Energy Consumption Anomaly Monitoring Model

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Abstract

Today's mainstream energy consumption anomaly monitoring models are determined by simple arithmetic averaging methods and the same loop ratio, which can lead to periodic alarms or persistent alarms. This article briefly introduces the predictors and comparators for the above problems, and points out the problem of identifying anomalies in the year-on-year or ring ratio changes. Through the concept of 95% prediction interval in statistics, the real-time abnormal warning technology is applied to the overall change and periodic change. The three-exponential smoothing algorithm is used to illustrate the better preservation of time series data trends and seasonal information effects. Finally, by selecting suitable parameters, the timeliness and accuracy of the anomaly detection model are further verified.

Keywords

Energy consumption monitoring, Energy consumption forecast, Real-time warning, Abnormal energy consumption.

1. Introduction

Using energy problems not only involves energy consumption, but also involves a lot of security issues. Today, with the rapid development of science and technology, higher requirements are put forward in terms of energy stability.When abnormal fluctuations occur in the system, it is particularly important to find out how to timely and accurately find the reasons for the fluctuations and to find the breakthrough of the solution.

There are two key requirements for real-time anomaly warning:

Timeliness:It is necessary to find the problem as soon as possible, so as to minimize the security risks and losses.

Accuracy:Accurate alarm can improve the sensitivity of business party for alarm, if there is a lot of false positives, is causing alarm on the regulation of business party used to as often, or even numbness, cannot handle exceptions in a timely manner.

Anomaly recognition based on historical data,gets the possible value range of the current time point,when the actual value is outside the range,that is, data exceptions.

2. Year on Year & Ring Ratio

The simplest way, of course, is to think that the data is abnormal when the change from the previous year or the previous month exceeds a certain threshold. But there are some problems with these two approaches:

ring ratio:Using only the previous value of the current value, periodic alarms may occur when the data changes periodically(If you have some energy consumption at 4:05 every day, the number of data increases periodically).

year on year:Using only one value of the current value, when a period of data integrity increases, it will continue to alarm(For example, the data on energy consumption at the beginning of the school year is much higher than that of the previous day).

If you combine the advantages of these two approaches, and consider the overall and cyclical changes of the data, even taking into account the impact of all the data on the current value, the error will be smaller.

3. Predictors & Comparators

The energy consumption anomaly detection model is divided into two parts, a predictor and a comparator. The historical data is used as the input of the predictor, and the predicted value of the current time point is output, and the predicted value and the real value of the current time point are detected by the comparator whether the data is abnormal.

3.1 Hot-Winters Predictor

Hot-Winters, also known as three-times exponential smoothing, predicts the current value based on historical time series. It divides the time series into three parts, the residual component (s), the trend component (t), and the periodic component (p), and (x) represents the predicted value. The cumulative formula is as follows:

$$s_i = \frac{\alpha x_i}{p_{i-k}} + (1-\alpha)(s_{i-1} + t_{i-1})$$

$$t_i = \beta(s_i - s_{i-1}) + (1-\beta)t_{i-1}$$

$$p_i = \gamma \frac{x_i}{s_i} + (1-\gamma) p_{i-k}$$

The values of α, β, γ are all between [0, 1] and can be tested several times for best results. The initial values of s, t, and p are not particularly affected by the selection of the initial value of the algorithm. The usual values are s0=x0, t0=x1-x0, p=0 when accumulating, and p=1 when multiplying.

Among them, the major expression time series of the trend component has a tendency to maintain the last change trend (see Fig. 1), while the periodic component mainly expresses the periodicity of the time series, as shown in Fig. 2.

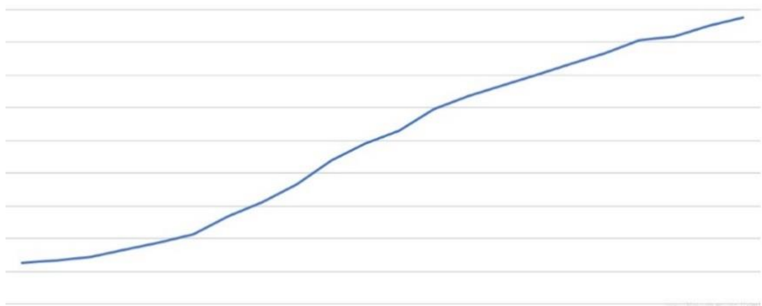

Fig 1. Trend Change Chart

Fig 2. Cycle Change Chart

In the energy consumption business, there is a significant cyclical change in the data, but there is no obvious trend change, so we consider removing the trend component (where k represents the number of time points in the cycle, (ik) represents the current time point of the previous cycle value).

