Volatility forecasting of crude oil market: A new hybrid method

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Abstract

Given the complex characteristics of crude oil price volatility, a new hybrid forecasting method based on the hidden Markov, exponential generalized autoregressive conditional heteroskedasticity, and least squares support vector machine models is proposed, and the forecasting performance of the new method is compared with that of well-recognized generalized autoregressive conditional heteroskedasticity class and other related forecasting methods. The results indicate that the new hybrid forecasting method can significantly improve forecasting accuracy of crude oil price volatility. Furthermore, the new method has been demonstrated to be more accurate for the forecast of crude oil price volatility particularly in a longer time horizon.

KEYWORDS

crude oil, EGARCH, HMM, LSSVM, volatility forecasting

1 | INTRODUCTION

Volatility forecasting of crude oil prices has been proven to be an important input into multifactorial decision making processes, including macroeconomic policy making, financial risk assessment such as value-at-risk (VaR) calculations, options pricing and portfolio management strategies (Sadorsky, 2006; Xu & Ouenniche, 2012). Considering the importance of crude oil in economic growth over recent years, price volatility forecasting has received increasing attention from governments, investors, analysts and academics, and abundant quantitative forecasting methods have been developed, which may be divided into three categories: (i) time series volatility models; (ii) implied volatility models; and (iii) hybrid models.

J. L. Zhang, Zhang, and Zhang (2015) presented a relatively systematic review of existing literature concerning typical models used to forecast crude oil prices and their volatility. In order to accurately forecast the volatility of crude oil prices, it is essential to scientifically identify the appropriate volatility models. In the past, generalized autoregressive conditional heteroskedasticity (GARCH) class models have often been employed to describe the volatility of crude oil prices. These models perform well in effectively modeling the time-varying variance and clustering features of the conditional variance of crude oil price returns. However, traditional GARCH models (such as the commonly used GARCH(1, 1) model) require that all parameters should be positive to ensure the positive variance of crude oil market returns. Given that the volatility of crude oil prices often
exhibits asymmetrical characteristics, this paper employs the exponential GARCH (EGARCH) model to more accurately describe the volatility of crude oil prices (Nelson, 1991). This approach has been shown to accurately model the asymmetry of crude oil price volatility and has no restraints requiring parameters to be positive (Mohammadi & Su, 2010).

In addition, the forecasting accuracy of volatility in the crude oil market is not only linked to the model selection but is also subject to volatility states. Specifically, price changes in the crude oil market are affected by many fundamental factors, including crude oil stock levels, supply disruptions and demand shocks, as well as some nonfundamental factors, including US dollar exchange rates, speculative activities, stock market turbulence, unexpected geopolitical events, etc. (Wu & Zhang, 2014; Zhang, 2013; Zhang et al., 2008; Zhang & Wei, 2011). As a direct result, crude oil prices may experience structural breaks and appear to have multiple volatility states over time (Zhang et al., 2015; Zhang & Yao, 2016; Zhang & Zhang, 2015). To obtain reliable forecasting results for crude oil price volatility, we have developed an accurate predictive model of volatility states.

For the application of models to predict commodity or financial market price volatility states, the Markov regime switching (MRS) model has been universally recognized in existing studies (Balcilar et al., 2015; Wang et al., 2016; Zhang & Zhang, 2015). The volatility states in the MRS framework are described by the mean conditional variances and a moderate difference value, which is subjectively determined and may bring about the biased definitions of various volatility states, resulting in relatively large errors in volatility forecasting. For this purpose, the current study applies the hidden Markov model (HMM) (Eddy, 1996) to forecast crude oil price volatility, which can not only accurately describe volatility states but also eliminate the misjudgment of volatility states caused by subjective reasoning (Dias et al., 2015; Holzmann & Schwaiger, 2016).

Besides, due to the complexity of factors driving crude oil prices, good performance has been difficult to achieve using volatility forecasting methods that use a single model. Based on the price volatility features of crude oil markets and existing forecasting methods, this paper incorporates the error correction model (ECM) to improve forecasting performance. Specifically, based on the original forecasting model of crude oil price volatility, we also bring the least squares support vector machine (LSSVM) model to forecast the residual series because of its superior nonlinear modeling capacity (Suykens & Vandewalle, 1999; Suykens et al., 2001; Yuan & Lee, 2015). The original forecasting results are modified by the residual series model, and the final price volatility forecasting results are obtained by repeated error corrections until the forecasting accuracy meets the required level.

