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Hybrid systems for Brent volatility data forecasting: A comparative study

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C H R O N I C L E

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A B S T R A C T

Crude oil price volatility dynamics are governed by nonlinear and chaotic behaviour. This paper presents and compares the performance of four hybrid systems used to estimate and predict crude oil price volatility data. A GARCH family model is employed to estimate oil price volatility data and the Elman artificial neural network (ENN) system is used to model and predict the obtained data. Indeed, unlike previous studies found in the literature, recurrent artificial neural networks are chosen in this paper to model and predict future crude oil price volatility data estimated by GARCH family models since they are nonlinear systems capable of learning noisy and nonstationary data. In particular, four hybrid systems are tested and compared; including the GARCH-ENN, EGARCH-ENN, APARCH-ENN, and TARCH-ENN system. Using Brent crude oil price data, the obtained out-of-sample simulation results indicate that all hybrid systems provide very accurate forecasts of Brent future volatility. In addition, they show evidence of the superiority of the GARCH-ENN system over the EGARCH-ENN, TARCH-ENN, and APARCH-ENN systems. The presented four hybrid systems achieved very low forecasting errors. Thus, they could be effective in oil industry management and applications.

1. Introduction

The risks associated to the oil market namely the uncertain political situation in the Middle East as well as the unstable world economy require developing efficient and powerful quantitative models to adequately forecast oil price volatility to improve investment decisions in an increasing uncertainty. Indeed, producers, retailers, large consumers, and governments all need accurate forecasts of price volatility in order to optimize their investments, consumption, or to assess market efficiency. In particular, sudden changes in oil price volatility may have critical impact on both consumer goods and industrial production and services. In other words, large volatility shifts strongly affect both producers and consumers investment decisions which are actually hard to make.

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Toward the objective of modelling and improving the forecasting accuracy of oil price volatility data, many studies have been developed in the literature. For instance, Narayan and Narayan (2007) concluded that the behaviour of oil prices tends to change over short periods based on various sub-samples in the 1991-2006 time period for three crude-oil price benchmarks: West Texas Instrument (USA), Brent (North Sea) and Dubai (Middle East). Cheong (2009) investigated the time-varying volatility of the West Texas Intermediate (WTI) and Europe Brent using the autoregressive conditional heteroskedasticity (ARCH) model to take into account volatility clustering, asymmetric news impact, and long memory volatility. He found that the generalized ARCH (GARCH) provides the best forecasted evaluations for the Brent crude oil data. Wei et al., (2010) used GARCH class models to capture the volatility features of Brent and WTI. They found find that no model can outperform all of the other models for either the Brent or the WTI market across different loss functions used to evaluate the forecasting performances. Chang et al., (2010) analyzed the volatility spillover and asymmetric effects across and within WTI, Brent, Dubai/Oman (Middle East), and Tapis (Asia-Pacific) using vector ARMA-GARCH (VARMA-GARCH) and vector ARMA-asymmetric GARCH (VARMA-AGARCH) models. They found evidence of volatility spillovers and asymmetric effects on the conditional variances across the four markets. Recently, Hou and Suardi (2012) used parametric GARCH models to characterize crude oil price volatility of Brent and WTI. They found that the out-of-sample volatility forecast of the nonparametric GARCH model yields superior performance relative to parametric GARCH models. As a result, they concluded that the nonparametric GARCH model offers an attractive and viable alternative to the commonly used parametric GARCH models.

In general, oil price volatility data are generated by a nonstationary distribution function; thus, they change dynamically over time due to short memory and seasonality. In other words, volatility dynamics are typically governed by nonlinear and chaotic behaviour. Then, it is difficult to capture the dominant properties of its fluctuations. Therefore, employing GARCH family models may be not appropriate for forecasting purpose since they are linear models in nature; but used to estimate nonlinear components. In other words, GARCH family models are not suitable to capture nonlinear dynamics in volatility data although they are employed to estimate it.

