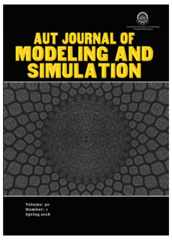

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Presenting a Model for Multiple-Step-Ahead-Forecasting of Volatility and Conditional Value at Risk in Fossil Energy Markets

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ABSTRACT: Fossil energy markets have always been known as strategic and important markets. They have a significant impact on the macro economy and financial markets of the world. The nature of these markets is accompanied by sudden shocks and volatility in the prices. Therefore, they must be controlled and forecasted using appropriate tools. This paper adopts the Generalized Auto Regressive Conditional Heteroskedasticity (GARCH)-type models, Exponential Smoothing (ES)-type models, and classic model in order to multiple-step-ahead forecast volatility, Value at Risk, and Conditional Value at Risk of Brent oil and natural gas in two different estimation window lengths, respectively. To evaluate the accuracy of the aforementioned models, eight different loss functions are utilized. There are a lot of financial terms in this the noted part. So, it's comprehensible for financial person and etc. Therefore, the HWES model is proposed to multiple-step-ahead forecast functions as a verb.

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1- Introduction

Fossil energy market is one of the most important energy sources, affecting the economy of many countries. Since the oil and gas prices are cardinal inputs in macro-economic models, volatility of these prices is always important for oil exporting and importing countries. Therefore, Brent oil and natural gas have a great impact on variables such as economic growth and inflation [1,2], energy markets [3,4], and financial markets [5-7]. The monetary variables and international financial variables have been identified as the most effective factors to oil prices. Also, the direct relationship between time and uncertainties and sudden shocks in energy markets have been previously proven [8-10]. One of these price shocks in the energy markets is the growth of oil price to 148 dollars per barrel in July 2008 and then the drop in oil price to 40 dollars per barrel in late December. This kind of volatility has caused the volatility and price predictions of oil and gas to be of great importance for studying. However, in previous studies, it has been emphasized that it is difficult to forecast the volatility and the price of oil [11]. There are two states concerning forecasting time series: a) according to tavailable data, time-series models are attributed to them; b) independent from the time series that is called model-free. One of the problems in the first state is the changes in the data and the extreme volatility that increases the model's error and, as a result, the forecasts would be far from reality. In fact, no particular model can ever be attributed to all data [12]. According to existing literature, there are different models to estimate and forecast volatility in energy markets. As for traditional econometric models, Auto-Regressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Cointegrated Vector Auto Regreurssive (VAR) and Artificial Neural Networks (ANN) have popularly been used for the forecasting of Brent oil and natural gas volatility. For example, Xiang and Zhuang [13] used the ARIMA model to forecast the monthly prices of Brent oil and crude oil in a sample period from November 2012 to April 2013. Farzanegan and Mrakwardt [14] utilized the Vector Auto Regressive (VAR) model to examine the dynamic relationship between the volatility of oil prices and macroeconomic variables in Iran such as inflation, industrial production growth rates, and net government expenditure. Kang et al. [15] modeled the volatility of Brent, Dubai and West Texas Intermediate (WTI) based on the GARCH, IGARCH, CGARCH, and FIGARCH models. Sozen and Arcaklioglu [16] presented a new model of ANN to forecast consumption of oil products in Turkey. They designed three different models in which different variables are used, and, in the end, by using error measure, they chose an appropriate model to forecast the consumption of oil products in Turkey. different definitions and different tools were suggested to forecast the risks related to price shocks in energy markets. In recent years, Value at Risk has been a popular measure. in a way that nowadays the risk metrics are known as the equivalent of Value at Risk [17]. A seminal paper in this regard is that of Cabedo and Moya [18] that estimated Value at Risk of daily oil price over 1992–1998 using the Historical Simulation Approach. Fan et al. [19] estimated Value-at-Risk via GARCH-type models based on the Generalized Error Distribution (GED) for both the extreme downside and upside of the daily spot WTI and Brent crude oil prices from May 20, 1987 to August 1, 2006, Simultaneously. Su [20] estimated the Value at Risk of the seven stock indices in developed and emerging markets by using EGARCH models with generalized student's distribution and Historical Simulation Approach. Owing to the fact that Value at Risk is

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not a coherent risk measure and is deprived of sub-additivity property, it can be bounded by coherent risk measures like Conditional Value at Risk. For example, Youssef et al. [21] multiple-step-ahead forecasted Value at Risk and Conditional Value at Risk of crude oil and gasoline market via three long-memory-GARCH-models, including FIGARCH, HYGARCH, FIAPARCH, and Extreme Value Theory (EVT). Kim and Lee [22] estimated Value at Risk and Conditional Value at Risk of stock returns of Hyundai Motors, Randgold Resources Limited (Gold), and NASDAQ by using nonlinear regression models of 2000 observations from October 11, 2005 to July 1, 2013. Mabrouk [23] estimated and multiple-step-ahead forecasted the volatility and Conditional Value at Risk of seven stock indices (Dow Jones, Nasdaq 100, S&P 500, DAX30, CAC40, FTSE100, and Nikkei 225) and three exchange rates vis-a-vis the US dollar (GBP- USD, YEN-USD and Euro-USD) via three long memory GARCH-type models (FIGARCH, HYGARCH, and FIAPARCH). Taylor [24] estimated and multiple-step-ahead forecasted Value at Risk and Conditional Value at Risk of FTSE 100, NIKKEI 225 and S&P 500 by using a semi-parametric approach based on the Asymmetric Laplace distribution at 95% and 99% confidence levels. Degiannakis and Potamia [25] estimated multiple-step-ahead forecasted Conditional Value at Risk of stock indices, commodities, and exchange rates by using GARCH-type models.

In recent studies, Exponential Smoothing (ES) models have been used to forecast demand [26, 27], heat [28], pig prices [29], and air transportation [30]. But the multiple-step-ahead forecasting of Value at Risk and Conditional Value at Risk has not been applied to any study by ES-type models. The Holt-Winters Exponential Smoothing model (a kind of ES models) modified the data at the level and trend with two parameters (λ_1, λ_2). This property has caused the aforementioned model to be robust and computationally stable. Thus, in this paper, volatility, Value at Risk, and Conditional Value at Risk of fossil energy markets are forecasted via Holt-Winters Exponential Smoothing model (HWES) and other ES-type models, and results were compared to GARCH-type models and Classic model.

