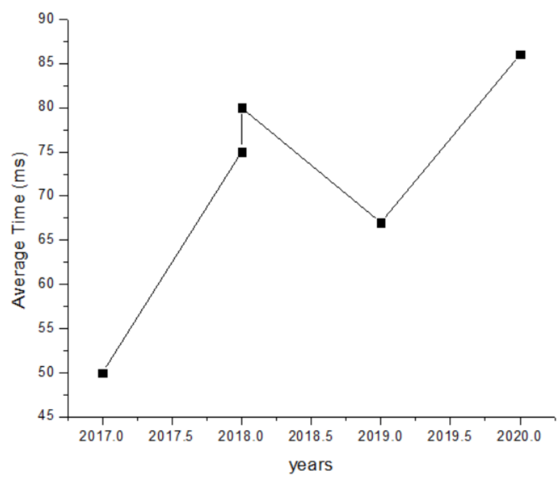


Fig.3 Moving average time sequence of power generation and total load

Based on Fig. 3, it is not difficult to find that the power generation and total load of the two kinds of energy are seasonal, because certain peaks in the time series occur in the same month. It is consistent with the data we have looked up before. We can draw the following conclusions:

(a) The annual peak value of wind power generation appears from January to March and shows an upward trend. The offshore and onshore wind power generation almost coincide, which indicate their power generation is flat and their trend is the same. We believe that it is related to the numerous oceans around Europe [5].

(b) The annual peak value of solar power generation is stable in July, and increase slightly with the year's growth. This may be due to the continuous construction of solar power generation facilities in Europe [6].

(c) In the overall seasonal fluctuation, the total load rises slightly at first and then decreases. It has two peaks every year, with a larger peak in February and a smaller peak in December. Because Europe is located in the north temperate zone and it need to consume more electricity in cold winter, there is a small rise and peaks. At the same time, we observe that the peak of the total load is low from April to October, which shows that the implementation of the summer time system in Europe can effectively reduce energy consumption.

We continue to study the change trend of these feature value in the month, week and day, calculate the feature mean value of each time rate, and draw charts [7].

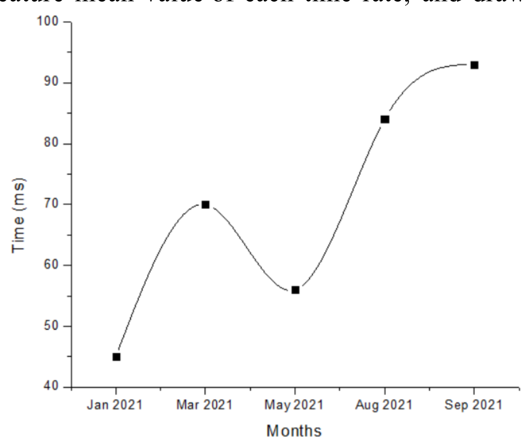


Fig.4 Monthly trend

As shown in Fig. 4, it is obvious that the wind power generation capacity and electricity price drop rapidly and reach the lowest value in the middle of each month; The total load reach the lowest value at the end and beginning of the month, and the solar power generation capacity steadily decreased after a large increase at the beginning of the month.

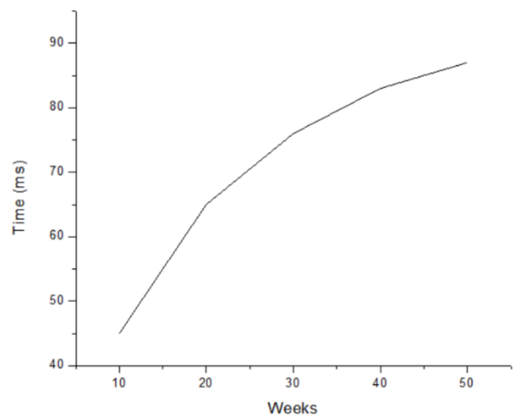


Fig.5 Weekly trend

As shown in Fig. 5, we can observe that the electricity price and the total load have almost the same trend both reach the maximum at the weekend and the minimum on Thursday. In contrast, wind power generation capacity reaches the peak on Thursday, while solar power generation capacity fluctuates only within a small range [8].

