Crude Oil Price Prediction Based On Multi-scale Decomposition

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Abstract. A synergetic model (DWT-LSSVM) is presented in this paper. First of all, the raw data is decomposed into approximate coefficients and the detail coefficients at different scales by discrete wavelet transforms (DWT). These coefficients obtained by previous phase are then used for prediction independently using least squares support vector machines (LSSVM). Finally, these predicted coefficients are combined into a final prediction. The proposed model is applied to oil price prediction. The simulation results show that the synergetic model has greater generalization ability and higher accuracy.

Keywords: crude oil price, wavelet transform, least squares vector machines.

1 Introduction

The forecasting of crude oil price has attracted many academic researchers and business practitioners, since the crude oil holds a strategic position in the international market. However the nonstationarity, nonlinearity and too many uncertain factors of crude oil price determination make its forecast an intractable task.

Traditional forecasting methods usually analyze the volatility of crude oil price under the framework of demand and supply or use data-driven model to fit the oil price series [1,2,3]. However, most of them failed to produce the consistently good results due to the nonlinear mechanism and intrinsic complexity of oil market. In the past the crude oil price was usually treated as a single series, the intrinsic complex modes involved in the price series are mixed and can not be explored deep.

Discrete wavelet transform (DWT) has outstanding scale separation ability. It could capture useful information on various resolution levels [4,5]. In this paper, DWT is used to decompose the original time series into separate components and each component is forecasted independently with least squares support vector machines (LSSVM) owing to its excellent forecasting performance [6,7]. Thus, a synergetic model based on multi-scale decomposition is presented. To validate the applicability of the proposed model, simulation experiments are conducted on crude oil spot price.

2 Multi-scale Based Forecasting

The forecasting framework is as follows (see Fig.1):

1 Decomposing the original series by DWT

A discrete wavelet transform can be computed with a fast filter bank algorithm called the *a-trous* algorithm. It is a non-decimated wavelet transform which produces smoother approximations of the signal [8].

Fig. 1. The framework of prediction model

Given the time series of oil price $\{x(1), x(2), \dots, x(n)\}$, the scaling coefficients at different scales can be obtained by the *a-trous* wavelet transform. Then the original series could be expressed as the sum of the approximate coefficients c_j and the detail coefficients $d_j (j = 1, 2, \dots, J)$:

$$x(t) = c_J + \sum_{j=1}^J d_j \quad (1)$$

2 Predicting the decomposed coefficients independently by LS-SVM

Instead of predicting the original series directly, we predict each decomposed coefficients by a separate LS-SVM:

$$\hat{c}_n(t+l) = f(c_n(t-1), c_n(t-2), \dots, c_n(t-m)) \quad (2)$$

$$\hat{d}_j(t+l) = f_j(d_j(t-1), d_j(t-2), \dots, d_j(t-n_j)) \quad (3)$$

Here m and n_j are referred as the embedding dimension. The l means l -th sample ahead prediction. For each value of l we train a separate forecasting architecture.

3 Reconstructing the predicted value

Using LS-SVM predictor, the predicted values of the approximate part and detail parts can be achieved. The reconstruction of predicted value can be expressed as:

$$\hat{x}(t+l) = \hat{c}_n(t+l) + \sum_{j=1}^n \hat{d}_j(t+l) \quad (4)$$

3 Material and Forecasting Results

3.1 Crude Oil Price Data

The data material consists of weekly and monthly WTI spot price (\$/bbl). The original data material stems from the website of Energy Information Administration, US Department of Energy. The weekly data was divided into two parts, training sets (2004.01.02--2005.12.30) and testing sets (2006.01.06--2006.12.15). The monthly data was treated similarly (training sets: 1999.01-2004.12, testing sets: 2005.01-2006.11).

To test the model, the forecasting procedure is repeatedly applied to the testing samples. For every testing sample, we adopted moving window to intercept the training samples.

3.2 Simulation

For the decomposition of the weekly data, db5 wavelet is selected as the wavelet function and decomposition level is 4. The original series and the decomposed series are shown in Fig.2 (a). The original time series is shown in the first subfigure, following are approximate c4 and detail d_j ($j=1,2,...,4$). The monthly data is dealt with the same processing and the results are shown in Fig.2 (b).

Fig. 2. (a) Decomposition results of weekly data (b) Decomposition results of monthly data

By eq.(2,3,4), the prediction for 1,2,3 and 4-step ahead is obtained.

To estimate the prediction performance of the synergetic model, pure LS-SVM model is used for comparison. Three criteria are used to evaluate the performance of the prediction model: the mean absolute relative error (MARE), the normalized mean square error (NMSE) and the direction statistics (Dstat¹). The results show in the table1. It can be obviously seen DWT-LS-SVM model outperforms the pure LS-SVM model.

¹ The direction statistics is defined as: $Dstat = \frac{1}{N} \sum_{i=1}^N a_i$, here as $x_{i+1} - x_i)(\hat{x}_{i+1} - x_i) \leq 0$

then $a_i = 1$; otherwise $a_i = 0$.

Table 1. Comparison of DWT-LS-SVM model and LS-SVM model

Prediction depth	DWT-LS-SVM			LS-SVM		
	MARE	NMSE	Dstat	MARE	NMSE	Dstat
1-week	0.017	0.062	0.960	0.421	0.422	0.720
2-week	0.021	0.095	0.958	0.448	0.456	0.673
3 week	0.022	0.101	0.917	0.516	0.547	0.646
4-week	0.027	0.138	0.894	0.556	0.624	0.596
1-month	0.021	0.036	0.913	0.091	0.643	0.622
2-month	0.036	0.128	0.909	0.095	0.735	0.575
3-month	0.035	0.103	0.857	0.094	0.729	0.554
4-month	0.041	0.177	0.8	0.097	0.802	0.530

4 Conclusion

In this paper, we propose a synergetic prediction model (DWT-LSSVM) to predict the crude oil price. The simulations show the method outperforms the pure LS-SVM model. The decomposition methods separate complex series into several components which include less and much similar dynamics features based on time scale. The useful information on various scales would be easily captured. Therefore, wavelet transform improve the time series forecasting accuracy, especially for oil price.

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