The purpose of this paper is to propose a hybrid system to estimate and predict oil price volatility data. The proposed system follows two steps. First, a GARCH family model is employed to estimate oil price volatility time series. GARCH family models are used in this study since they are widely employed in the literature to estimate volatility data (Narayan & Narayan, 2007; Cheong, 2009; Wei et al., 2010; Chang et al., 2010; Hou & Suardi, 2012). In particular, four models are considered to estimate oil price volatility since there is no consensus in the literature as to which volatility model is the most appropriate. The considered models are the standard GARCH introduced by Bollerslev (1986), exponential GARCH (EGARCH) of Nelson (1991), asymmetric power GARCH (APARCH) introduced by Ding et al., (1993), and Threshold GARCH (TARCH) model of Zakoian (1994). In the second step, the Elman artificial neural network (ENN) (Elman, 1990) is used to model and predict the obtained volatility data. Thus, the proposed hybrid systems are GARCH-ENN, EGARCH-ENN, APARCH-ENN, and TARCH-ENN. Artificial neural networks are chosen to model and predict future crude oil price volatility because -unlike GARCH family models- they nonlinear systems capable of learning noisy and nonstationary data, and have been shown to be effective in many different applications; including forecasting inflation (Aiken, 1999), text classification (Zaghloul et al., 2009), improving of traffic safety programs (Solomon et al., 2006), and detecting fraudulent financial reporting (Huang et al., 2012).

In this study RNN is adopted because unlike the standard backpropagation neural network of Rumelhart et al., (1986), it is a local recurrent artificial neural network system with the addition of a feedback (recurrent) connection; called context nodes; from the output of the hidden layer to its input. The recurrent nodes provide a dynamic memory to the network system (Elman, 1990). Thus, the recurrent connections allow learning and recognizing temporal patterns in the data. As a recurrent network with dynamic memory, the ENN is suitable for time-varying system modelling (Zhou et al., 2013); namely time series data modelling and forecasting. Therefore, it is superior to the multi-layer perception and radial basis function networks (Zhou et al., 2013). Indeed, ENN was successfully applied in various industrial engineering problems recently; including turbine control (Lin, 2013), industrial time series prediction (Kelo & Dudul, 2012; Chandra & Zhang, 2012; Zhao et al., 2013), performance prediction of computer-aided-design users (Hamade et al., 2012), and temperature error data processing (Chen & Shen, 2013).

The contributions of our paper follow. First, we hybridize classical GARCH models with Elman artificial neural network system to estimate and better model and forecast oil price volatility data. Second, each hybrid system is evaluated in terms of forecasting performance for comparison purpose. The goal is to find out which proposed hybrid system better captures the dynamics of volatility data. Third, most recent data of oil price is used to cover period of recent world economic crisis and the Arab Spring.

The paper is structured as follows: Section 2 deals with our methodology which provides a brief introduction to GARCH family models, Elman neural network, and statistical performance measures. Simulation results of each hybrid system are provided in Section 3, whereas the discussion is presented in Section 4. Finally, Section 5 concludes.

2. Research methodology

The overall methodology is presented in Figure 1. First, the oil price $p(t)$ is transformed to instant variations $r(t)$. Second, volatility $h(t)$ is estimated using a GARCH family model; namely standard GARCH, EGARCH, TARCH, and APARCH. Third, future volatility $h(t+1)$ is predicted using the Elman neural network. Finally, statistical performance measures are employed to assess the effectiveness of each proposed system that hybridizes GARCH-family models and ENN. Our generic proposed oil price volatility prediction system is detailed next.

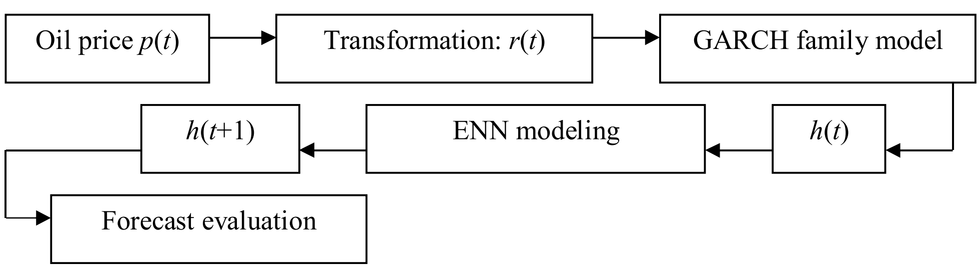

Fig. 1. Generic GARCH-family-ENN system

2.1 Volatility models

This section briefly describes the generalized autoregressive conditional heteroskedasticity (GARCH) type models. Let p_t denotes daily oil price and r_t denotes the corresponding daily return or variation at time t:

$$r_t = \log(p_t) - \log(p_{t-1})$$

The return data can be converted with the following conditional mean and variance dynamics equation which is governed by an autoregressive moving average (ARMA) process (Box et al., 1994) as follows:

$$r_t = \mu + \sum_{j=1}^{m} \phi_j r_{t-j} + \sum_{i=1}^{n} \delta_i \varepsilon_{t-i} ,$$

where, μ is the constant term, ϕ is the autoregressive coefficient, δ is the moving average coefficient, ε is white noise, and m and n are the ARMA process orders determined based on the autocorrelation and partial autocorrelation functions (Box et al., 1994). The white noise equation is given by:

$$\varepsilon_t = v_t \sqrt{h_t^2} ,$$

where v_t is independent and identically distributed with N(0,1) and h_t^2 is the conditional variance which can be estimated with GARCH family models including GARCH, EGARCH, APARCH, and TARCH. They are described in Table 1. For instance, the GARCH model includes q lags of the conditional variance h_t^2 in the linear ARCH(p). Thus, the ARCH parameters correspond to α and the GARCH parameters to β (See first equation in Table 1). The EGARCH model is an extension of the GARCH model to account for asymmetric volatility and to guarantee that forecasts of the conditional variance are nonnegative. The coefficients ω, β, α, and γ are constant parameters. The EGARCH model imposes no restrictions on these parameters. The variance component h_t^2 is defined as an asymmetric function of lagged values of the disturbance term ε. TARCH model was introduced to account for news effect on conditional volatility. For instance, good $(\varepsilon_{t-i} > 0)$ and bad news $(\varepsilon_{t-i} < 0)$ have differential effects on the conditional variance. In particular, good news has an impact of $(\alpha_i + \gamma_i)$ and bad news has an impact of $(\gamma_i > 0)$. In the APARCH model, the standard deviation is modelled rather than the variance, and the power parameter δ of the standard deviation can be estimated rather than imposed. In addition, the optional parameters γ are added to capture asymmetry of up to order r. More details about these models can be found in Bollerslev (1986), Nelson (1991), Ding et al., (1993), and Zakoian (1994). The orders q and p of GARCH type models used in this study are set to one since they provided statistically highly significant coefficients.

Table 1
GARCH type models

GARCH family	Model	Parameters
GARCH(p,q)	$h_t^2 = \omega + \sum_{j=1}^{q} \beta_j h_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2$	β and α are respectively GARCH and ARCH coefficients
EGARCH(p,q)	$\log\left(h_t^2\right) = \omega + \sum_{j=1}^{q} \beta_j \log\left(h_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left\lvert \frac{\varepsilon_{t-i}}{h_{t-i}} \right\rvert + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}}$	The parameter γ_k captures asymmetric effects
TARCH(p,q)	$h_t^2 = \omega + \sum_{j=1}^{q} \beta_j h_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{d} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^-$	I_t^-=1 if ε_t< 0, and 0 otherwise.
APARCH(p,q)	$h_t^\delta = \omega + \sum_{j=1}^{q} \beta_j h_{t-j}^\delta + \sum_{i=1}^{p} \alpha_i \left(\lvert\varepsilon_{t-i}\rvert - \gamma_i \varepsilon_{t-i}\right)^\delta$	$\delta>0$, $\lvert\gamma_i\rvert\leq 1$ for i=1,…,r, γ_i=0 for all $i>r$, and $r\leq p$.