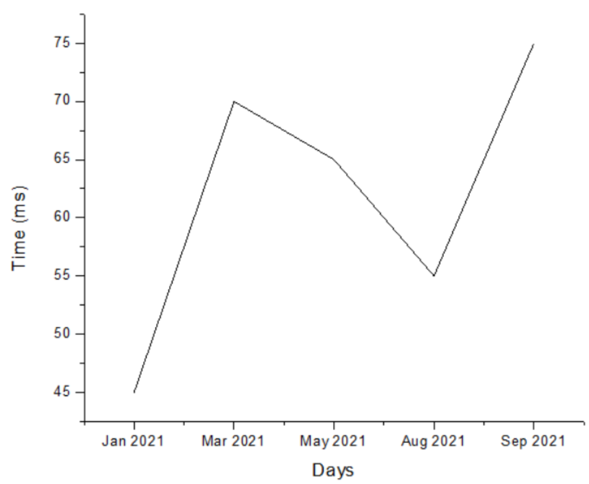


Fig.6 Daily trend

As shown in Fig. 6, we find that these features have very interesting rules. The total load is high during the day and drops sharply at night. The electricity price has two peaks and one valley in the daytime, but it is lowest at night. The value of the solar power generation capacity reaches its peak at noon but is 0 at night because there is no sunshine at that time. Wind power generation capacity is very active at night and reaches its lowest value in the morning [9].

3.3 Model Principle

In this section, we introduce three time prediction models, namely ARIMA(p, q, d), Holt linear trend, and LSTM neural network.

Holt Linear Trend Model:

Holt linear trend model contains one prediction equation and two smoothing equations, which can predict data with trends. On the basis of simple exponential smoothing coefficient α, A trend smoothing coefficient named β is added. So, it is also called "two parameter smoothing method". The forecast consists of two parts: One is the horizontal part, which is updated with simple exponential smoothing method based on the horizontal part of the previous period; The other part is the trend part, which is a smooth adjustment based on the trend part of the previous period. Add the two parts and we will get the next forecast.

$$\begin{cases} l_t = \alpha x_t + (1-\alpha)(l_{t-1} + b_{t-1}) \\ b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \\ \hat{x}_{t+h} = l_t + hb_t, h = 1,2,3,\cdots \end{cases} \tag{1}$$

ARIMA (p, q, d):

ARIMA is usually used in demand forecasting and planning. The generation form of ARIMA model is:

$$\left(1 - \sum_{i=1}^{p} \alpha_i L^i\right)(1-L)^d y_t = \alpha_0 + \left(1 + \sum_{i=1}^{q} \beta_i L^i\right)\varepsilon_t \tag{2}$$

Among them, $\left(1 - \sum_{i=1}^{p} \alpha_i L^i\right)$ represents AR(q) model, $(1-L)^d$ represents d-order difference, $(1 + \sum_{i=1}^{q} \beta_i L^i)\varepsilon_t$ represents MA(q) model.

LSTM Neural Network:

LSTM (Long Short Term Memory Network) is an improved recurrent neural network, which can solve the problem that the original recurrent neural network (RNN) cannot handle long-distance dependence. The following Fig. 7 shows the construct of LSTM.

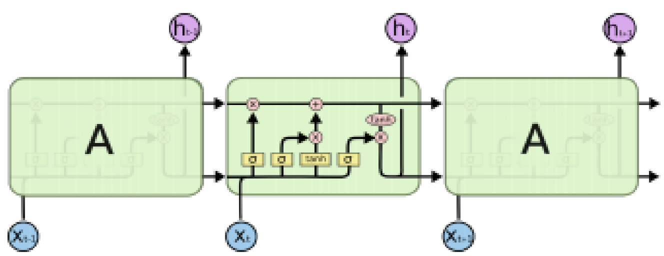


Fig.7 Repeat network layer of LSTM

Based on the above structure, LSTM influences the cell state through forgetting gate, input gate and output gate, and continuously circulates output and learns.

3.4 The Results of Forecast

We have cleaned the dataset previously. Next, we average the features with different time resolutions (year, month, week and day) to obtain four sub datasets.

For the annual and monthly data, we use Holt linear trend and ARIMA models to forecast the next three years because of the small amount of data:

Annual forecast. We have annual data from 2015 to 2020. For the actual total load, we establish ARIMA (0, 2, 0) model; For wind and solar power generation, we build Holt linear trend model. The prediction curves can well fit the original data. The prediction results are as follows:

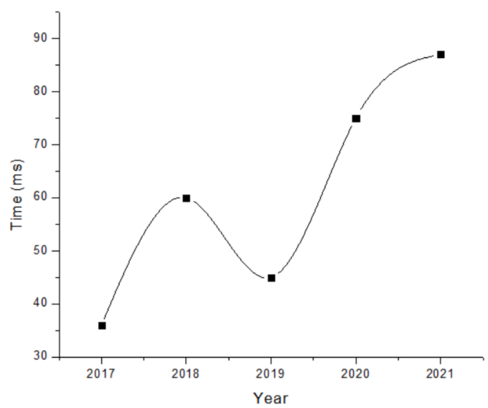


Fig.8 Annual forecast

The Annual forecast is shown in Fig. 8. The annual total energy consumption decreases by a greater margin, which may be due to two reasons. On the one hand, under the guidance of low carbon and environmental protection in European countries, traditional petrochemical energy has withdrawn from the market prematurely, when the supply of clean energy is not stable. On the other hand, unexpected factors such as the COVID-19 epidemic and climate change are disrupting the energy situation in Europe. Fortunately, the power generation of clean energy such as wind energy and solar energy continued to rise steadily, related to Europe's efforts to replace traditional energy with clean energy [10].

