An artificial neutral network augmented GARCH model for Islamic stock market volatility: Do asymmetry and long memory matter?

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Abstract

The aim of this paper is to study the volatility and forecast accuracy of the Islamic stock market. For this purpose, we construct a new hybrid GARCH-type models based on artificial neural network (ANN). This model is applied to daily prices for DW Islamic markets during the period June 1999-December 2016. Our in-sample results show that volatility of Islamic stock market can be better described by the FIAPARCH approach that take into account asymmetry and long memory features. Considering the out of sample analysis, we have applied a hybrid forecasting model, which combines the FIAPARCH approach and the artificial neural network (ANN). Empirical results show that the proposed hybrid model (FIAPARCH-ANN) outperforms all other single models such as GARCH, FIGARCH, FIAPARCH and ANN in terms of all performance criteria used in our study.

JEL classification: C45, C53, G1, G17

Keywords: Forecasting, Islamic stock market, GARCH family models, Artificial neural networks.

1. Introduction

An important task in the risk management is the choice of the optimal model in forecasting accuracy of stock market volatility. Indeed, the ability to forecast stock price movements with greater precision is essential mission for investors, policy makers and financial analysts. Such assessment should influence the investment decision through the calculating of the Value at Risk and the optimal hedge ratio and the determination of the optimal portfolio diversification strategy.

Several previous studies have focused on the forecasting performance of stock markets. These studies have used the traditional model such the ARIMA and GARCH-type models (Li et al., 2013; Hansen et al., 2012, Bali et Demirats, 2008; Hansen and Lunde, 2005; Yu, 2002; Tse and Tung, 1992 Lee, 1991). More recently, the papers have employed more hybrid models that combine volatility approach to artificial neural network model. These types of model overcome the drawback of the GARCH-based models such as linearity. Qiu and Akagi (2016) suggest that ANN approach can map any nonlinear function without a preliminary assumption to predict the behavior of stock market returns. In the same way, Zahedi and Rounaghi (2015) emphasize that ANN models were developed to depict and forecast the structure of financial and commodity assets without referring to prior assumptions and error distributions.

The studies that interested to the estimation and forecasting of stock market dynamics, using the artificial neutral network model are limited. Donaldson and Kamastra (1997) built a semi nonparametric nonlinear GARCH model based on the artificial neural network approach. Then, they verify its ability to forecast the volatility of some international stock markets namely in London, New York, Tokyo and Toronto. They conclude that the ANN outperforms the traditional GARCH type models. In the same vein, Qiu et al. (2016) apply an ANN approach to predict the return of the Japanese Nikkei 225 index. Their results point out that the hybrid model improves prediction accuracy significantly.

Tseng et al. (2008) develop a new hybrid asymmetric volatility framework into an ANN option-pricing model in order to enhance the forecasting ability of the Taiwan stock index option prices. Their results show on the one hand that the considered model decreases significantly the stochastic and nonlinearity of the error term and capture the asymmetric volatility feature of stock market. On the other hand, the hybrid model provides greater predictability compared to traditional volatility models.

Fatima and Hussain (2008) compare the performance of ANN with ARIMA and ARCH/GARCH models in forecast accuracy of the Karachi stock exchange index. They find that the ANN augmented ARCH/GARCH models provide better forecasting capability for stock prices. More precisely the ANN with ARCH/GARCH frameworks is superior to the standard ANN and the ANN with ARIMA model in forecasting the volatility of Karachi stock market.

Zhang (2003) suggests that the hybrid methodology that combines both ARIMA and ANN models has superiority in forecasting performance compared to the use of single ARIMA and ANN in linear and nonlinear modeling. The author applies the hybrid model to three data sets. He concludes that this model outperforms each component model employed in isolation.

