Forecasting the Price of Fuel Oil: A STL-(ELM+ARIMA) Combination Approach

Yu Fangping, Liu Yanqing and Zhang Chenxi
Dalian Maritime University, Dalian, Liaoning Province, 116026, China
*Corresponding author’s e-mail: yufangping@dlmu.edu.cn

Abstract. Focusing on fuel oil price forecasting, we propose a "decomposition-prediction-integration" route and STL-(ELM+ARIMA) combination forecasting model. This model decomposes the fuel oil price time series by STL, and effectively combines the advantages of high frequency seasonal cycle and short-term fluctuation time series forecasting in ELM non-parametric model with the advantages of low frequency trend forecasting in ARIMA parametric model. Finally, this paper conducts an empirical study on the spot price of Singapore’s Platts fuel oil 180CST to verify the effectiveness of the proposed forecasting method. The results show that the forecasting accuracy of 180 CST fuel oil price model based on STL-(ELM (1)+ARIMA (2)+ELM (3)) is highest.

1. Introduction
Fuel oil is one of the most important refined oil, widely used in power generation, transportation, metallurgy, chemical industry, light industry and other industries. Historically, large fluctuations in fuel oil have brought great cost management pressure to downstream related consumer industries and enterprises. Therefore, how to forecast fuel oil price as accurately as possible is particularly important for the fuel oil consumption industry and enterprises.

Oil price prediction methods can be roughly divided into three categories:

Firstly, these were the parametric models. These models mainly estimated relevant parameters to determine the prediction equation. Baumeister and Kilian (2012) [1] predicted the spot price of crude oil in the short term by VAR, and the results showed that VAR had lower prediction error than the AR and ARMA. Xiang and Zhuang (2013) [2] investigated the accuracy of prediction of crude oil price by ARIMA. Miao, Ramchander and Wang (2017) [3] used LASSO regression method to predict oil prices and found that eight-step forward prediction can significantly reduce the mean square prediction error. Funk (2018) [4] compared and analyzed the effect of ARMA, VAR method and their combination on the prediction of actual crude oil price. Zhao, Wang and Guo et al. (2018) [5] predicted oil prices using VTFM, and the results showed that the prediction error was less than 4%.

Secondly, these were the non-parametric models. Non-parametric models did not need to estimate relevant parameters to determine the prediction equation, and are widely used to predict the price of crude oil. For example, Guo, Li and Zhang (2012) [6] set up an improved oil price prediction model of SVM based on genetic algorithm optimization parameters. Shin, Hou and Park et al. (2013) [7] used Semi-supervised Learning (SSL) machine learning algorithm to predict oil prices, and the prediction quality was higher than traditional methods such as AR, ANN and SVM. Godarzi, Amiri and Talaei et al. (2014) [8] constructed a dynamic nonlinear autoregression model and used NARX as a neural network to predict the trend of oil prices. Polanco-martinez and Abadie (2016) [9] studied the spot price dynamics and long-term futures price trends of crude oil by using wavelet analysis. Ding (2018) [10]...
established a crude oil price prediction model based on EEMD-ANN-ADD, and the empirical evidence showed that the model could effectively insight into the future price of crude oil.

Thirdly, these were the hybrid models, which were mainly used to combine parametric and non-parametric methods for prediction. These models could effectively avoid the shortcomings of parametric and non-parametric methods. For example, Zhang, Zhang and Zhang (2015) [11] used the EEMD-SVM-GARCH hybrid model to predict oil prices. E, Bao and Ye (2017) [12] proposed a prediction model of influencing factors of crude oil price based on VMD-ICA-ARIMA method. The results showed that the model was more accurate compared with ARIMA and EEMD-ICA-ARIMA. Wang, Zhao and Du et al. (2018) [13] proposed a DFN-AI crude oil price prediction method based on complex network science and artificial intelligence algorithm. It is worth noting that with the rapid development of the Internet and big data mining technology, abundant online data information is considered as a key factor of oil price prediction and incorporated into the oil price prediction model. For example, Li, Xu and Yu et al. (2016) [14] constructed a prediction method of oil price trend based on network emotions, and the results showed that the strong prediction power of emotions on oil price trend was statistically supported. Li, Shang and Wang (2018) [15] proposed a new crude oil price prediction model based on online media text mining deep learning technology, and the empirical results show that the prediction accuracy was better than the traditional methods such as random forest, SVR and linear regression.

