Research and Practice of Steam Demand Forecasting Model in Intelligent System for Industrial Enterprises

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Abstract. Under the environment of China's continuous promotion of energy conservation and emission reduction, the idea of on-demand energy supply of steam power system in tobacco manufacturing industry is put forward. Through the research and optimization of prediction algorithm, we analyze the historical data and energy supply process of steam energy, and establish the on-demand energy supply prediction model of steam energy, in order to realize the on-demand energy supply prediction of steam energy in tobacco manufacturing industry.

Keywords: Steam demand, Forecasting model, Mathematical analysis, Industrial enterprises.

1. Introduction
As the largest manufacturing country, China is facing huge energy consumption and environmental damage while obtaining economic benefits. Optimizing industrial structure and promoting energy conservation and emission reduction are important measures for manufacturing industry to achieve cost reduction, efficiency increase and green sustainable development.

The "13th five year plan" notice on energy conservation and emission reduction issued by the State Council puts forward that China's energy demand is growing rigidly. The resource and environment problem is still one of the bottlenecks restricting China's economic and social development. The situation of energy conservation and emission reduction is still grim and the task is arduous.

Cigarette manufacturing industry is one of the important parts of China's manufacturing industry, which also faces the above problems. Energy supply on demand is one of the important measures to continuously promote energy conservation and emission reduction [1-3], realize cost reduction and efficiency increase and green sustainable development of enterprises [4-5]. Steam energy is one of the main energy consumption in tobacco manufacturing industry. In this paper, through time series, data fitting, clustering and other algorithms, based on production planning, process requirements and other data, the prediction model of steam energy consumption is constructed to realize rolling prediction of steam boiler start-up strategy, so as to achieve the purpose of steam energy supply on demand, energy conservation and emission reduction.

2. Model Algorithm
Time series can be divided into two categories: stationary series and non-stationary series. Stationary series are basically non trend series. The observed values in this kind of series basically fluctuate at a certain fixed level. Although the fluctuation degree is different in different time periods, there is no certain rule. The fluctuation can be regarded as random. The nonstationary series includes trend, seasonality or periodicity. It may contain only one component or a combination of several components.

A trend is a kind of continuous upward or downward change in a long period of time series, also known as a long-term trend. The trend in time series can be linear or nonlinear.
Seasonality, also known as seasonal variation, is a cyclical fluctuation that occurs repeatedly in a year in a time series. Of course, the term "season" in seasonality is generalized. It not only refers to the four seasons of a year, but also refers to any kind of periodic change. Periodicity, also known as cyclic fluctuation, is a wave or oscillatory change around a long-term trend in time series. It is different from the trend change. It is not a continuous movement in a single direction, but an alternating fluctuation between fluctuations. It is also different from seasonal variation. Seasonal variation has relatively fixed rules, and the change period is mostly one year, while the cyclic fluctuation has no fixed rule. The change period is more than one year, and the cycle length is different.

The accidental fluctuation after removing trend, periodicity and seasonality in time series is called randomness, also known as irregular fluctuation.

2.1. Multiplication Model and Addition Model

The components of time series can be divided into four types: trend $T$, seasonal or seasonal variation $s$, periodic or cyclical fluctuation $C$, random or irregular fluctuation $I$.

One of the main contents of traditional time series analysis is to separate these components from time series, and express the relationship between them with certain mathematical relations, and then analyze them separately. According to the influence of four components on a time series, the time series can be divided into several models, such as additive model and multiplication model.

Additive model:
$$Y_t = T_t + S_t + C_t + I_t$$

Multiplication model:
$$Y_t = T_t \times S_t \times C_t \times I_t$$

2.2. Prediction of Stationary Series

Stationary time series usually contain only random components, and the prediction methods mainly include simple average method, moving average method and exponential smoothing method. These methods mainly smooth the time series to eliminate its random fluctuations, so they are also called smoothing methods.

Smoothing method can be used not only for short-term prediction of stationary time series, but also for smoothing time series to describe the trend (including linear trend and nonlinear trend).

2.3. Simple Average Method

The simple average method is based on the existing $t$-period observations to predict the next period of values. If the observed value of $T$ period in time series is $Y_1, Y_2, \ldots, Y_t$, then the predicted value of $F_{t+1}$ period is:
$$F_{t+1} = \frac{1}{t} (Y_1 + Y_2 + \cdots + Y_t) = \frac{1}{t} \sum_{i=1}^{t} Y_i$$

The simple average method is suitable for the prediction of more stable time series, that is, when the time series has no trend, it is better to use this method. However, if the time series has trend or seasonal components, the prediction of this method is not accurate enough.

2.4. Moving Average Method

Moving average method is a forecasting method which takes the average value of time series as the prediction value, including simple moving average method and weighted moving average method. The simple moving average is to average the values of the latest $K$ period as the prediction value of the next period. If the moving interval is $K$ ($1 < K < T$), then the moving average value of $T$ period is:
The moving average method only uses the data of the latest K period, and the moving interval is k when calculating the moving average. This method is also suitable for the prediction of relatively stable time series.