2- Methodology

2- 1- Framework

In this study, we seek to obtain the best model for multiple-step-ahead forecasting of volatility, Value at Risk, and Conditional Value at Risk of fossil energy markets from February 2010 to December 2016. To this end, we divide the historical Brent oil and natural gas data into a training dataset (from February 2010 to August 2016) and a testing dataset (from August 2016 to December 2016). In the training dataset, Value at Risk and Conditional Value at Risk are estimated by using the GARCH-type models consisting of GARCH, Exponential GARCH (EGARCH), and Threshold GARCH (TGARCH) with two Estimation window lengths of 600 and 1000 samples. To identify a benchmark model (the model that has the lowest estimation of Value at Risk's and Conditional Value at Risk's errors), the unconditional coverage test, conditional coverage test, and Lopez loss function test are utilized. Then, in the testing dataset, the Value at Risk and Conditional Value at Risk are forecasted based on the benchmark model one, five, and twenty steps ahead via the ES-type models consisting of Simple ES (ESE), Holt-Winters ES (HWES), and Double Holt-Winters ES (DHWES). To assess the performance, the proposed models are compared with the classic model (the most common model for multiple-step-ahead forecasting of Value at Risk and Conditional Value at Risk in previous studies) via Blanco and Ihle loss function test and Lopez loss function test. In addition, the volatility is forecasted by using GARCH-type models and ES-type models one and five steps ahead. Then, the aforementioned models are ranked by the Root-Mean-Square Error (RMSE), RMSE-LOG, Mean Absolute Error (MAE), and MAE-LOG.

2- 2- Value at Risk

Value at Risk is a statistical measure of risk, and it estimates how much a set of investments might lose, given normal market conditions, in a time period such as a day [31]. Value at Risk can suggest that a certain amount of money be kept. Therefore, even if the maximum loss occurs, the investors will be able to fulfil their obligations. That is why the Value at Risk is referred to as a Capital Adequacy Ratio (CAR) for financial institutions and capital markets. Value at Risk can be described as a measure to a percentile of profit distribution or loss distribution for any given time horizon and confidence level of α. Value at Risk follows the following equation [32]:

$$VaR_{(\alpha)}(X) = -q^{\alpha}(x), \tag{1}$$

where:

$$q^{\alpha}(x) = \inf\left[X : P(X \le x) > \alpha\right]. \tag{2}$$

Value at Risk can also be formulated as follows [33]:

$$\Pr(V_{t+1} - V_t \ge |VaR^{c}{}_{t+1}|) \le \alpha \quad \text{or}$$

$$\Pr(V_{t+1} - V_t \le |VaR^{c}{}_{t+1}|) \ge 1-\alpha, \tag{3}$$

where V_t and V_{t+1} are the values of the portfolio at the present time and V_{t+1} is the value of the portfolio at the future time, respectively. However, Value at Risk is not a coherent risk measure because it is deprived of sub-additivity property. Sub-additivity property suggests that if a portfolio is composed of several sub-portfolios, then the risk of the portfolio will not be greater than the sum of the risks of the sub-portfolios. Sub-additivity property is shown as follows [34]:

$$X, Y, X+Y \in V, \quad X \ge Y \Rightarrow P(X+Y) \le P(X) + P(Y) \tag{4}$$

Therefore, Conditional Value at Risk is used instead of Value at Risk in recent studies.

2- 3- Conditional Value at Risk

If X is a continuous random variable, then conditional Value at Risk is defined as follows:

$$CVaR_p(X) = E(X \mid X > x_p) = \frac{\int_{x_p}^{\infty} x dF(x)}{1 - F(x_p)} \tag{5}$$

And, if the function is a discrete distribution, then Conditional Value at Risk is calculated as follows:

$$CVaR_{\alpha} = -\frac{n}{w}\left(\frac{1}{n}\sum_{i=1}^{n} X_{i,n} I_{X_i} - X_{w,n}\left(\frac{1}{n}\sum_{i=1}^{n} I - \frac{n}{w}\right)\right) \tag{6}$$

Also, if the function is a continuous distribution, then Conditional Value at Risk is formulated as follows [35]:

$$CVaR_\alpha = -\frac{1}{\alpha}\left(E(X \mid X \le q_\alpha(X) - q_\alpha(\Pr[X \le q_\alpha(X)] - \alpha\right) \quad (7)$$

2- 4- Estimating and forecasting methodology

2- 4- 1- Autoregressive Conditional Heteroscedasticity (ARCH)

Autoregressive Conditional Heteroscedasticity was introduced by Engel [36] as one of the nonlinear models for financial time series. ARCH models assume that the volatility is time-dependent. This property helps models to maintain the dynamics. ARCH model is shown as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2, \quad (8)$$

where σ^2_t is the variance of the forecast at time t, ε^2_{t-1} is the error (return residuals) at time $t-1$, and α_0, α_1 denote constant coefficient and ARCH coefficient, respectively. Also, the ARCH model (q) can be formulated as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 . \quad (9)$$

2- 4- 2- Generalized Auto Regressive Conditional Heteroskedasticity (GARCH)

The GARCH was presented as a generalized ARCH model by Bollerslev [37]. The most common version of the model is GARCH (1, 1). This model can be written as follows:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (10)$$

where σ^2_t is the variance of forecasts at time t, σ^2_{t-1} is the variance of forecasts at time $t-1$, and ω, α, β are constant coefficient, ARCH coefficient, and GARCH coefficient, respectively. Also, the GARCH (p, q) model can be formulated as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (11)$$

GARCH model is used to estimate the parameters of the maximum likelihood model:

$$\varepsilon_t = z_t \sigma_t , \; z_t = \frac{\varepsilon_t}{\sigma_t} = \frac{r_t - E(r_t)}{\sqrt{\omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2}} \quad (12)$$

The above fraction has the standard normal distribution and the denominator of the fraction is calculated by using the maximum likelihood model:

$$\max L = \max \prod_{t=1}^{T} \varphi_t(z_t | \mu_t, \sigma_t) = \max \prod_{t=1}^{T} \left(\frac{1}{\sqrt{2\pi}} \exp\left(\frac{-z_t^2}{2} \right) \right) \quad (13)$$