For the monthly forecast of total load, solar power generation and wind power generation, we establish ARIMA (2, 0, 12), ARIMA (1, 1, 6) and ARIMA (1, 1, 0) models respectively. In order to show intuitiveness, we will draw the result into line charts as follows:

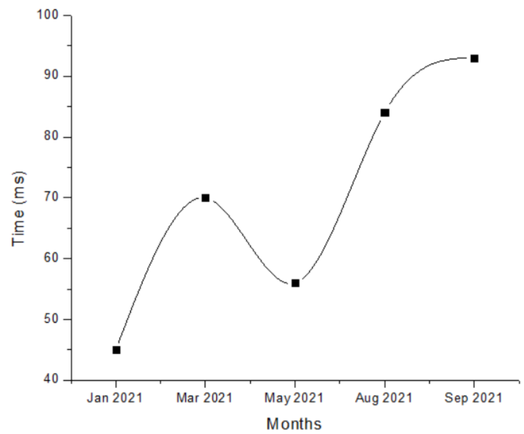


Fig.9 Monthly forecast

The monthly forecast is shown in Fig. 9. The prediction results of ARIMA model are relatively smooth, but it can be seen that the total load will decrease and the power generation of clean energy will increase in the future. The forecast effect is a little bit worse, which may be caused by the periodicity and the small amount of monthly data.

For weekly and daily data, the data volume is larger and the periodicity is stronger. So we use LSTM neural network to predict:

Weekly forecast. We selected 90% of the time series data as the training set and 10% as the test set.In order to show intuitiveness, we will draw the result into line charts as follows:

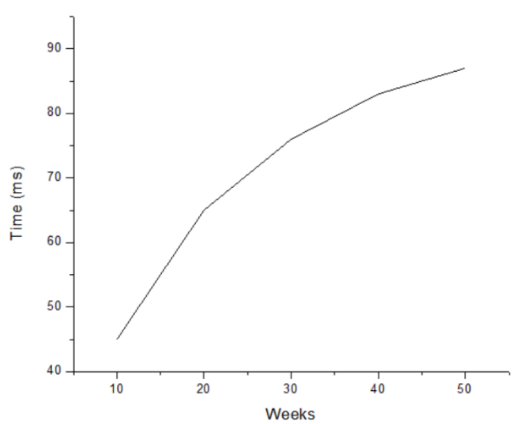


Fig.10 Weekly forecast

We find that the LSTM model can well fit the waveform of the past data and predict the future. Then, we predict the consumption level in the next 60 weeks, which have the same periodicity and consistent overall trend with the above.

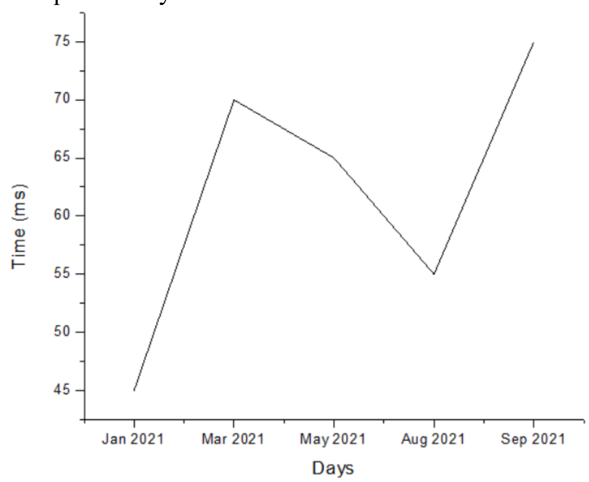


Fig.11 Daily forecast

The daily forecast is shown in Fig. 11. Although the daily data shows the strongest periodicity and volatility, LSTM model can perfectly fit. The conclusion is very similar to the weekly data, so we don't elaborate more here Due to space,

To sum up, we have selected suitable models for power forecasting different time resolutions for different data volumes and features, and given accurate results. The total load of Europe will decrease, but the clean energy power generation will increase, which means Europe may face certain energy challenges in the future, and will increase the proportion of clean energy to optimize the energy structure.