In summary, this paper is aimed at presenting a new method to improve the accuracy of crude oil price volatility forecasting and presents three novel aspects of price volatility forecasting in the literature. Firstly, the error correction model is developed to modify the forecasting results without distorting the original crude oil price volatility series. Secondly, a new hybrid forecasting method is composed using the HMM, EGARCH and LSSVM models, which has never previously been presented. Finally, the new method for crude oil price volatility forecasting demonstrates outstanding forecasting performance in comparison with established and commonly used GARCH class and other related forecasting methods.

The rest of the paper is structured as follows: Section 2 introduces the forecasting methods, Section 3 describes the data and forecasting results, and Section 4 concludes the paper.

## 2 | METHODS

### 2.1 | The EGARCH model

Based on the work of Engle (1982), the most established volatility model is the GARCH model proposed by Bollerslev (1986). Sadorsky (2006) demonstrates that the GARCH(1, 1) model is suitable for forecasting crude oil volatility. The standard GARCH(1, 1) model for daily returns is given as follows:

\[
\begin{align*}
\sigma_t^2 &= \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \\
\varepsilon_t &= \sigma_t z_t
\end{align*}
\]

where \( \omega \) denotes the conditional mean and \( \sigma_t^2 \) is the conditional variance with parameter restrictions \( \omega > 0, \alpha > 0, \beta > 0, \alpha + \beta < 1 \).

However, Chang (2012) indicates that crude oil markets have some stylized facts observed in the stock markets such as volatility asymmetric effect. The EGARCH model proposed by Nelson (1991) can depict the asymmetric effect of volatility, and the variance equation of the EGARCH(1, 1) model is specified in Equation 2:

\[
\begin{align*}
\log(\sigma_t^2) &= \omega + \alpha z_{t-1} + \gamma |z_{t-1}| - E[z_{t-1}] \\
&\quad + \beta \log(\sigma_{t-1}^2),
\end{align*}
\]
where $\gamma$ is the asymmetric leverage coefficient used to describe the volatility of the leverage effect.

### 2.2 The hidden Markov model (HMM)

Baum and Petrie (1966) first proposed the HMM, which was built on the probabilistic framework for modeling a time series of multivariate observations. Lee, Hu, and Chiou (2010) show that some sudden events (e.g., the Iraqi invasion of Kuwait) result in an increase in the permanent component of the conditional variance, which is evidenced by structural breaks in crude oil prices. The HMM can capture the structural shifts in the volatility of crude oil prices. HMM is based on the Markov process, which is characterized by the following elements (Rabiner, 1989).

1. $N$: the number of states of the Markov chain. We denote individual states as $S = \{S_1, S_2, ..., S_N\}$, and the state at time $t$ is defined as $q_t$.
2. $M$: the number of distinct observation symbols per state. These correspond to the physical output of the system being modeled. We denote the individual symbols as $V = \{V_1, V_2, ..., V_M\}$.
3. $A = \{a_{ij}\}$: the state transition probability matrix, where $a_{ij} = P[q_{t+1} = S_j | q_t = S_i]$, $1 \leq i, j \leq N$.
4. $B = \{b_{k}(j)\}$: the symbol emission probability distribution in state $S_j$, where $b_{k}(j) = P[V_k | q_t = S_j]$, $1 \leq j \leq N$, $1 \leq k \leq M$.
5. $\pi = \{\pi(i)\}$: the initial state probability distribution, where $\pi(i) = P[q_1 = S_i], 1 \leq i \leq N$.

The details of the HMM can be found in Baum and Petrie (1966).

### 2.3 The LSSVM method

The LSSVM method was originally proposed by Suykens and Vandewalle (1999). This model has been chosen as the LSSVM regression algorithm can achieve a global solution by solving a set of linear equations, which allows the LSSVM to be faster than the more commonly used SVM model. Given a series of crude oil return volatility $(z_t, y_t) \{z_t, y_t\}_{t=1}^{N}$ with input data $z_t \in \mathbb{R}^n$ and output data $y_t \in \mathbb{R}^n$, the decision function can be defined as in Equation 4:

$$y(z) = w^T \varphi(z) + b, \tag{4}$$

where $\varphi(z)$ is the nonlinear function that maps the input space to a higher-dimension feature space; $w$ denotes the weight vector; and $b$ is the bias term.