More recently, Lahmiri (2016) evaluates the forecast accuracy of GARCH family models and hybrid GARCH-ANN model. These models are applied to two foreign exchange rate namely US/Canada and US/Euro currency exchange rate. The author conclude the hybrid GARCH-type approach can be used by traders and portfolio managers to predict US currency volatility in order to better choice of risk hedging instruments.

This paper contributes to the existing literature in two ways. First we focus in our analysis on Islamic stock market volatility. This market has occupied a significant place in the area of finance during the last two decades (Chkili, 2017; Abdullah et al., 2016; Hammoudeh et al., 2014). However, few studies are explored the volatility of Islamic equity markets and the opportunity to invest in these assets in order to enhance the risk-return of portfolio. Such decision requires a better forecasting of the behavior dynamics this market. Second, we develop a methodology that combine an Artificial Neural Network (ANN) and GARCH family models that take into account two important features of time series namely asymmetry and long memory. Then, we evaluate its ability to forecast stock return volatility for Islamic market. To the best of our knowledge, ours is the first study that conducts conditional volatility forecasts using a hybrid model in the presence of asymmetry and long memory.

The remainder of the paper is organized as fellows. Section 2 presents the econometric methodology. Section 3 describes the data and their statistical proprieties. Section 4 reports and discusses the empirical results. Section 5 provides some concluding remarks.

2. Methodology

2.1. GARCH family models

In our study, we consider three GARCH type models. Practically, we employ the standard GARCH model which used for comparison purpose and the FIGARCH and FIAPARCH frameworks. These two later models integrate two important features for time series analysis namely the long memory or simultaneously the asymmetry and long memory in the conditional variance. Let r_t be the stock return series, according to Bollerslev (1986), the standard GARCH model can be written as follows

$$r_t = \mu_t + \varepsilon_t$$

$$\varepsilon_t = \sigma_t z_t, z_t \approx NDD(0,1)$$

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

Where μ_t and σ^2 are the conditional mean and the conditional variance, respectively, z_t is a standardized error term, ω is a constant, α and β design the ARCH and GARCH parameters. These parameters must satisfy the positivity and stationarity conditions: $\omega>0$, $\alpha>0$, $\beta>0$ and $\alpha+\beta>0$. The standard GARCH model assumes only a short-term volatility. To overcome this problem, Baillie et al. (1996) develop the Fractionally integrated GARCH (FIGARCH) model which allows to fractional orders of integration to vary between zero and one. The FIGARCH (1,*d*,1) can be written as follows:

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \left[1-(1-\beta L)^{-1}(1-\varphi L)(1-L)^d\right]\varepsilon_t^2$$

where $0 \le d \le 1, \omega > 1, \varphi, \beta < 1$; d is the fractional difference parameter and measures the degree of persistence in Islamic stock market volatility. L is the lag operator.

More recently, Tse (1998) develops the fractional integrated asymmetric power ARCH (FIAPARCH) model. This model takes into account two important characteristics namely the long memory and asymmetry in the conditional volatility. The FIAPARCH (1,*d*,1) is defined as follows:

$$\sigma_t^\delta = \omega(1-\beta)^{-1} + \left[1-(1-\beta L)^{-1}(1-\varphi L)(1-L)^d\right](|\varepsilon_t| - \gamma\varepsilon)^\delta$$

where $0 \le d \le 1, \omega, \delta > 0, \varphi, \beta < 1$ and $0 < \gamma < 1$.

2.2. ANN model description

ANN is a nonlinear mathematical model inspired from the human brain function. This model consists generally of an input layer, one or more hidden layers and output layer. The standard architecture of an ANN is depicted in Fig. 1. In the recent years, ANN is widely applied in various computational intelligence problems such as forecasting (Moghaddam et al., 2016; Hamdi et al., 2016; Vhatkar and Dias, 2016), classification (Anousouya Devi et al., 2016 ; Namatēvs et al., 2016), signal processing (Azad et al., 2016) and pattern recognition (Kouamo and Tangha, 2016).