The final forecast results are shown in Fig. 3:

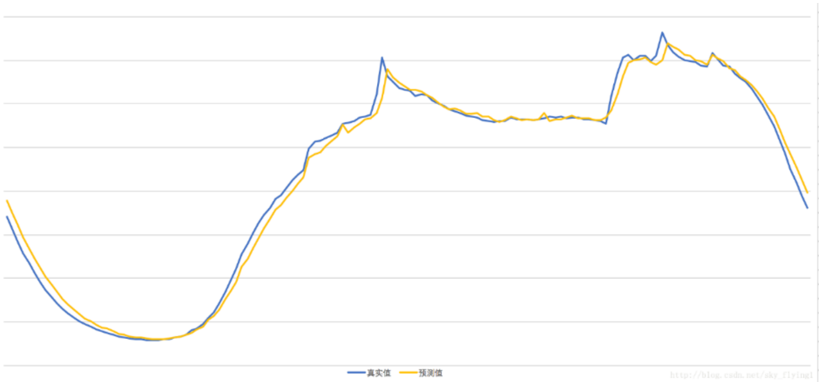

Fig 3. Cycle change forecast

The prediction formula for exponentially smoothing by three times is:

$$x_i + h = (s_i + ht_i) p_{i-k} + (h \bmod k)$$

3.2 Comparator

The first guess is that the error should be concentrated in a certain range. By drawing the error histogram, the error value is similar to the normal distribution.

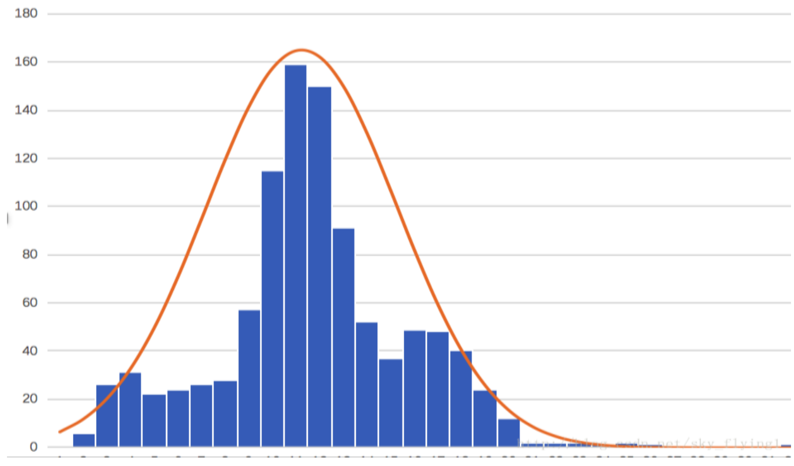

Fig 4. Error histogram

3.3 95% Forecast Interval

For the normal distribution, there is a concept of 95% prediction interval in statistics, that is, there is a 95% probability that the value falls within the prediction interval.

The range of the 95% prediction interval is [μ - 1.96*δ, μ + 1.96*δ], where μ represents the expected value and δ represents the standard deviation.

[μ - 1.96*δ, μ + 1.96*δ]: 95% interval

[μ - 2*δ, μ + 2*δ]: 95.44% interval

[μ - 2.58*δ, μ + 2.58*δ]: 99% interval

Therefore, the prediction value of the current value is calculated by using the error values of the first 50 time points, and the data is abnormal when the excess value is exceeded.

According to the characteristics of the above methods, it is not difficult to conclude that real-time abnormal early warning technology is suitable for overall changes and periodic changes, and school building energy has such characteristics with seasons, so it can be perfectly combined with campus energy consumption monitoring.

4. Seasonal Fluctuations in Energy Consumption

Seasonal description is the periodic fluctuation of data, such as the annual or weekly cycle, as shown below:

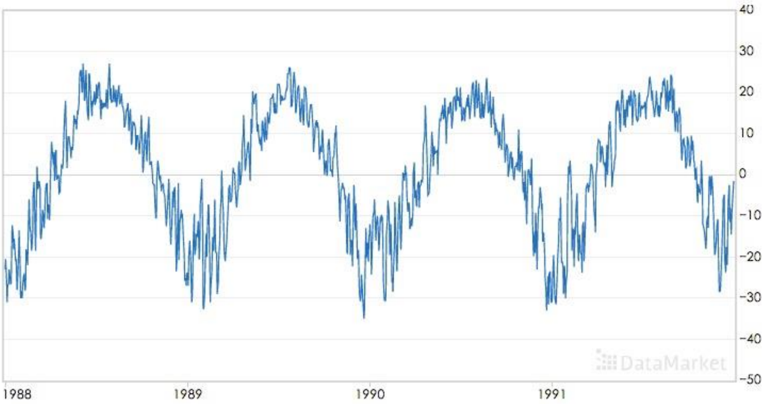

Fig 5. Seasonal fluctuation diagram of energy consumption

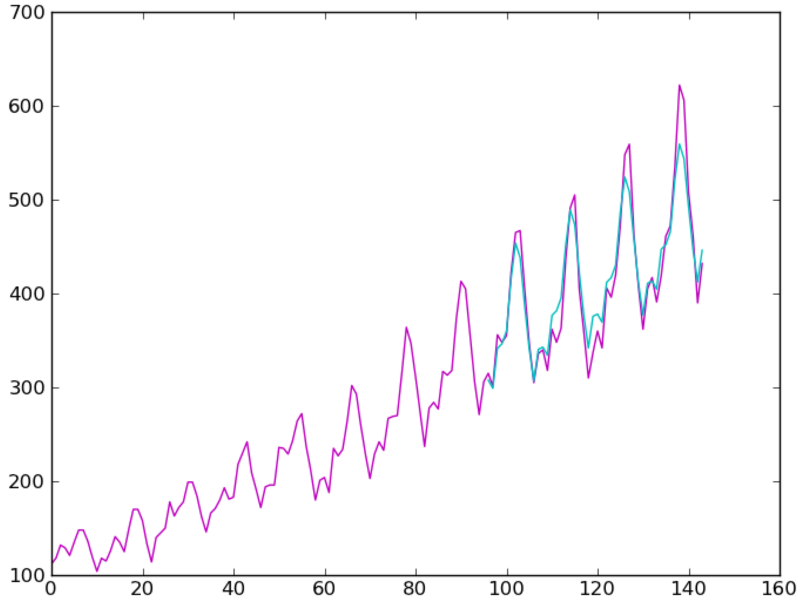

Fig 6. Seasonal fluctuation forecast of energy consumption

Data Market's International Airline Passengers data was used to test the performance of the accumulative and exponential cubic exponential smoothing algorithm, which recorded monthly electricity usage (see Fig. 6):

The following figure shows the effect of using cumulative cubic exponential smoothing: where red is the source time series and blue is the predicted time series, the values for α, ß, and γ are 0.45, 0.2, and 0.95:

The following figure shows the effect of three exponential smoothing predictions. The values of α, ß, γ are 0.4, 0.05, and 0.9:

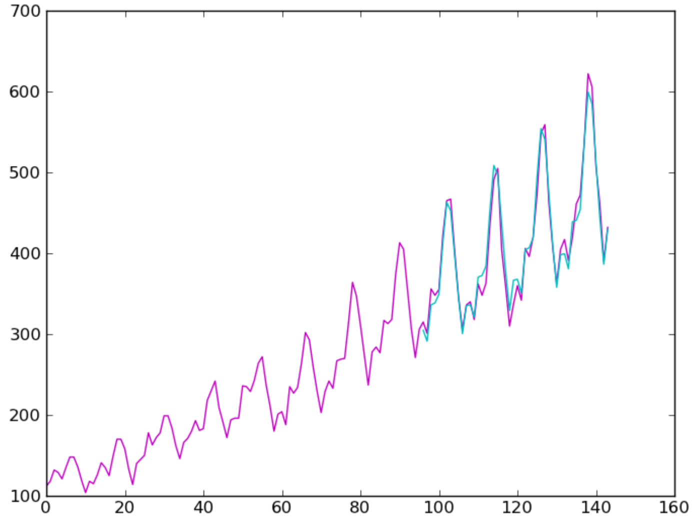

Fig 7. Seasonal fluctuation forecast of energy consumption

It can be seen that the three-exponential smoothing algorithm can well preserve the trend and seasonal information of the time series data, and the effect of multiplying the smoothness index algorithm on the International Airline Passengers dataset is better.

5. Conclusion

This article presents a better solution to the algorithm by introducing a simple introduction to the monitoring model of energy anomalies and analyzing related issues.The whole energy consumption monitoring system has extraordinary significance, making it more timely and accurate in energy consumption monitoring and energy consumption forecasting.

References

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