Each parameter that maximizes L can maximize $\ln L$ as well. Therefore, we maximize the logarithmic likelihood function as follows,

$$\max \ln L = \max \ln \prod_{t=1}^{T} \varphi_t(z_t | \mu_t, \sigma_t) = \max \ln \prod_{t=1}^{T} \left(\frac{1}{\sqrt{2\pi}} \exp\left(\frac{-z_t^2}{2} \right) \right) \quad (14)$$

$$= \max \sum_{t=1}^{T} \left(\ln \frac{1}{\sqrt{2\pi}} - \frac{z_t^2}{2} \right),$$

$$\max \ln L = \max \ln \prod_{t=1}^{T} \varphi_t(z_t | \mu_t, \sigma_t) = \max \ln \prod_{t=1}^{T} \left(\frac{1}{\sqrt{2\pi}} \exp\left(\frac{-z_t^2}{2} \right) \right) \quad (15)$$

$$= \max \sum_{t=1}^{T} \left(\ln \frac{1}{\sqrt{2\pi}} - \frac{z_t^2}{2} \right).$$

2- 4- 3- Threshold Generalized Auto Regressive Conditional Heteroskedasticity (TGARCH)

TGARCH model was introduced by Zakoian [38]. The TGARCH model can be defined as follows:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta \sigma_{t-1}^2 \quad (16)$$

where I_{t-1} follows the following equation:

$$I_t = \begin{cases} 1, if & \varepsilon_t < 0 \\ 0, if & \varepsilon_t \ge 0 \end{cases} \quad (17)$$

In this model, the good news, i.e. $\varepsilon_t \ge 0$, and bad news, i.e. $\varepsilon_t < 0$, have different effects on the conditional variance. The good news has the α effect and the bad news has the $\alpha + \gamma$ effect. If $\gamma > 0$ then, we can conclude that there is a leverage effect. On the other hand, if $\gamma \ne 0$ then, the effect of news is asymmetric. Also, the TGARCH (p, q) model is formulated as follows [39]:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 . \quad (18)$$

2- 4- 4- Exponential Generalized Auto Regressive Conditional Heteroskedasticity (EGARCH)

EGARCH model was introduced by Nelson [40]. The aforementioned model follows the following equation:

$$\log(\sigma_t^2) = \omega + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \log(\sigma_{t-1}^2) \quad (19)$$

This equation suggests that the leverage effect is exponential. Also, the non-negative predictions of the conditional variance in this equation are guaranteed. The original version of EGARCH model can be written as follows:

$$\log(\sigma_t^2) = \omega + \alpha \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \log(\sigma_{t-1}^2) \quad (20)$$

2- 4- 5- Simple Exponential Smoothing (SES) model

The Simple Exponential Smoothing model is based on a recursive formula. The forecast for each new observation is updated and the newer information gains more weight than older information [41]. The forecasted value of each year in this model is equal to the sum of the total forecasted amount of the previous year; In addition to difference between the actual amount of the same year, and the forecasted amount of the previous year [42].

$$\hat{Y}_{t+1} = \lambda \cdot Y_t + \lambda \cdot (1-\lambda) \cdot Y_{t-1} + \lambda \cdot (1-\lambda)^2 \cdot Y_{t-2} + \cdots$$
$$\hat{Y}_{t+1} = \lambda \cdot Y_t + (1-\lambda) \cdot [\lambda \cdot Y_{t-1} + \lambda \cdot (1-\lambda) \cdot Y_{t-2} + \cdots] \quad (21)$$
$$\hat{Y}_{t+1} = \lambda \cdot Y_t + (1-\lambda) \cdot \hat{Y}_t \Rightarrow$$
$$\hat{Y}_{t+1} = \lambda \cdot Y_t + \hat{Y}_t - \lambda \cdot \hat{Y}_t \Rightarrow \hat{Y}_{t+1} = \hat{Y}_t + \lambda \cdot (Y_t - \hat{Y}_t)$$

where $\hat{Y}_{t+1}$ is the forecasted amount at time $t+1$, Y_t is the actual amount at time t and λ is the smoothing coefficient.

2- 4- 6- Holt-Winters Exponential Smoothing model (HWES)

Whenever there is an increasing or decreasing trend, the results obtained from the Simple Exponential Smoothing model are lower or higher than the actual value, respectively. To solve this problem, a trend parameter is added to the Simple Exponential Smoothing model, which is referred to as Holt-Winters Exponential Smoothing model [43].

$$\hat{Y}_{t+1} = \lambda_1 \cdot Y_t + (1-\lambda_1)(\hat{Y}_t + F_t), \qquad \text{:Level equation (22)}$$

$$F_{t+1} = \lambda_2 \cdot (Y_{t+1} - Y_t) + (1-\lambda_2) \cdot F_t, \qquad \text{:Trend equation (23)}$$

$$\hat{Y}_{t+h|t} = \hat{Y}_t + hF_t, \qquad \text{:Forecasting equation (24)}$$

where F_{t+1} is smoothing index at time $t+1$; $\hat{Y}_{t+1}$ is the forecasted value based on Simple Exponential Smoothing at time $t+1$; Y_t is the actual amount at time t. The parameters λ_1 and λ_2 are the smoothing coefficients in the level and trend, respectively, and h is the number of steps in forecasting.

2- 4- 7- Double Holt-Winters Exponential Smoothing model (DHWES)

DHWES model can be considered as a special case of Holt-Winters Exponential Smoothing model where λ_1 is equal to λ_2 [44].

$$\hat{Y}_{t+1} = \lambda \cdot Y_t + (1-\lambda_1)(\hat{Y}_t + F_t), \qquad \text{:Level equation (25)}$$

$$F_{t+1} = \lambda \cdot (Y_{t+1} - Y_t) + (1-\lambda_2) \cdot F_t, \qquad \text{:Trend equation (26)}$$

$$\hat{Y}_{t+h|t} = \hat{Y}_t + hF_t \quad . \qquad \text{:Forecasting equation (27)}$$