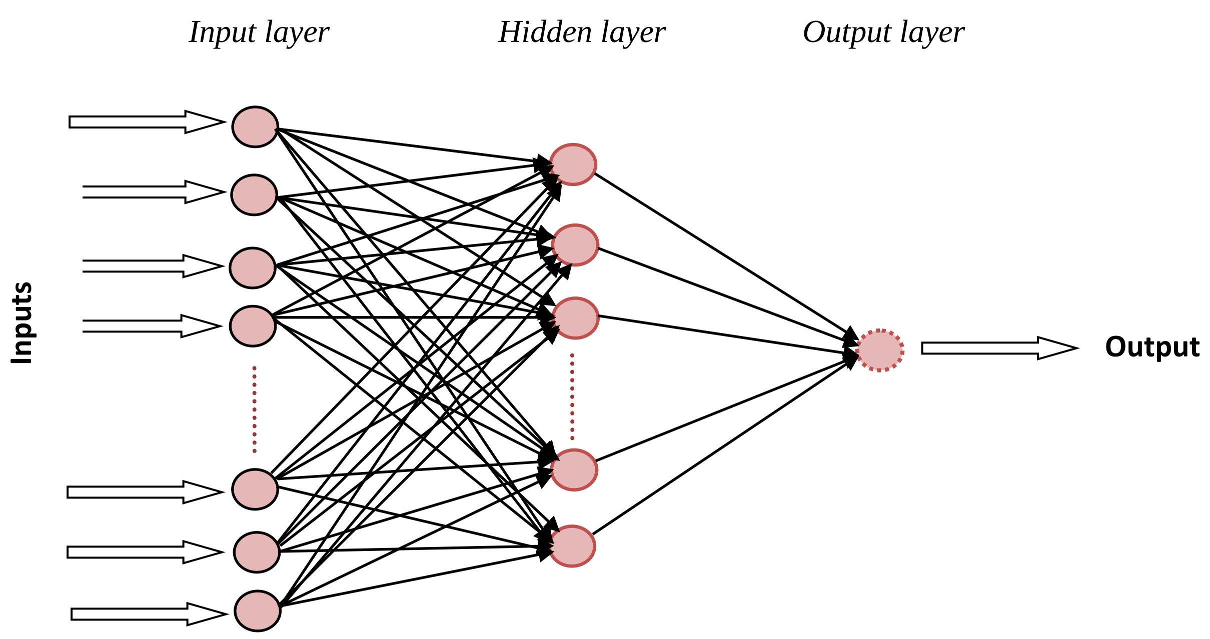

Fig. 1. The Standard architecture of ANN model

2.3. *ANN augmentations of GARCH models*

The proposed hybrid model consists of combining a FIAPARCH approach with the neural network back propagation (NNBP) model in order to deal with the linear and nonlinear parts of the time series under study, respectively. To construct a hybrid FIAPARCH-NNBP we follow three main steps. The first is the step of taking residuals from FIAPARCH process. The second stage is devoted to forecast the residuals by using the NNBP. The third and the last step consist of adding the forecasted returns from the FIAPARCH approach with the forecasted residuals from the NNBP model. The design of the hybrid methodology is described by Fig. 2.