For the problems regarding function estimation, the structural risk minimization is used to formulate the following optimization problem:

$$\min_{w} \frac{1}{2} \|w\|^2 + \frac{c}{2} \sum_{i=1}^{l} \xi_i^2,$$

subject to $y_i = w^T \varphi(z_i) + \xi_i + b, i = 1, 2, ..., l$, where $c$ represents the regularization constant and $\xi_i$ denotes the training error.

According to the Kuhn–Tucker conditions (Kuhn & Tucker, 1950), the final result of the LSSVM model for function estimation can be described as

$$y(z) = \sum_{i=1}^{l} \delta_i K(z, z_i) + b, \tag{6}$$

where the dot product $K(z, z_i)$ is known as the kernel function. This paper employs the radial basis function (RBF), which is a commonly used function regarding nonlinear regression problems (Keerthi & Lin, 2003; Schölkopf et al., 1997). The RBF with a width of $\theta$ can be defined as

$$K(z, z_i) = \exp(-0.5\|z-z_i\|^2/\theta^2). \tag{7}$$

### 2.4 The hybrid method for crude oil price volatility forecasting

The procedure for forecasting crude oil price volatility includes the following six steps:

1. The HMM method is adopted to describe the volatility states of crude oil returns.
2. Based on the volatility state of crude oil prices, a specific EGARCH model is developed to forecast the volatility $\sigma^2_t$, that is, $\sigma^2_t$.
3. The residual series is calculated, that is, $R_t = \sigma^2_t - \sigma^2_{\hat{r}}$. The residual series is detected if it meets the accuracy requirement of 0.0001. If not, the method proceeds to step 4; otherwise the method proceeds to step 6.
4. The LSSVM model is used to forecast the residual series, that is, $R_t$, and the forecasted residual series is denoted as $\hat{R}_t$. The total forecast volatility series is then $\hat{\sigma}^2_t + \hat{R}_t$.
5. The residual series is calculated again as $R'_t = R_t - \hat{R}_t$, and tested to see whether it has met the accuracy requirement. If not, the method goes to step 4; otherwise it proceeds to step 6.
6. The forecasted results of final crude oil volatility are obtained by the forecasted values of original volatility plus the residual.
2.5 | The evaluation criteria for forecasting accuracy

As discussed by Lopez (2001), it is not obvious which loss function is more appropriate for the evaluation of volatility models. Therefore, rather than making a single choice, we use six different loss functions as the evaluation criteria of forecasting performance (see Equations 8–13). In fact, the forecasting performance evaluation criteria used in this paper are also well employed in a number of previous studies (Brailsford & Faff, 1996; Lopez, 2001; Marcucci, 2005; Wei et al., 2010):

\[
\text{MSE} = \frac{1}{n} \sum_{t=1}^{n} \left( r_t^2 - \hat{r}_t^2 \right)^2
\]

(8)

\[
\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} \left| r_t^2 - \hat{r}_t^2 \right|
\]

(9)

\[
\text{HMSE} = \frac{1}{n} \sum_{t=1}^{n} \left( 1 - r_t^2 / \hat{r}_t^2 \right)^2
\]

(10)

\[
\text{HMAE} = \frac{1}{n} \sum_{t=1}^{n} \left| 1 - r_t^2 / \hat{r}_t^2 \right|
\]

(11)

\[
\text{QLIKE} = \frac{1}{n} \sum_{t=1}^{n} \left( \ln \left( \hat{r}_t \right) + r_t^2 / \hat{r}_t^2 \right)
\]

(12)

\[
\text{R}^2\text{LOG} = \frac{1}{n} \sum_{t=1}^{n} \left[ \ln \left( r_t^2 / \hat{r}_t^2 \right) \right]^2
\]

(13)

where \( n \) is the number of forecasting observations, \( r_t \) and \( \hat{r}_t \) denote the actual and forecasted volatility, respectively. MSE and MAE are the mean square error and mean absolute error, respectively. HMSE and HMAE are the MSE and MAE adjusted for heteroskedasticity, respectively. QLIKE corresponds to the loss implied by a Gaussian likelihood, and \( R^2\text{LOG} \) is similar to the \( R^2 \) of the Mincer–Zarnowitz regressions (Mincer & Zarnowitz, 1969).