Family of Exponential Smoothing models requires to determine the smoothing coefficient. If the smoothing coefficient is close to zero, then, it obtains more weight to the recent events. By increasing the weight of recent events, the number of days decreases in the volatility forecasting. On the other hand, if the smoothing coefficient is near to one, then it is less sensitive to the recent events, making forecasting more stable (not necessarily more accurate). Therefore, the smoothing coefficient is between 0 and 1 and the optimal value is obtained from the following equation [45]:

$$\lambda^{opt} = \arg\min \sum_{t=1}^{n} (Y_t - \hat{Y}_{t|t-1})^2. \qquad (28)$$

2- 4- 8- Classic model

The classic model is the most common model for multiple-step-ahead forecasting of Value at Risk and Conditional Value at Risk in previous studies. The following equations are used to multiple-step-ahead forecasting of Value at Risk and Conditional Value at Risk via classic model [46]:

$$VaR_{T\ day} = VaR_{1\ day}\sqrt{T} \qquad (29)$$

$$CVaR_{T\ day} = CVaR_{1\ day}\sqrt{T} \qquad (30)$$

For example, in most banks the covered time period is one day; on the other hand, the Basle Committee requires ten days. This means that Value at Risk must be accumulated. If risks are not correlated over time, then, aggregation is simple, summarized by their sum. In this case, moving from a one-day to a ten-day Value at Risk is calculated as follows:

$$VaR_{10\ day} = VaR_{1\ day}\sqrt{10} \quad , \qquad (31)$$

where *VaR* denotes Value at Risk.

2- 5- Estimation and forecast evaluation

2- 5- 1- Estimation and forecast evaluation of volatility

To evaluate the forecasting performance of volatility models, four loss functions were used [47]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=T+1}^{T+N}(\delta_t^2 - \hat{\delta}_t^2)^2}\ , \qquad (32)$$

$$RMSE\_LOG = \sqrt{\frac{1}{N}\sum_{t=T+1}^{T+N}(Log(\delta_t^2) - Log(\hat{\delta}_t^2))^2}\ , \qquad (33)$$

$$MAE = \frac{1}{N}\sum_{t=T+1}^{T+N}|\delta_t^2 - \hat{\delta}_t^2|, \qquad (34)$$

$$MAE\_LOG = \frac{1}{N}\sum_{t=T+1}^{T+N}|Log(\delta_t^2) - Log(\hat{\delta}_t^2)| \qquad (35)$$

where $\hat{\delta}_t^2$ denotes the volatility forecast obtained using a GARCH-type model or ES-type models at time t; δ^2_t is the actual volatility, and N is the number of time horizon.

2- 5- 2- Evaluation of VaR and CvaR estimation

a) Unconditional coverage test

This test was presented by Kupiec [48] which is based on the rate of failure. If the amount of the actual loss is larger than the VaR, then it is known as a failure. If the probability of each failure is constant, then, the total number of failures follows a binomial distribution $B(\nu, a)$ in which ν and α are the number of samples and coverage level, respectively. The statistical hypothesis testing is as follows:

$$\begin{cases} H_0: & \hat{\alpha} = \alpha \\ H_1: & \hat{\alpha} \neq \alpha \end{cases} \qquad (36)$$

where $\hat{\alpha}$ is the ratio of a number of failures to the total forecasting. The statistical likelihood of this test is as follows:

$$LR_{ucc} = 2Ln\left[\frac{\hat{\alpha}^{\nu_0}(1-\hat{\alpha})^{\nu-\nu_0}}{\alpha^{\nu_0}(1-\alpha)^{\nu-\nu_0}}\right], \qquad (37)$$

where R_{ucc} has the chi-square distribution with one degree of freedom. If the ratio of the failure probability is higher than this, the null hypothesis is rejected, and it cannot be accepted that the model forecasted the VaR correctly; hence the model is invalid. Otherwise, the accuracy of the forecasted VaR is confirmed.

b) Conditional coverage test

Christoffersen [49] presented conditional coverage test based on first-order Markov chain. To implement the conditional coverage test, a transition matrix is formed as follows:

$$\prod = \begin{bmatrix} \pi_{00} & \pi_{01} \\ \pi_{10} & \pi_{11} \end{bmatrix}, \qquad (38)$$

where π_{ij} is equal to $\Pr[I_t = j \mid I_{t-1} = i]$ and calculated as follows:

$$\pi_{01} = \frac{\nu_{01}}{\nu_{01}+\nu_{00}} \qquad \pi_{11} = \frac{\nu_{11}}{\nu_{10}+\nu_{11}} \qquad \pi_{00} = 1-\pi_{01} \qquad \pi_{10} = 1-\pi_{11} \qquad (39)$$

where ν_{ij} denotes the number of times that the state j

happens after i. Finally, the test statistic is calculated by the following equation:

$$LR_{cc} = 2Ln\left[\frac{(1-\pi_{01})^{v_{00}}\pi_{01}{}^{v_{01}}(1-\pi_{11})^{v_{10}}\pi_{11}{}^{v_{11}}}{\hat{\alpha}^{v_0}(1-\hat{\alpha})^{v-v_0}}\right]. \quad (40)$$

The LR_{cc} statistic has a chi-square distribution with one degree of freedom, and when the ratio probability of failure is higher than this, the null hypothesis is rejected. Otherwise, it will obtain a passing mark.

c) Lopez loss function test

The lopez loss function test assumes each loss higher than VaR as a failure and assigns one to that number. Otherwise, this function adopts a zero. The lopez loss function is defined as follows [50]:

$$C_t = \begin{cases} 1 & if \quad L_t > VaR_t \\ 0 & if \quad L_t < VaR_t \end{cases}. \quad (41)$$

d) Blanco and Ihle loss function test

This loss function is similar to Lopez loss function. If the loss is higher than the VaR, then it is assumed as a failure and the function is as follows:

$\frac{(L_t - VaR_t)}{VaR_t}$, i.e.

the Blanco and Ihle loss function test are defined as follows [51]:

$$C_t = \begin{cases} \frac{(L_t - VaR_t)}{VaR_t} & f \quad L_t > VaR_t \\ 0 & f \quad L_t < VaR_t \end{cases} \quad (42)$$

The final score of Lopez loss function test and Blanco and Ihle loss function test are calculated by equation (43), where C_t is equation (41) or equation (42), P is confidence level, and n is the number of observations,

$$QPS = \frac{2}{n}\sum_{i=1}^{n}(C_t - P)^2. \quad (43)$$

3- Results and discussion

3- 1- Results

In this paper, as mentioned earlier, the data used is the daily Brent oil and natural gas logarithmic returns from February 2010 to December 2016. They follow the equation $R_t = Log(\frac{P_t}{P_{t-1}})$,

where R_t is return at time t ; P_t and P_{t-1} are prices at time t and $t-1$, respectively. The diagrams of prices and logarithmic returns of Brent oil and natural gas are shown in Figs. 1 and 2, respectively.