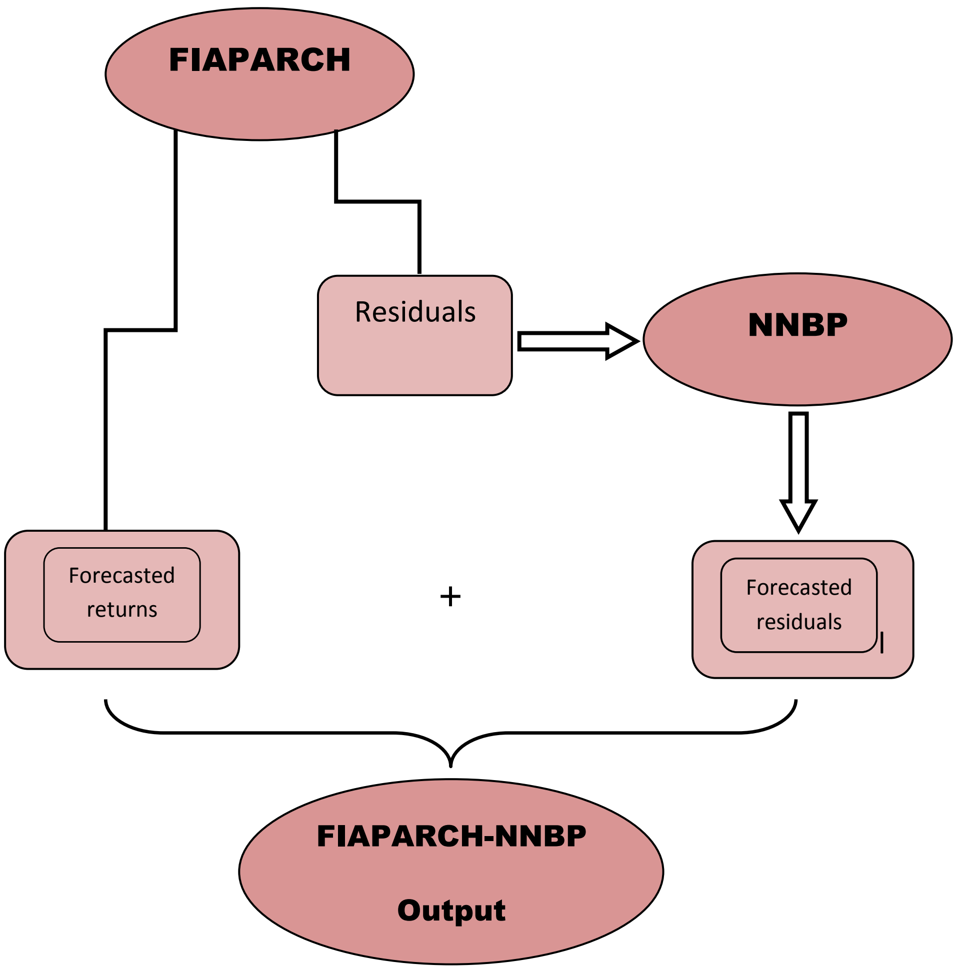

Fig. 2. The hybrid FIAPARCH-NNBP design

To note a three layer NNBP is used in our study with a tangent hyperbolic activation function in the hidden layer which is composed on 18 hidden nodes fixed by trial and error approach, and an identity transfer function in the output layer.

3. Data and preliminary analysis

The dataset consist of daily Dow Jones Islamic (DJI) stock market index for the period Jun 1999 to December 2016 yielding a total of 4455 observations. Given our main objective to forecast the dynamic of Islamic market price, the period is divided into subsample. Our in-sample period runs from Jun 1, 1999 to December 31, 2014, while the out of sample period runs from January 1, 2015 to December 31, 2016. The Islamic stock index prices are collected from Datastream international. The return is calculated by taking the difference in the natural logarithm of two consecutive prices.

Table 1 presents some descriptive statistics and stationarity tests for the considered stock return. As shown in Panel A, the mean return of the Dow Jones Islamic market is positive and is in the order of 0.9625%. The volatility as measured by the standard deviation is lower (1.1033). The Skewness and Kurtosis normality tests show that return series is negatively skewed and has fatter tails than corresponding normal distributions. The Jarque-Bera test rejects the null hypothesis confirming the departure from normality. Both the Ljung-Box test and the Engle (1982) test for conditional heteroscedasticity statistics are significant at 1% significance level rejecting the null hypothesis of no autocorrelation and suggesting the ARCH effects in returns, respectively. Panel B displays results of some stationarity tests applied to return series. We use three conventional tests namely the Augmented Dickey-Fuller (ADF), the Philips-Perron (PP) and Kwiatkowski et al. (1992). We see that the ADF and PP test statistics are significant at 1% significance level rejecting the null hypothesis of unit root. The KPSS test cannot reject the null hypothesis of stationarity for the Islamic market. Our return series is therefore stationary and suitable for further statistical modeling.