2.2 Elman neural network

The Elman neural network (ENN) comprises four layers. The first (i) layer is the input layer, the second layer (j) is the hidden layer, the third layer (r) is the context layer, and the forth layer (o) is the output layer. The topology of ENN is shown in Fig. 2. The hidden layer (j layer) is fed by the outputs of the context layer (r layer) and the input layer (i layer) neurons. The context layer neurons are memory units used to store the previous output of hidden layer neurons. Following the notation in Chen and Shen (2013), the ENN descriptive equations are given by:

$$y_0(k) = \sum_{i=1}^{N} w_{jo}^2 x_j(k),$$
$$x_j(k) = f\left(w_{ij}^1 e_i(k) + w_{cj}^3 x_T^c(k)\right),$$
$$x_T^C(k) = x_j(k-1),$$

where, $y_0(k)$ is the output of the ENN, x_j is the input vector of the hidden layer, x_T^c is the input of the context layer, w_{jo}^2 are the connective weights of hidden neuron to output neurons, w_{ij}^1 are the connective weights of input neuron to hidden neuron, w_{cj}^3 are the connective weights of hidden neuron to context neuron, N is the number of hidden layer node; and $f(\cdot)$ s the nonlinear activation function in the hidden layer node. The sigmoid function is chosen in this study as the activation function. The learning strategy of Elman network is based on the minimization of network error function using the well-known Levenberg-Marquardt algorithm.

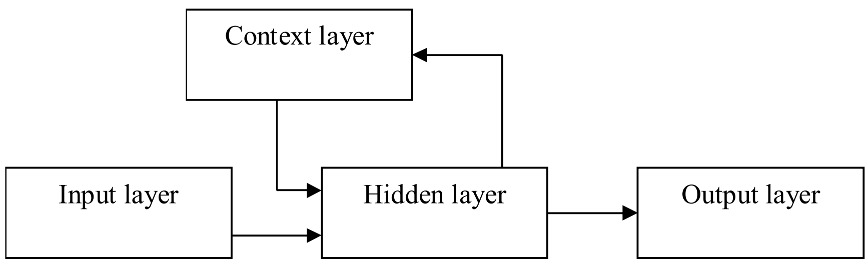

Fig. 2. Architecture of the Elman neural network

2.3 Performance measures

In order to evaluate the performance of the GARCH-family-ENN systems, two evaluation criteria are used as accuracy measures; namely the mean absolute error (MAE) and the root mean-square error (RMSE). These evaluation criteria are calculated as follows:

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|h(t) - h_p(t)\right|,$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(h(t) - h_p(t)\right)^2},$$

where $h(t)$ and $h_p(t)$ are respectively the true volatility and the forecasted volatility over the testing (out-of-sample) period $t = 1$ to N. The smaller the values of these performance measures, the closer are the forecasted volatility values to the true volatility values. Then, the lower are the evaluation criteria, the better is the performance of forecasting.

3. Data and simulation results

The data for our experiments are Brent crude oil spot price. The main reason of selecting this oil price indicator is being one of the famous benchmark prices. The sampling data covers the period from January 2nd, 2008 to January 29, 2013 with a total of 1274 observations. The data set is partitioned into a training set (first 80% of the data) and a testing set (remaining 20%) used to evaluate the performance of prediction, based on evaluation criteria; namely MAE and RMSE. Figures 4 to 6 exhibit the estimated Brent spot price volatility and the predicted volatility using GARCH, EGARCH, TARCH, and APARCH respectively. All figures indicate that for all volatility estimation models the ENN-based predictions are close to the true estimated volatility. Table 2 provides the performance of each GARCH-family-ENN system based on the statistical evaluation criteria. The results indicate that GARCH-ENN system achieved the lowest values of MAE and RMSE, whilst the EGARCH-ENN system achieved the highest values of these performance measures. Finally, both the TARCH-ENN and the APARCH-ENN systems achieved similar values of MAE and RMSE.

In summary, the obtained simulation results show that the ENN is effective in forecasting future Brent spot price volatility since all GARCH-family-ENN systems have very small errors according to the performance statistics used in the study. In addition, the GARCH-ENN system outperforms the other systems; namely the EGARCH-ENN, TARCH-ENN, and APARCH-ENN.