According to Fig. 2, it can be noticed that the daily Brent oil and natural gas logarithmic returns have an extreme volatility which can be regarded as outlier data. Ignoring the outlier data reduces the accuracy of forecasting models. Also, a summary of statistics of the variables is presented in Table 1.

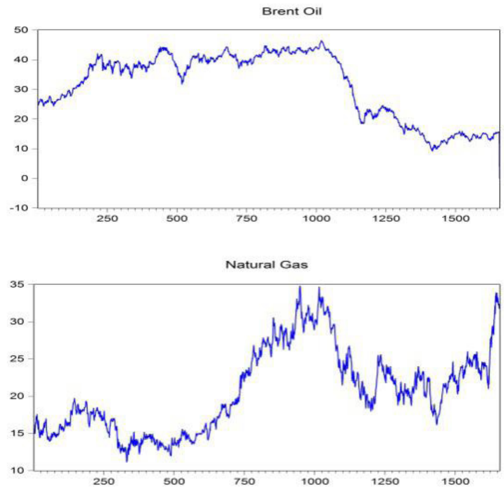

Fig. 1. Daily Brent oil and natural gas prices (from February 2010 to December 2016)

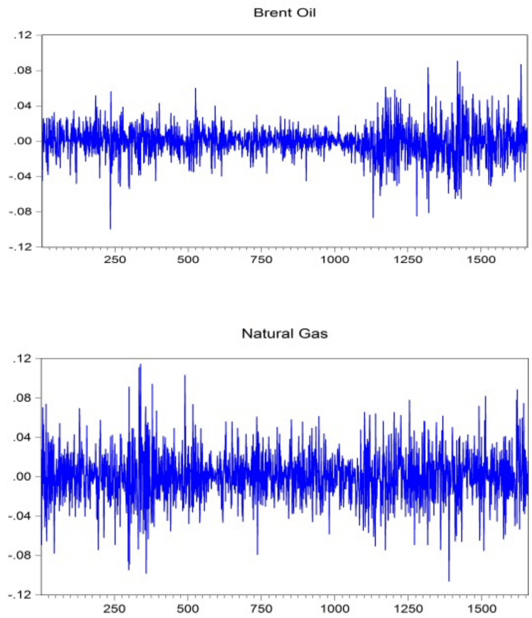

Fig. 2. Daily Brent oil and natural gas logarithmic returns (from February 2010 to December 2016)

Table 1. Statistics of Brent oil and natural oil.

	Brent oil	Natural gas
Mean	-0.000295	0.000431
Maximum	0.090605	0.114388
Minimum	-0.099605	-0.106044
Std. Dev.	0.018727	0.025353
Skewness	-0.061051	0.080059
Kurtosis	5.763912	4.456162

Table 1 shows that the daily logarithmic returns of Brent oil and natural gas have an asymmetric distribution with positive and negative skewness coefficient, respectively. On the other hand, kurtosis coefficient of both indices is higher than three whereas the kurtosis coefficients of the normal distribution is approximately equal to three. This implies that both indices have kurtosis coefficients that are bigger than kurtosis coefficients of the normal distribution. Finally, the high Jarque-Bera coefficients in Figs. 3 and 4 show that aforementioned indices are far apart from a normal distribution (the Jarque-Bera coefficient of the normal distribution is equal to zero). Thus, based on the skewness, kurtosis, and Jarque-Bera coefficients, it can be concluded that the data of Brent oil and natural gas follows student's t distribution. For this reason, the estimating and multiple-step-ahead forecasting are assumed with student's t distribution.

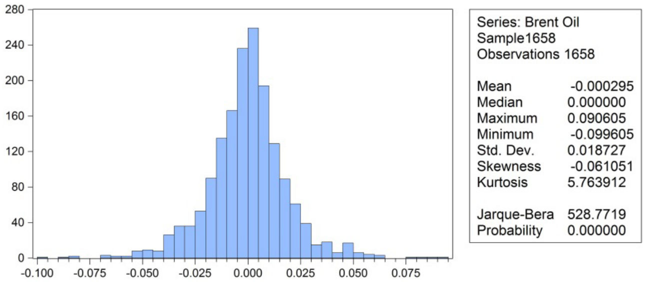

Fig. 3. Normality test results of Brent oil

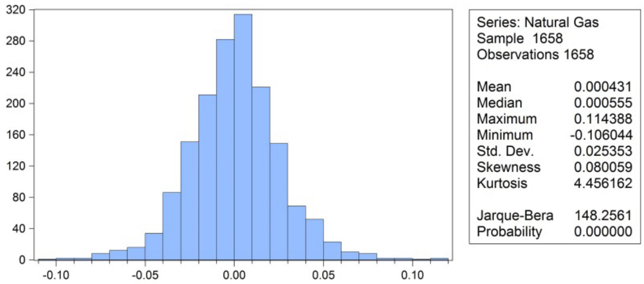

Fig. 4. Normality test results of natural gas

Table 2. Results of unit root tests.

Variable	ADF	PP
Level (Constant and trend)		
Brent oil	-42.53023(0.0)	-42.49038(0.0)
Natural gas	-44.13243(0.0)	-44.79599(0.0)
(Constant, no trend)		
Brent oil	-42.47023(0.0)	-42.43689(0.0)
Natural gas	-44.13987(0.0)	-44.79344(0.0)

Figures in brackets are probability values.

Table 2 presents the results of unit root tests based on Augmented Dickey–Fuller (ADF) test and Phillips–Perron (PP) test. In ADF and PP tests, the null hypothesis implies the time-series has a unit root against the alternative of stationarity. Results of unit root tests show that the Brent oil and natural gas series are stationary.