3 | DATA AND RESULTS

3.1 | Data descriptions

The effectiveness of the proposed forecasting method is validated on volatility forecasting using data from the West Texas Intermediate (WTI) and Brent crude oil spot markets. A previous research by Wei et al. (2010) has shown excellent crude oil volatility forecasting and therefore provides justification for the application of a number of GARCH class models. We compare the crude oil volatility forecasting results generated using the newly proposed method in this paper with those reported by Wei et al. For this comparison, we use the same datasets as Wei et al. from January 6, 1992 to December 31, 2009, which were obtained from the US Energy Information Administration (EIA). Market participants are generally more interested in the out-of-sample model performance than the in-sample performance, because they are more concerned about how well they can do using these volatility models in the future (Wang et al., 2016). To allow accurate comparison with previous studies, the in-sample data from January 6, 1992 to December 29, 2006 are considered for the development of the forecasting model and out-of-sample data from January 2, 2007 to December 31, 2009 are used for the evaluation of the model. Moreover, we also employ Brent crude oil prices in 2016 to compare the forecasting performance of the newly proposed method in this paper with some well-recognized methods in the literature, so as to confirm the superiority of the new method.

Taking \( P_t \) as the crude oil price on day \( t \), we employ the percentage daily price return \( r_t \) that is, \( r_t = 100 \times (\ln(P_t) - \ln(P_{t-1})) \). The squared daily return is taken as the index for actual volatility (Li, Huang, & Zhang, 2013; Merton, 1980). Figure 1 plots the volatility of WTI crude oil prices during 1992–2009, which shows that some aggregate demands and supply shocks can cause large fluctuations in crude oil markets. For example, as a typical case of a crude oil demand shock, the Asian financial crisis in 1998 resulted in large crashes in crude oil prices. From this general review, it can be seen that crude oil prices demonstrate a high level of uncertainty over time; therefore, the HMM is suitable for forecasting crude oil price volatility.

Table 1 provides the descriptive statistics of the WTI and Brent crude oil returns. It can be seen that the WTI and Brent returns present similar statistical characteristics. The mean values of the two returns are close to zero. The Jarque–Bera statistic shows that the null hypothesis of normality is rejected at the 1% significance level, which is also evidenced by the negative skewness and high excess kurtosis. The Ljung–Box statistic for the serial correlation indicates that the null hypothesis of no 20-order auto-correlation is rejected, illustrating the existence of autocorrelation in the crude oil returns.

The augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) statistics both support the rejection of the null hypothesis for a unit root at the 1% significance level. The \( F \)-statistic of the ARCH test indicates the presence of the ARCH effect in the two crude oil returns. Thus the GARCH class models can be widely used for forecasting crude oil price volatility.
3.2 Forecasting results for WTI crude oil market

Wei et al. (2010) employed a greater number of linear and nonlinear GARCH class models to describe the important stylized facts concerning volatility, including clustering volatility, long-memory volatility and the asymmetric leverage effect in volatility. Their models are shown to forecast crude oil price volatility well. In order to obtain fair and convincing results, we compare the forecasting performance of the new hybrid method with Wei et al., who use the GARCH class models, during the same sample period. An explanation regarding the forecasting procedures is specified below:

1. We describe the crude oil return volatility dynamics using a Markov Switching Model (MSM) with parameter $N$ from 1 to 10, as mentioned in Section 2.2. We find that when $N = 6$ the MSM fits the WTI crude oil returns accurately and performs better than the other MSMs.

2. The EGARCH model is developed to forecast the volatility $\sigma_t^2$. The parameters of $\omega$, $\alpha$, $\beta$, and $\gamma$ are 1.84, 0.53, 0.89 and 0.07, respectively.

3. The LSSVM model is used to forecast the residual series $R_t$. The parameters of $c$, $\sigma$ and $b$ are 45, 1.3 and 2.5, respectively.

4. The total forecast volatility series is described as $\hat{\sigma}_t^2 + \hat{R}_t$, where $\sigma_t^2$ and $R_t$ are the forecasted volatility and residual series, respectively.

Table 2 shows the loss function values of forecasting results for the WTI crude oil volatility using different methods, from which several important findings are identified.

For one thing, the six different loss functions of the newly proposed method are almost smaller than those of other GARCH class models. This finding indicates that the newly proposed method outperforms commonly used GARCH class models in most cases for accurately forecasting crude oil volatility. When energy economists or crude oil market analysts explore crude oil price volatility using the GARCH class models, the newly proposed method in this paper could also be applied to the analysis. Anyway, we have to admit that those GARCH class models in Table 2 also have acceptable forecasting performance based on the evaluation criteria concerned, although their forecasting performance proves relatively inferior to the new method in this paper in most cases.