This paper emphasizes the seasonal and trend characteristics of fuel oil price with the help of the mixed model framework, and integrates the Seasonal Trend Decomposition (STL) [16] and Extreme Learning Machine (ELM) [17] and Autoregressive Integrated Moving Average (ARIMA) methods were used to build a combined prediction model, and the fuel price was predicted and analysed using 11/25/2002-11/22/2018 spot price sequence of Singapore Platts fuel oil 180SCT.

2. The STL-(ELM+ARIMA) Combination Forecasting Model

2.1. Introduction to Related Models

STL is a widely used time-series decomposition method. It decomposes time series \{Y_i\} into seasonal decomposing components \{S_i\}, trend decomposing components \{T_i\} and residual decomposing components \{R_i\} using robust local weighted regression as smoothing method, and the formula is [16]:

\[
Y_i = S_i + T_i + R_i
\]  

(1)

STL decomposition is based on locally weighted regression smoothing (LOESS) decomposition.

ELM is an artificial intelligence machine learning algorithm based on feedforward neural network, which is widely used to solve problems such as classification, regression, clustering and feature learning [17]. Considering the training sample \((x_t, o_t)\), for \(x_t \in \mathbb{R}^n\), \(o_t \in \mathbb{R}^m\), \(t = 1, 2, ..., T\). Containing \(L\) hidden nodes \((L \leq T)\) is defined as follows:

\[
\sum_{l=1}^{L} \beta_l G(x_t) = \sum_{l=1}^{L} \beta_l G(w_{tl}x_t + b_l) = o_t (t = 1, 2, ..., T)
\]  

Where, \(\omega_t = [\omega_{1t}, \omega_{2t}, ..., \omega_{L_t}]^T\) \((l = 1, 2, ..., L)\) is the weight vector between the input node and the \(l\)th implicit node. \(\beta = [\beta_1, \beta_2, ..., \beta_m]^T\) \((l = 1, 2, ..., L)\) is the weight vector between the output node and the \(l\)th implicit node. \(b_l (l = 1, 2, ..., L)\) is the bias vector of the \(l\)th implicit node. \(G(\cdot)\) is an excitation function, which can be an arbitrary nonlinear piecewise continuous function, with specific functional forms such as triangle, gaussian, radial basis, Sigmoid, etc [17].

ELM method has a good effect on fitting and predicting intermediate frequency and high frequency time series data.

The differential integrated moving average autoregressive model (ARIMA) is one of the time series prediction analysis methods. In ARIMA \((p, d, q)\), \(p\) is the number of autoregression items, \(q\) is the
number of moving average terms, and \( d \) is the number of differences made to make it a stationary sequence. ARIMA can be expressed as:

\[
\left(1 - \sum_{i=1}^{p} \phi_i L^i \right) \left(1 - L\right)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i \right) \epsilon_t
\]

Where, \( L \) is the lag operator, \( \phi \) is the AR coefficient, \( \theta \) is the MA coefficient, \( d \in \mathbb{Z}, d > 0 \).

2.2. Prediction Steps

**Step 1:** Fuel oil price decomposition by STL. With the help of the internal and external circulation mechanism of STL, the sub-sequences of seasonal component 1, trend component 2 and residual component 3 were obtained by repeated solving.

**Step 2:** Forecasting seasonal and residual components by ELM. The seasonal component 1 and residual component 3 were used as the original data, to rolling learn by ELM which containing \( L \) hidden layer nodes and \( M \) output layer nodes, and prediction results of seasonal decomposition component 1 and residual decomposition component 3 are carried out.

**Step 3:** Forecasting the trend component by ARIMA. By using ARIMA \((p, d, q)\) to fit the trend component 2 of fuel oil price, the parameter values of \( p, d \) and \( q \) were calculated. Using this ARIMA after parameter estimation, the predicted value of trend decomposition component 2 of fuel oil price can be obtained.

**Step 4:** integration prediction. Add up the predicted sub-series values of the seasonal component 1, the trend component 2 and the residual component 3, and the predicted value is obtained by:

\[
\hat{Y}_t = \hat{S}_t + \hat{T}_t + \hat{R}_t
\]

**Step 5:** prediction accuracy test. In order to test the effectiveness and accuracy of STL-(ELM+ARIMA) fuel oil price forecasting model, two widely used prediction error measurement methods, root mean square error (RMSE) and mean absolute error percentage (MAPE) are adopted.

\[
RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (\hat{Y}_t - Y_t)^2}
\]

\[
MAPE = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{\hat{Y}_t - Y_t}{Y_t} \right|
\]

Where, \( N \) is the length of the tested sample, \( Y_t \) is the actual value.