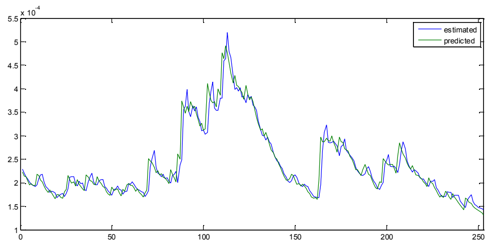

Fig. 3. GARCH-based volatility

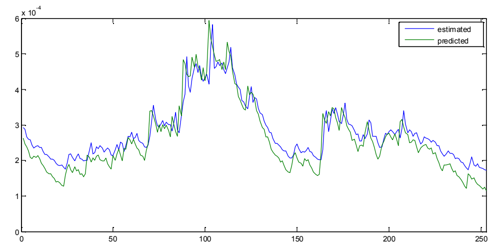

Fig. 4. EGARCH-based volatility

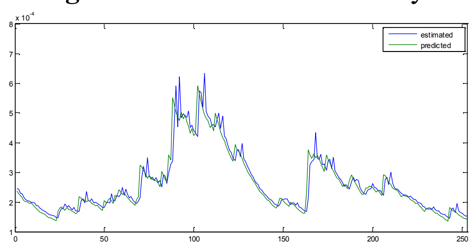

Fig. 5. TARCH-based volatility

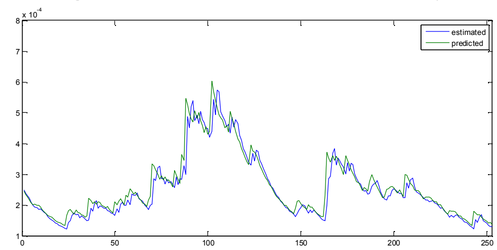

Fig. 6. APARCH-based volatility

Table 2
Simulation results

	GARCH	EGARCH	TARCH	PARCH
MAE	0.000011852	0.000031706	0.000018165	0.000018711
RMSE	0.000020030	0.000037733	0.000032155	0.000032898

4. Discussion

Recently, modelling and forecasting oil crude price volatility has received considerable attention by both academics and practitioners. In this work, we explore the use of recurrent neural networks; namely the Elman neural network to forecast oil price data volatility which is estimated by four models: GARCH, EGARCH, TARCH, and APARCH. To evaluate the performance of each prediction method, the mean absolute error and the root of mean of squared errors were calculated for all hybrid systems. Findings reveal that accurate predictions of Brent oil price volatility data can be made based on hybrid GARCH-family-ENN systems; particularly those obtained using the hybrid GARCH-ENN system.

Some important issues need to be addressed in our future work. First, this study will be extended to other energy prices such as the West Texas Intermediate (WTI) crude oil spot price and electricity load for volatility modeling and prediction. Second, evolutionary soft computing methods such as genetic algorithms (Goldberg, 1989) will be used to optimize ENN architecture and parameters. Third, other volatility models such as the component GARCH (CGARCH) model of Engle and Lee (1999) will be considered. Its main advantage is accounting for persistent volatility dynamics and to be superior to GARCH in describing volatility dynamics (Christoffersen et al., 2008). Then, it would be interesting to compare CGARCH-ENN to GARCH-ENN.

5. Conclusion

Oil price volatility data forecasting as a major indicator of oil markets stability plays a key role in oil industry management. There are many statistical methods available for estimating oil price volatility data. Data mining technique; namely Elman recurrent artificial neural network is used to model and predict the estimated crude oil price volatility by virtue of GARCH, EGARCH, TARCH, and APARCH statistical model. The purpose of this paper is to compare the performance of four hybrid systems for volatility estimating and prediction. The hybrid system integrates one of volatility estimating model with ENN system. Using Brent crude oil price data, the obtained out-of-sample simulation results indicate that all hybrid systems provide very accurate forecasts of Brent future volatility. In addition, they show evidence of the superiority of the GARCH-ENN system over the EGARCH-ENN, TARCH-ENN, and APARCH-ENN system. The presented four hybrid systems of Brent volatility data estimation and prediction could be effective in real oil industrial applications.

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