We also check the presence of long memory in the conditional variance of return series. Practically, we employ two popularly-used tests in the related literature namely the log periodogram regression (GPH) test (Geweke and Porter-Hudak, 1983) and the Gaussian semi-parametric (GSP) test (Robinson, 1995). The results of the two tests applied to the absolute and squared returns of the Islamic stock index are reported in Table 2. From the table, we can reject the null hypothesis of no long-range memory for the stock market in all cases as the statistical values are significant at 1% significance level. These results make clear the existence of long memory effects for the Islamic stock markets. Past studies focusing on Islamic and conventional markets display similar results (see e.g. El Mehdi and Mghaieth, 2017 and Ben Nasr et al., 2016).

Table 1
Descriptive statistics and unit root tests

Panel A: Descriptive statistics			
Mean	0.9625	JB	33465**
Standard dev.	1.1033	$Q^2(10)$	1408.05 **
Skewness	-0.0639	ARCH(5)	146.19**
Kurtosis	13.426	ARCH(10)	86.448 **

Panel B: Stationarity tests		
ADF	PP	KPSS
-39.314**	36.872**	0.1064

Note: JB is the Jarque–Bera test for normality. Q2(10) is the Ljung–Box tests for autocorrelations of order 10 applied to squared returns. ARCH (5) and ARCH(10) refers to statistics of the Engle (1982) test for conditional heteroscedasticity with 2 and 10 lags, respectively. ADF, PP and KPSS design the empirical statistics of Augmented Dickey-Fuller, Philips Perron and Kwiakowski-Phillips-Shmidt-Shin tests for unit root and stationarity, respectively.
**Indicates the rejection of null hypotheses at the 1% level.