3- 2- Estimation and forecasting results of volatility models

Table 3 presents the estimation parameters of the volatility models for Brent oil natural gas returns. In accordance with prior discussions, it is necessary to measure constant coefficient (ω), ARCH coefficient (α), GARCH coefficient (β), level coefficient (λ_1), and trend coefficient (λ_2) for the estimating and the multiple-step-ahead forecasting of volatility. They are as follows:

Table 3. Estimation parameters of models for Brent oil and natural gas returns.

Parameter	GARCH(1,1)	EGARCH(1,1)	TGARCH(1,1)	SES	DHWES	HWES
ω	0.000072* 0.000036**	0.117696* 0.011376**	0.000049* 0.000386**			
α	0.777902* 0.094581**	0.080747* 0.299495**	0.071853* 0.119911**			
β	0.112460* 0.400846**	0.984699* 0.310087**	0.817557* 0.373282**			
γ		-0.084558* 0.003139**	0.074499* -0.048233**			
λ_1				0.365000* 0.096000**	0.743000* 0.069400**	0.215000* 0.59500**
λ_2					0.743000* 0.069400**	0.133000* 0.038000**

Estimates marked with an asterisk (*) and (**) are those of Brent oil and natural gas returns, respectively.

Table 4. Evaluation of one-step-ahead volatility forecast of Brent oil and natural gas return: GARCH as a benchmark

Parameter	RMSE (Rank)		RMSE_LOG (Rank)		MAE (Rank)		MAE_LOG (Rank)	
	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)
GARCH(1,1)	Benchmark							
EGARCH(1,1)	0.00000354 (5)	0.00000049 (2)	0.00981328 (5)	0.00074601 (2)	0.00000015 (5)	0.00000002 (2)	0.00043886 (5)	0.00003336 (2)
TGARCH(1,1)	0.00000148 (3)	0.00000027 (1)	0.00386991 (3)	0.00042217 (1)	0.00000006 (3)	0.00000001 (1)	0.00017306 (3)	0.00001888 (1)
SES	0.00000182 (4)	0.00000329 (5)	0.00432911 (4)	0.00479113 (5)	0.00000008 (4)	0.00000015 (5)	0.00019360 (4)	0.00021427 (5)
DHWES	0.00000084 (2)	0.00000242 (4)	0.00204770 (2)	0.00357013 (4)	0.00000003 (2)	0.00000011 (4)	0.00009157 (2)	0.00015966 (4)
HWES	0.00000081 (1)	0.00000102 (3)	0.00198407 (1)	0.00159105 (3)	0.00000002 (1)	0.00000005 (3)	0.00008873 (1)	0.00007115 (3)

Table 5. Evaluation for the five-step-ahead volatility forecast of Brent oil and natural gas return: GARCH as a benchmark

Parameter	RMSE (Rank)		RMSE_LOG (Rank)		MAE (Rank)		MAE_LOG (Rank)	
	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)
GARCH(1,1)	Benchmark							
EGARCH(1,1)	0.00005175 (4)	0.00027530 (5)	0.02191496 (4)	0.19036017 (5)	0.00000517 (4)	0.00002753 (5)	0.00219150 (4)	0.01903602 (5)
TGARCH(1,1)	0.00007396 (5)	0.00014068 (4)	0.03302477 (5)	0.05706500 (4)	0.00000740 (5)	0.00001407 (4)	0.00330248 (5)	0.00570650 (4)
SES	0.00001511 (2)	0.00000007 (2)	0.00558826 (2)	0.00002133 (2)	0.00000151 (2)	0.00000001 (2)	0.00055883 (2)	0.00000213 (2)
DHWES	0.00002306 (3)	0.00000025 (3)	0.00840692 (3)	0.00007734 (3)	0.00000231 (3)	0.00000003 (3)	0.00084069 (3)	0.00000773 (3)
HWES	0.00001488 (1)	0.00000002 (1)	0.00550421 (1)	0.00000632 (1)	0.00000149 (1)	0.00000000 (1)	0.00055042 (1)	0.00000063 (1)

Tables 4 and 5 show the evaluation results of one- and five-step-ahead volatility forecast of Brent oil and natural gas return. In the one-step-ahead forecasting, HWES and TGARCH models have an acceptable forecasting performance for volatility estimation. Also, in five-step-ahead forecasting, HWES and SES models have an accurate forecasting. Overally, the HWES model has the least prediction volatility error compared to other models across all forecasting horizons and subsamples used.

3- 3- Estimating and forecasting results of VaR and CVaR

To forecast Value at Risk and Conditional Value at Risk, GARCH models were combined with HWES model (the model that has the least forecasting volatility error compared to other models). Therefore, the Y_t parameter in the equation of HWES model is estimated by the most accurate estimation between GARCH models (benchmark model). To identify the benchmark model (on which the Value at Risk and Conditional Value at Risk forecasted via HWES model are based), the unconditional coverage test, conditional coverage test, and Lopez loss function test are utilized. The results of the aforementioned tests are as follows:

Table 6. Backtesting results of Value at Risk (VaR) estimation: window length of 600 samples.

Parameter	Unconditional Coverage test				Conditional Coverage test				Lopez loss function test	
	Oil (P_value)		Gas (P_value)		Oil (P_value)		Gas (P_value)		Oil (Rank)	Gas (Rank)
GARCH(1,1)	4.3433 (0.0372)	accept	5.4759 (0.0193)	accept	0.6237 (0.4297)	accept	0.6956 (0.4043)	accept	0.0170 (3)	0.0180 (1)
EGARCH(1,1)	1.0138 (0.3140)	accept	5.5671 (0.4337)	accept	0.3759 (0.5398)	accept	3.0353 (0.0815)	accept	0.0132 (1)	0.0208 (2)
TGARCH(1,1)	3.3239 (0.0683)	accept	5.4759 (0.0193)	accept	0.5558 (0.4560)	accept	0.6956 (0.4043)	accept	0.0161 (2)	0.0180 (1)

Table 7. Backtesting results of Value at Risk (VaR) estimation: estimation window length of 1000 samples.