2.5. Exponential Smoothing Method
Exponential smoothing method is a method to predict the weighted average of past observations. The method makes the predicted value of T + 1 period equal to the weighted average of actual observation value of T period and prediction value of T period. Exponential smoothing method is a special form of weighted average. The longer the observation time is, the weight will decrease exponentially, so it is called exponential smoothing.
Once exponential smoothing method is also called single exponential smoothing method, which has only one smoothing coefficient. Moreover, the longer the observation value is from the prediction period, the smaller the weight becomes. First order exponential smoothing takes the linear combination of predicted value and observed value in a period as the predicted value of T + 1 period:

$$Y_t = \frac{Y_{t-k+1} + Y_{t-k+2} + \cdots + Y_{t-1} + Y_t}{k}$$

$Y_t$ is the actual observation value of T period, $F_t$ is the predicted value of T period, and $\alpha$ is the smoothing coefficient (0 < $\alpha$ < 1).

When using exponential smoothing method, the key problem is to determine an appropriate smoothing coefficient $\alpha$, because different $\alpha$ will have different effects on the prediction results. For example, when $\alpha = 0$, the predicted value only repeats the prediction result of the previous period; when $\alpha = 1$, the predicted value is the actual value of the previous period. The closer $\alpha$ is to 1, the more timely the model responds to the change of time series, because it gives the current actual value more weight than the predicted value. Similarly, the closer $\alpha$ is to 0, the greater the weight is given to the current forecast value, so the slower the response of the model to the change of time series.

Generally speaking, when the time series has large random fluctuations, the larger $\alpha$ should be selected to keep up with the recent changes quickly. When the time series is relatively stable, the smaller $\alpha$ should be selected.

3. Forecast Process
The steam energy consumption of cigarette factory is mainly divided into air conditioning and tobacco production. According to the similarities and differences of energy consumption characteristics, different prediction algorithms and prediction models are used to study. The prediction process is shown in Figure 1. The steam energy consumption prediction process in the process of tobacco production is mainly described.
3.1. Data Extraction and Cleaning

The extracted data are used for prediction model training and validation, and the extracted data work order information, steam flow information, regional environmental temperature and humidity information, process line information.

- **Work order information**
  Work order information includes work order number, product code, production date, start time, end time, output, process line and process section.

- **Steam flow information**
  The steam flow information includes collection time point, flow value and collection point position.

- **Regional environmental temperature and humidity information**
  Regional environmental temperature and humidity information refers to the environmental temperature and humidity of each production area, including time point, temperature and humidity.

- **Process line information**
  The process line information includes the process line code, the process section code and the sequence of each process section.

Not all the extracted data meet the requirements of modeling, and corresponding cleaning methods are adopted for the above different types of data.

The steam flow and ambient temperature and humidity belong to the continuous change, and the missing data should be supplemented and the abnormal data should be eliminated.

Each work order information is an independent variable, which can not be supplemented or modified by other data. Therefore, the data missing or abnormal situation should be eliminated.

3.2. Construction of Prediction Model

From the above analysis, the steam energy prediction model in the production process includes four prediction models: work order steam energy consumption prediction model, work order start-up and shutdown prediction model, steam energy supply prediction model and boiler start-up strategy prediction model. The obtained data are divided into training set and verification set. For the four prediction models, the steam energy consumption prediction process is shown in Figure 1.

![Figure 1. Steam energy consumption prediction process.](image-url)
models, time series, mean fitting and clustering algorithms are used respectively. The construction of the prediction model, and verify the prediction model, select the most suitable algorithm. The steam energy consumption prediction model of work order is based on the relative time, and the output prediction time is relative time, and we finally need to get the prediction value of absolute time (real time). Here, we modify the output of the steam energy consumption prediction model of the work order through the output of the work order start stop prediction model, and modify the predicted value of the relative time to the predicted value of the absolute time.

Through the above steps, we get the predicted value of steam energy consumption terminal, but this prediction value can not be used as the prediction value of steam energy supply demand. In the actual scenario, steam from the boiler generation to the end of the use process, is through the shunt and pipeline transportation, in this process there is a certain loss, we need to build another end steam energy consumption prediction model output as the input, the output of this model is the final predicted value of steam energy supply demand.

3.3. Forecast Results

On the basis of the model, the process parameters, scheduling plan, work order real-time status and other data are used as input, and the results are shown in Fig. 2 and Fig. 3. The predicted output of Fig. 2 and Fig. 3 shows the real-time predicted value of steam end use flow, and Fig. 3 shows the predicted value of steam energy supply and boiler strategy start-up strategy. It can be seen from the figure that the predicted value has a high degree of fitting with the real value.

![Figure 2. Prediction of end steam energy consumption.](image)

![Figure 3. Prediction of steam energy supply and boiler start-up strategy.](image)
4. Summary
In this paper, we did not study particularly the seasonal, equipment status, continuous production and other related factors affecting steam energy consumption. In the follow-up study, more factors can be added to the study to optimize the algorithm model, so as to obtain more accurate prediction results.

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