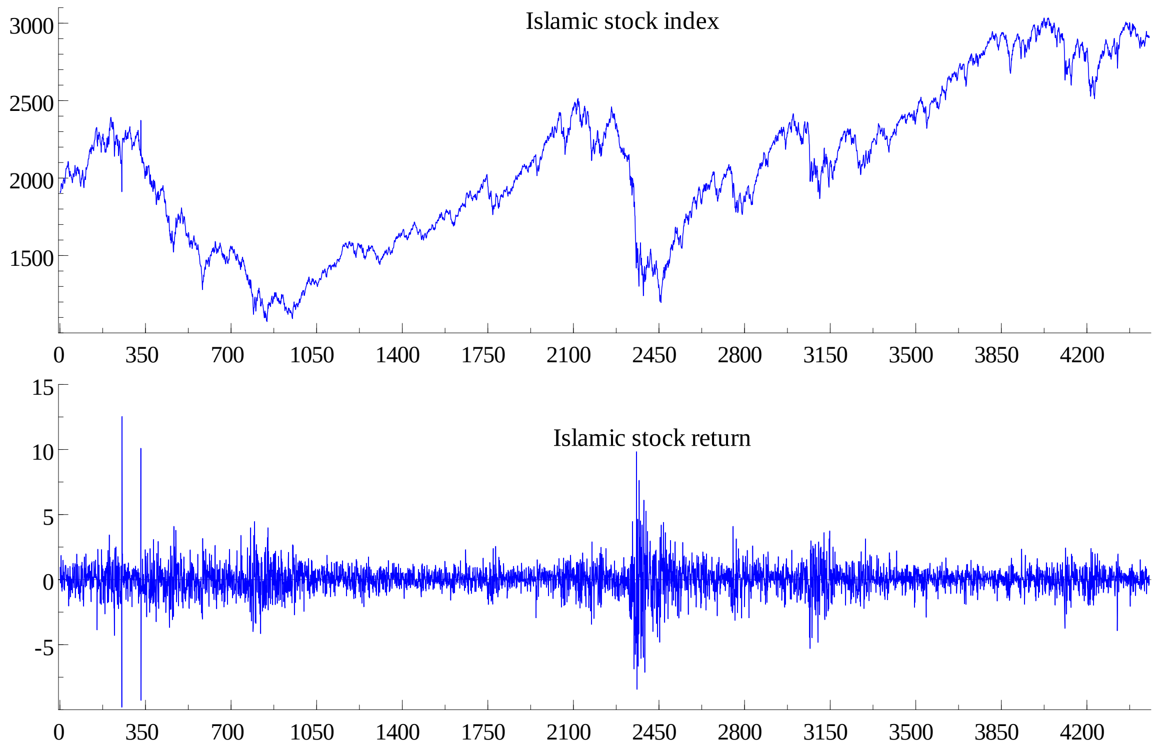

Fig. 3. Prices and returns for DJI stock market

Fig. 3 displays the evolution of the price (upper panel) and return (lower panel) series for the considered Islamic stock market. As shown, the stock index prices experienced a continuously increasing trend with two substantial fall phases. The first phase appeared after the September 11, 2001 terrorist attack while the second occurred during the 2007-2008 global financial crisis. From the lower Panel we observe the presence of volatility clustering for the return series. This feature confirms the existence of ARCH effects and confirms the use of GARCH family models.

Table 2
Long memory test results

	Squared return		Absolute return	
	statistics	Probability	statistic	Probability
GPH test				
$m = T^{0.5}$	0.264	[0.002]	0.496	[0.000]
$m = T^{0.6}$	0.422	[0.000]	0.560	[0.000]
GSP test				
m = T/8	0.319	[0.000]	0.478	[0.000]
m = T/16	0.406	[0.000]	0.584	[0.000]

Note: m indicates the bandwidth for the Geweke and Porter-Hudak (1983) (GPH) test, the Gaussian semi-parametric (GSP) test of Robinson (1995). *P*-value are displayed in brackets

4. Results

4.1. Model estimation and in-sample diagnostics

Table 3 presents the estimation results of three GARCH models. We start our analysis by determining the optimal lag in the mean equation. According to the Akaike and Schowrtz information criteria, the appropriate autoregressive order is equal to one. The estimated coefficient of the autoregressive is significant for all cases suggesting that stock returns depend on their past observations. Turning to the variance equation, we note that the stationarity condition for the GARCH standard model is guaranteed since the sum of the ARCH and GARCH parameters is less than unity. Table 3 indicates also that the estimated coefficients of the model are significant at 1 % significance level. We observe that the magnitude of the GARCH coefficient is higher (0.885) suggesting the persistence of volatility over time. The result estimations of the FIGARCH show that all the estimated parameters are statistically significant. Indeed, the fractionally differencing parameter (*d*) is highly significant confirming the evidence of the long memory in conditional volatility of Islamic stock market. Diagnostic tests present in Panel B show that the model is well specified as we cannot reject the null hypothesis of no serial correlation and ARCH effects in the squared residual series.

The estimation results of the FIAPARCH model are similar to the FIGARCH modeling. The long memory parameter is statistically significant and differs from zero and unity. The APARCH (δ) coefficient is positive and significant suggesting that Islamic stock market volatility react asymmetrically to unexpected news. In addition, the APARCH (γ) coefficient is positive and significant at the conventional levels. This proves that negative shocks have more impact on conditional volatility than positive shocks of same magnitude.