3. Empirical Results and Analysis

3.1. Prediction Steps

This paper forecasts the spot price of Singapore Platts fuel oil 180CST, which is the benchmark of global fuel oil prices. The full sample data period of 180CST daily price is 11/25/2002-11/22/2018 (3946 data) and the span is 16 years, which is from the economic sub-module database of the iFind software. The full sample data is divided into two parts: the first part, the data during 11/25/2002-05/24/2018 is used as the training interval. In the second part, the period of 05/25/2018-11/22/2018 (half year, 125 trading days) is used as the prediction test interval. The timing sequence of fuel oil price of 180CST full sample 11/25/2002-11/22/2018 is shown in Figure.1.
3.2. The results
Combined with the above prediction steps of STL-(ELM+ARIMA) model, the three components decomposed by STL are firstly obtained, as shown in Figure 1.

![Figure 1. 180CST price decomposition by STL (2002/11/25-2018/11/22)](image1)

According to the subsequent prediction steps of STL-(ELM+ARIMA), we used ELM forecasting component 2 and component 3, ARIMA forecasting component 1. This detailed model is denoted as STL-(ELM(1)+ARIMA(2)+ELM(3)). According to formula (7), the predicted values of the three components were added to obtain the fuel oil 180CST price predicted value during 05/25/2018 - 11/22/2018, as shown in Figure 2.

![Figure 2. Comparison of 7 models forecast value and actual value of 180CST price](image2)

In order to compare the prediction accuracy of this model, we selected ELM, SVM (Cortes and Vapnik (1995) [18]), ARIMA models and STL-ELM, STL-SVM, STL-ARIMA integrated models. The 6 models forecasting results are also shown in Figure 2.
Table 1 is the comparison of the forecasting errors of 7 models. In general, the MAPE and RMSE of STL-(ELM(1)+ARIMA(2)+ELM(3)) were the smallest, indicating that the forecasting accuracy of STL-(ELM(1)+ARIMA(2)+ELM(3)) was higher than that of other 6 models.

| Model 1     | Model 2              | Model 3     | Model 4     | Model 5     | Model 6     | Model 7     |
|------------|----------------------|-------------|-------------|-------------|-------------|-------------|
| STL-ELM    | STL-SVM              | STL-ARIMA   | ELM         | SVM         | ARIMA       | STL-(ELM(1)+ARIMA(2)+ELM(3)) |
| MAPE       | 14.635%              | 6.700%      | 4.448%      | 18.694%     | 13.788%     | 5.139%      | 4.294%      |
| RMSE       | 73.794               | 36.774      | 25.056      | 91.045      | 66.988      | 26.743      | 22.848      |

3.3. Discussion

It can be seen from Table 1 and Figure.2 that the prediction accuracy of 180CST model based on STL-(ELM(1)+ARIMA(2)+ELM(3)) model is the highest, and the MAPE and RMSE of STL-(ELM(1)+ARIMA(2)+ELM(3)) model is the smaller than the other 6 models.

The forecast model of fuel oil price of 180CST presented in this paper neither increases the difficulty of model estimation, but also reflects a good empirical effect. More importantly, the result has a more reasonable economic explanation, and can predict the long-term, medium and short price trend of 180CST from the perspective of seasonality, long trend and short-term fluctuations, which can help better assist fuel oil stakeholders in making decisions.

4. Conclusion

We propose a model for forecasting fuel oil price based on the "factory-forecast-integration" route and STL- (ELM+ARIMA) method. In this model, the STL is used to decompose fuel oil price, and effectivly combines the seasonal cycle and short-term fluctuation prediction advantage of ELM non-parametric model and the long-term trend prediction advantage of ARIMA parametric model. This ensures that the STL - (ELM + ARIMA) model can achieve accurate prediction. The prediction method of STL - (ELM + ARIMA) was verified by the spot price of Singapore Platts fuel oil 180CST. The results show that the accuracy of STL- (ELM(1)+ARIMA(2)+ELM(3)) prediction of 180CST price is higher than that of other 6 typical models, and it has strong generalization ability and stability.

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