Parameter	Unconditional Coverage test				Conditional Coverage test				Lopez loss function test	
	Oil (P_value)		Gas (P_value)		Oil (P_value)		Gas (P_value)		Oil (Rank)	Gas (Rank)
GARCH(1,1)	4.9273 (0.0264)	accept	11.5996 (0.0007)	reject	0.5249 (0.4688)	accept	0.9032 (0.3419)	accept	0.0197 (2)	0.0258 (1)
EGARCH(1,1)	3.0157 (0.0416)	accept	11.5996 (0.0007)	reject	0.3759 (0.5398)	accept	0.9032 (0.3419)	accept	0.0137 (1)	0.0208 (1)
TGARCH(1,1)	4.9273 (0.0264)	accept	7.9898 (0.0047)	reject	0.5249 (0.4688)	accept	0.7010 (0.4024)	accept	0.0197 (2)	0.0208 (1)

Table 8. Backtesting results of Conditional Value at Risk (CVaR) estimation: window length of 600 samples.

Parameter	Unconditional Coverage test				Conditional Coverage test				Lopez loss function test	
	Oil (P_value)		Gas (P_value)		Oil (P_value)		Gas (P_value)		Oil (Rank)	Gas (Rank)
GARCH(1,1)	0.1845 (0.6675)	accept	1.6512 (0.1988)	accept	0.2756 (0.5996)	accept	0.4319 (0.5111)	accept	0.0113 (3)	0.0142 (2)
EGARCH(1,1)	0.6940 (0.4048)	accept	1.7542 (0.1736)	accept	0.1220 (0.7269)	accept	0.4327 (0.5107)	accept	0.0076 (1)	0.0142 (2)
TGARCH(1,1)	0.2510 (0.6163)	accept	0.5212 (0.4703)	accept	0.1546 (0.6942)	accept	0.3238 (0.5694)	accept	0.0085 (2)	0.0123 (1)

Table 9. Backtesting results of estimation Conditional Value at Risk (CVaR) estimation: window length of 1000 samples.

Parameter	Unconditional Coverage test				Conditional Coverage test				Lopez loss function test	
	Oil (P_value)		Gas (P_value)		Oil (P_value)		Gas (P_value)		Oil (Rank)	Gas (Rank)
GARCH(1,1)	0.2896 (0.5905)	accept	0.8064 (0.3692)	accept	0.1972 (0.6570)	accept	0.2500 (0.6171)	accept	0.0122 (3)	0.0137 (3)
EGARCH(1,1)	0.7710 (0.1344)	accept	2.4950 (0.1142)	accept	0.0769 (0.7815)	accept	0.3746 (0.5405)	accept	0.0076 (2)	0.0167 (2)
TGARCH(1,1)	0.0265 (0.8706)	accept	1.5490 (0.2133)	accept	0.1508 (0.6978)	accept	0.3091 (0.5782)	accept	0.0106 (1)	0.0152 (1)

Based on the previous discussions presented in this study, the LR_{ucc} and LR_{cc} statistics have a chi-square distribution with one degree of freedom (6.63). When the probability ratio of failure is higher than those, the null hypothesis is rejected; otherwise, it will obtain a passing mark in the unconditional coverage test and conditional coverage test, respectively. The estimation models of Value at Risk and Conditional Value at Risk have been approved in all tables except Table 8 for estimation Value at Risk of Brent oil natural gas with an estimation window length of 600 samples. According to Lopez loss function test, the EGARCH and TGARCH models are the best models to estimate the Value at Risk and Conditional Value at Risk in both two estimation window lengths of 600 and 1000 samples for Brent oil and natural gas markets, respectively. Therefore, the EGARCH and TGARCH models are the benchmark models for estimation of Value at Risk and Conditional Value at Risk.

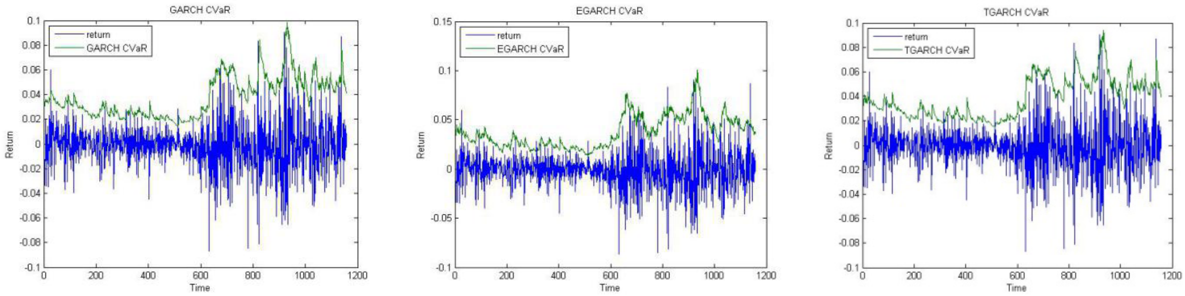

Fig. 5. Conditional Value at Risk of Brent oil returns with an estimation window length of 600 samples

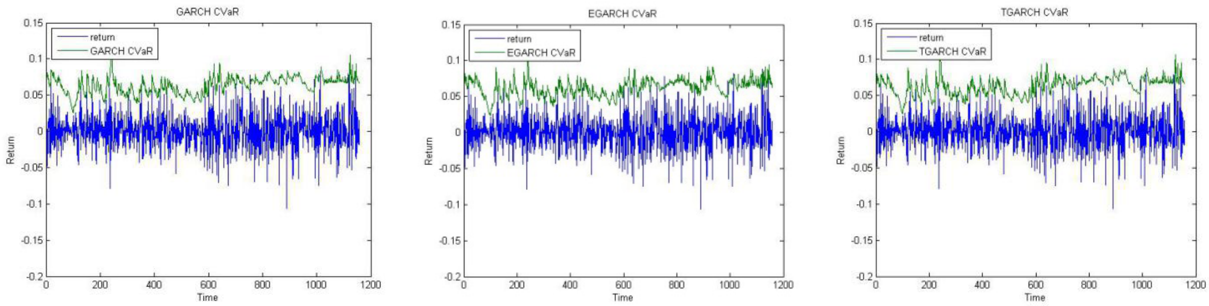

Fig. 6. Conditional Value at Risk of natural gas returns with an estimation window length of 600 samples