Further, the newly proposed method and other nonlinear GARCH class models perform better than linear models such as the standard GARCH model. The reason is that the new method and other nonlinear GARCH class

### Table 1: Descriptive statistics for the two benchmark crude oil price returns

<table>
<thead>
<tr>
<th></th>
<th>WTI</th>
<th>Brent</th>
<th></th>
<th>WTI</th>
<th>Brent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.03</td>
<td>0.03</td>
<td>Jarque–Bera</td>
<td>4429.50*</td>
<td>4801.22*</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>2.48</td>
<td>2.32</td>
<td>Q(20)</td>
<td>49.21*</td>
<td>45.15*</td>
</tr>
<tr>
<td>Maximum</td>
<td>16.41</td>
<td>18.13</td>
<td>ADF</td>
<td>−26.58*</td>
<td>−16.51*</td>
</tr>
<tr>
<td>Minimum</td>
<td>−17.09</td>
<td>−19.89</td>
<td>Phillips–Perron</td>
<td>−67.55*</td>
<td>−65.45*</td>
</tr>
<tr>
<td>Skewness</td>
<td>−0.19</td>
<td>−0.09</td>
<td>ARCH(20)</td>
<td>34.52*</td>
<td>22.56*</td>
</tr>
<tr>
<td>Excess kurtosis</td>
<td>4.87</td>
<td>5.07</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Denotes rejection of the null hypothesis at the 10% significance level.
models can predicate the asymmetric leverage effects in volatility and exhibit greater forecasting capability than linear models. In addition, it can be noted from Table 2 that as the forecasting time horizon increases from 1 to 5 days and further to 20 days, the forecasting results of the new method show improved forecasting performance.

### 3.3 Forecasting results for the Brent crude oil market

To illustrate the superiority of the newly proposed method, we also use the data of the Brent crude oil market in 2016 to detect the forecasting performance, and compare the results with some well-recognized methods in the literature, including the EGARCH model, the EGARCH model combined with the LSSVM (EL) and the HMM combined with the EGARCH model (HE). Moreover, since crude oil price volatility forecasting accuracy may vary across different time horizons (Zhang et al., 2015), three different time horizons are randomly selected in this paper, that is, the 1-day-ahead, 5-day-ahead, and 20-day-ahead forecast, which correspond to the forecast periods January 4, 2016, March 1–7, 2016, and December 1–29, 2016, respectively. Besides, both the MSE and MAE

<table>
<thead>
<tr>
<th>Method</th>
<th>(A) One-day ahead forecasting results</th>
<th>(B) Five-day ahead forecasting results</th>
<th>(C) Twenty-day ahead forecasting results</th>
</tr>
</thead>
<tbody>
<tr>
<td>GARCH</td>
<td>0.933 0.693 0.020 0.000 0.890 0.020</td>
<td>0.108 0.264 0.095 0.001 0.028 0.625</td>
<td>0.935 0.648 0.048 0.000 0.127 0.658</td>
</tr>
<tr>
<td>IGARCH</td>
<td>0.690 0.000 0.049 0.008 0.974 0.000</td>
<td>0.016 0.001 0.075 0.046 0.008 0.000</td>
<td>0.144 0.009 0.029 0.008 0.110 0.000</td>
</tr>
<tr>
<td>GJR-GARCH</td>
<td>0.847 0.000 0.017 0.000 0.087 0.000</td>
<td>0.294 0.314 0.098 0.002 0.031 0.972</td>
<td>0.938 0.648 0.040 0.000 0.125 0.372</td>
</tr>
<tr>
<td>EGARCH</td>
<td>0.058 0.000 0.660 0.499 0.086 0.000</td>
<td>0.514 0.074 0.008 0.000 0.281 0.000</td>
<td>0.010 0.002 0.001 0.000 0.000 0.000</td>
</tr>
<tr>
<td>APARCH</td>
<td>0.846 0.031 0.016 0.000 0.162 0.000</td>
<td>0.501 0.668 0.000 0.000 0.312 0.028</td>
<td>0.522 0.821 0.037 0.002 0.108 0.620</td>
</tr>
<tr>
<td>FIGARCH</td>
<td>0.501 0.668 0.000 0.000 0.190 0.000</td>
<td>0.792 0.601 0.234 0.144 0.737 0.229</td>
<td>0.967 0.029 0.277 0.918 0.158 0.000</td>
</tr>
<tr>
<td>FIAPARCH</td>
<td>0.546 0.000 0.006 0.000 0.000 0.000</td>
<td>0.023 0.000 0.082 0.001 0.007 0.000</td>
<td>0.023 0.000 0.000 0.000 0.000 0.000</td>
</tr>
<tr>
<td>HYGARCH</td>
<td>0.032 0.001 0.000 0.000 0.034 0.000</td>
<td>0.023 0.000 0.082 0.001 0.007 0.000</td>
<td>0.001 0.002 0.011 0.000 0.000 0.000</td>
</tr>
</tbody>
</table>