4 Model Testing

We test the prediction model of the third question. First, we calculate the residual sequence of the fitting model:

$$\text{error } i = \text{Actual } i - \text{Prediction } i \qquad (3)$$

Error i represents the ith value of the residual sequence. Actual i and Prediction i represents real value and model fitting value respectively.

After obtaining the model fitting residual sequence, we can visualize them as follows:

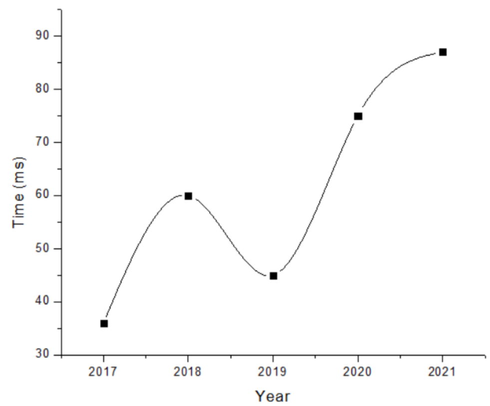
According to Fig. 12 and Fig. 13, we can find that the residual value fluctuates around a value, meeting the image rule of white noise. In addition, we can further test by LB statistics:

$$\Lambda B = v(v+2)\sum_{k=1}^{m}\left(\frac{\hat{\rho}_k^2}{n-k}\right) \qquad (4)$$

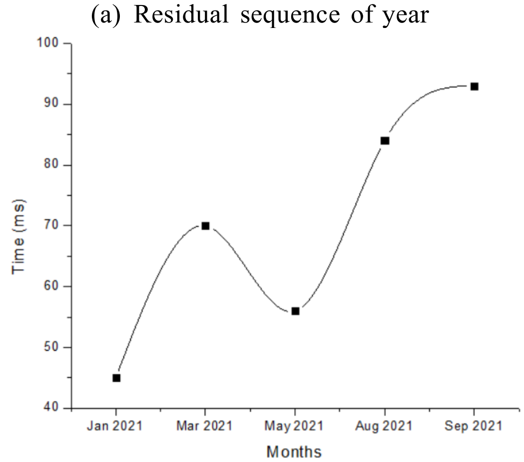
In this equation, n is the number of sequential observation.

Periods and mis the number of specified delay periods. $\hat{\rho}k$ is the k-order autocorrelation coefficient.

If the P value of LB statistic test is greater than 0.05, we will believe that the sequence is a white noise sequence when the significance level is 0.05.



(a) Residual sequence of year



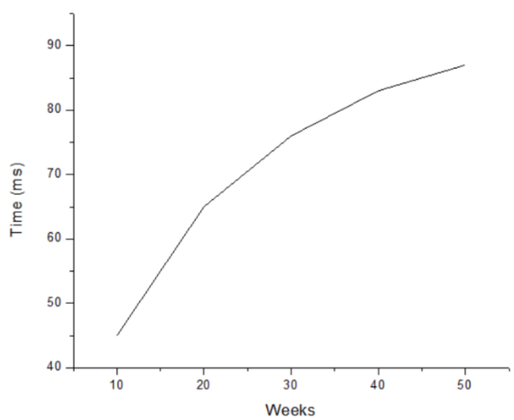
(b) Residual sequence of month

Fig.12 Residual sequence of year and month

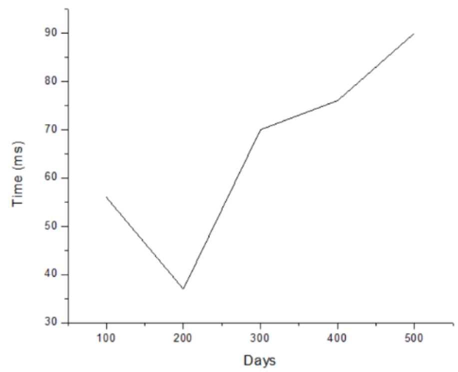
For the residual data of year, month, week and day, we set the number of delay periods as 4, 24, 24 and 24 respectively. Through inspection, we find that the corresponding LB statis- tics are greater than 0.05, which can be explained that the residual is white noise significantly and the prediction model is significantly established.

5 Conclusions

We take the average level of the overall data as the research targets. First, we process the data through the moving average algorithm and observe the data rules. Next, use the Holt linear trend model, ARIMA and LSTM neural network models to predict the time series of different data with different time resolutions. Through model testing, it is judged that the prediction effect is good and the model is significantly established. The algorithm and model focus on data processing and use a representative cross-section of existing data to show the current situation of the European power system. Finally, based on the existing results, we give constructive policy suggestions.



(a) Residual sequence of week



(b) Residual sequence of day

Fig.13 Residual sequence of week and day

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