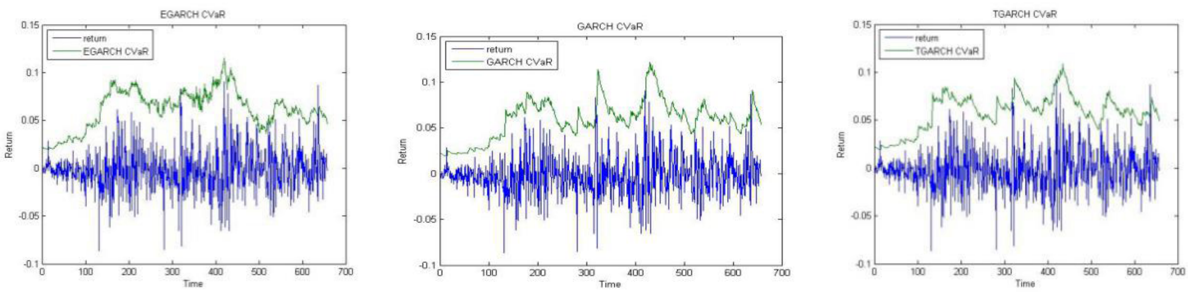

Fig. 7. Conditional Value at Risk of Brent oil returns with an estimation window length of 1000 samples

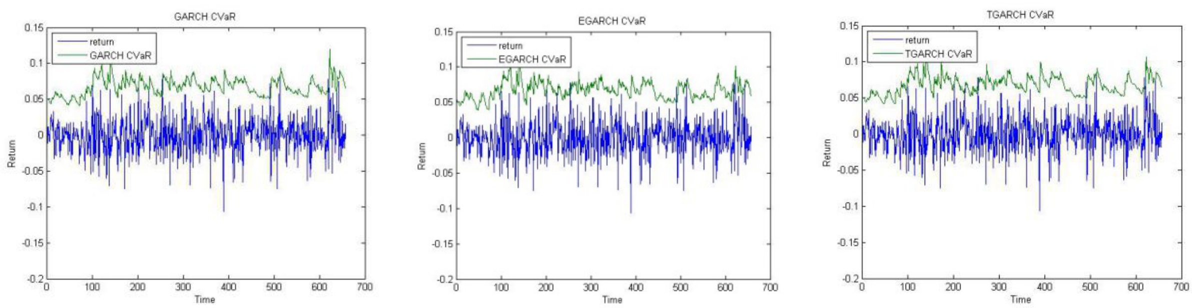

Fig. 8. Conditional Value at Risk of natural gas returns with an estimation window length of 1000 samples

Table 10. Backtesting results of one-, five- and twenty-step-ahead forecasting Value at Risk (VaR)

Parameter	One-step-ahead				Five-step-ahead				Twenty-step-ahead			
	Lopez loss function test		Blanco & Ihle loss function test		Lopez loss function test		Blanco & Ihle loss function test		Lopez loss function test		Blanco & Ihle loss function test	
	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)
Classic model	0.0831 (2)	0.0138(2)	0.0073 (1)	0.0516 (2)	0.0900 (2)	0.0900 (2)	0.0900 (2)	0.0900 (2)	0.0900 (1)	0.0900 (1)	0.0900 (2)	0.0900 (1)
HWES model	0.0312 (1)	0.0035 (1)	0.0304 (2)	0.0313 (1)	0.0814 (1)	0.0043 (1)	0.0425 (1)	0.0899 (1)	0.2100 (2)	0.0900 (1)	0.0269 (1)	0.0900 (1)

Table 11. Backtesting results of one-, five- and twenty-step-ahead forecasting Conditional Value at Risk (CVaR)

Parameter	One-step-ahead				Five-step-ahead				Twenty-step-ahead			
	Lopez loss function test		Blanco & Ihle loss function test		Lopez loss function test		Blanco & Ihle loss function test		Lopez loss function test		Blanco & Ihle loss function test	
	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)	Oil (Rank)	Gas (Rank)
Classic model	0.1004 (2)	0.0138 (2)	0.0223 (2)	0.0497 (1)	0.0900 (2)	0.0900 (2)	0.0900 (2)	0.0900 (1)	0.0900 (1)	0.0900 (1)	0.0900 (2)	0.0900 (1)
HWES model	0.0485 (1)	0.0035 (1)	0.0199 (1)	0.0715 (2)	0.0814 (1)	0.0043 (1)	0.0870 (1)	0.0900 (1)	0.2100(2)	0.0900 (1)	0.0297 (1)	0.0900 (1)

According to all the figures, it can be stated that the number of failures is almost less than or equal to the limit allowed for estimation of Conditional Value at Risk with estimation window length of 600 and 1000 samples. In addition, there is no evidence for a cluster of failures occurrence.

After determining the benchmark models, the Value at Risk and the Conditional Value at Risk are forecasted via HWES model. To evaluate the forecasting performance of the HWES model, this model was compared to the classic model (the most common model for the multiple-step-ahead forecasting of Value at Risk and Conditional Value at Risk in previous studies) via Lopez loss function test and Blanco and Ihle loss function test. The results of the aforementioned tests are as given in Table 10.

4- Conclusions

There are several models for forecasting volatility, Value at Risk, and Conditional Value at Risk. This paper analyzed the forecasting performance of two classes of volatility models, namely GARCH-type models and ES-type models and two classes of Value at Risk and Conditional Value at Risk models, namely ES-type models and Classic model via seven different loss functions. The Holt-Winters Exponential Smoothing model modified the data at the level and trend with two parameters and it is a well-known adaptive model used to model time series characterized by trend [52]. The multiple-step-ahead forecasting of Value at Risk and the Conditional Value at Risk by ES-type models have not been used in any study erstwhile. According to Tables 4 and 5 HWES model (a kind of ES models) has the least forecasting volatility error compared to other models. This model is proposed to forecast the volatility of fossil energy markets. So, when HWES model is adopted, it leads to investigating of the level and trend, simultaneously, and filters the sudden changes by smoothing coefficients. Consequently, it provides a robust and computationally stable forecasting. Also, according to Lopez loss function test scores and Blanco and Ihle loss function test scores in Tables 10 and 11, it can be concluded that the HWES model has a better forecasting performance than the classic model in one-, five-, and twenty-step-ahead forecasting of Value at Risk and Conditional Value at Risk. Overally, the Holt-Winters Exponential Smoothing model provides a robust forecasting for volatility, Value at Risk, and Conditional Value at Risk, that fits the continuous Brent oil and natural gas price movements and provides an efficient risk quantification across all forecasting horizons.

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