**Note.** The forecasting performance values of GARCH, IGARCH, GJR-GARCH, EGARCH, APARCH, FIGARCH, FIAPARCH, and HYGARCH models come from Wei et al. (2010). The sample period in this table is from January 6, 1992 to December 31, 2009.
of the forecasting results are considered for all the time horizons, and the results are shown in Table 3.

From Table 3, it can be seen that the MSE and MAE values of the newly proposed method for forecasting the Brent crude oil volatility across the entire time horizon are smaller than those achieved using the other well-recognized methods. Specifically, the mean MAE value of the newly proposed method for the three time horizons is 1.33, which is sharply less than that obtained using the EGARCH (14.41), EL (8.62) and HE (7.89) methods. Similarly, the mean MSE value of the newly proposed method for the three time horizons is 0.033, which is also much less than that of the EGARCH (0.069), EL (0.070) and HE (0.064) methods. Moreover, no matter any time horizon forecasts are concerned, as shown in Table 3, the MSE and MAE values of the new proposed method are much less than those the other well-recognized methods; and the newly proposed method has better performance for forecasting crude oil price volatility in a longer time horizon. These results indicate that, in the new hybrid method, the HMM can accurately capture the structural shifts in crude oil price volatility and the LSSVM model can well modify the forecasting results.

In addition, the new hybrid forecasting method shows improved performance compared with the EL method, due to the sharp decline of MAE and MSE, thereby confirming the assumption that HMM can capture structural shifts in the volatility of crude oil prices.

Finally, the forecasting performance of the HE method appears to be inferior to the newly proposed method, which explains why the volatility forecasting with error corrections may achieve a higher level of accuracy. Overall, the forecasting results of the newly proposed hybrid method are more accurate and have greater predictive power than those well-recognized forecasting methods in literature.

4 | CONCLUDING REMARKS

In this paper, a new hybrid forecasting method based on the HMM, EGARCH, and LSSVM models is proposed for forecasting the volatility of crude oil markets. The newly proposed method is compared with the well-recognized GARCH class models and some other related forecasting methods. Publicly available data from WTI and Brent crude oil markets are evaluated to compare the forecasting accuracy of the newly proposed method and other methods.

Numerical simulations indicate that the newly proposed method can significantly improve the forecasting accuracy of crude oil price volatility compared with the GARCH class models proposed by Wei et al. (2010) and other well-recognized forecasting methods in literature. The superior forecasting performance of the newly proposed method can be attributed to three causes. Firstly, the HMM can capture structural shifts in price volatility; secondly, the EGARCH model can well depict the asymmetric volatility effect; and thirdly, the LSSVM can modify the forecasting results. By combining the distinct features of each model, the hybrid method can forecast the complex patterns in the volatility of crude oil prices.

Future development of the model will include the addition of other advanced volatility forecasting models for comparison with the GARCH class models. Other additional complex components that impact crude oil price volatility will also be considered to be integrated into the hybrid method.

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| TABLE 3 | MSE and MAE of volatility forecasting results for Brent oil prices |
|----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Time horizon | EGARCH MSE | MAE | EL MSE | MAE | HE MSE | MAE | New method MSE | MAE |
| One-day-ahead | 0.081 | 22.2 | 0.079 | 14.9 | 0.075 | 10.8 | 0.042 | 2.38 |
| Five-day-ahead | 0.073 | 12.5 | 0.070 | 5.72 | 0.065 | 7.76 | 0.035 | 0.91 |
| Twenty-day-ahead | 0.065 | 8.53 | 0.061 | 5.24 | 0.054 | 5.12 | 0.024 | 0.71 |
| Average | 0.069 | 14.41 | 0.070 | 8.62 | 0.064 | 7.89 | 0.033 | 1.33 |

Note. EL means the EGARCH model combined with LSSVM, and HE means the HMM combined with EGARCH. The forecasting performance comparison is based on the data in 2016.
References


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