Overall, according to the log-likelihood and information criteria, our estimation results show that the FIAPARCH model outperforms the GARCH and FIGARCH specification in modeling the conditional volatility of Islamic stock market. The superiority of this model results from its ability to take into account two important futures in time series namely asymmetry and long-run memory. Our findings are in line with several previous papers interesting to conventional and Islamic stock market volatility. For instance, Chkili et al. (2014) explore the dynamic volatility of some international stock markets. They suggest the superiority of FIAPARCH model relative to GARCH and FIGARCH specifications. El Mehdi and Mghaieth (2017) find quite similar results for some Dow Jones Islamic markets.

Table 3
Estimation results of GARCH family models

	GARCH	FIGARCH	FIAPARCH
Panel A: estimation results			
Const (*m*)	0.059^{***} (0.019)	0.055^{***} (0.016)	0.017 (0.018)
AR(1)	0.075^{***} (0.016)	0.081^{***} (0.017)	0.066^{***} (0.020)
Const (*v*)	0.013^{***} (0.005)	0.024^{***} (0.010)	0.059^{**} (0.028)
ARCH	0.096^{***} (0.020)	0.182^{**} (0.068)	0.272^{***} (0.044)
GARCH	0.896^{***} (0.019)	0.584^{***} (0.114)	0.614^{***} (0.079)
d		0.478^{***} (0.103)	0.432^{***} (0.097)
APARCH(γ)			0.731^{*} (0.421)
APARCH(δ)			1.285^{***} (0.319)
Log-Likelihood	-5320.346	-5300.44	-5221.18
Panel B: diagnostic tests			
AIC	2.6929	2.6834	2.6443
SIC	2.7009	2.6929	2.6570
$Q^2(10)$	10.594 [0.226]	19.397 [0.013]	8.341 [0.500]
$Q^2(20)$	13.791 [0.742]	22.893 [0.195]	24.637 [0.173]
ARCH(5)	1.7856 [0.112]	1.4274 [0.125]	
JB	5585.5 [0.000]	3546.7 [0.000]	2678.7 [0.00]

Notes: Const *(m)* and Const (*v*) are the constants of the mean and variance equations, respectively. *d* is the long memory parameter. $Q^2(.)$ is the Ljung–Box test for autocorrelation applied to squared standardized residuals. ARCH(5) is the Engle (1982) test for conditional heteroscedasticity applied to standardized residuals. The p-values associated with the statistical tests are presented in brackets. Standard deviations are reported in parentheses. *,** and *** denote significance at the 10%, 5% and 1% levels, respectively.

4.2. Forecast evaluation measures

We choice three commonly used forecasted evaluation measures to assess the predictive ability of the hybrid model compared to GARCH-type models (Mei et al, 2017; Lahmiri, 2016; Chkili et al., 2014; Li et al., 2013). The selected criteria are the mean squared error (MSE), the root mean squared error (RMSE) and the normalized mean squared error (NMSE).

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(d_i - o_i)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(d_i - o_i)^2}$$

$$NMSE = \frac{1}{n}\sum_{t=1}^{m}\frac{(d_i - o_i)^2}{\left(d_i - \overline{d_i}\right)^2}$$

where n is the total number of observations. d_i is the actual realized values and O_i is the forecast values. Finally, the model that displays the smallest mean losses is the best one for forecasting the volatility of Islamic stock market.

4.3. Short term forecasting results and interpretations

Accuracy is the first criterion used to check the predictive capability of our proposed models. Therefore, Table 4 presents comparison results of the aforementioned metrics employed to check the accuracy of forecasts.

Table 4
One-step-ahead forecasting evaluation

Models	GARCH	FIGARCH	FIAPARCH	Hybrid FIAPARCH-NNBP
MSE	0.511195873	2.38778772	0.51090815	0.506785126
RMSE	0.714979631	1.54524665	0.71477839	0.711888423
NMSE	0.470948734	2.1997935	0.47068367	0.466885252
Rank	3	4	2	**1**

Based on Table 4, we find that the proposed hybrid model is the best forecasting model which represents the smallest prediction error, 0.5068, 0.7119 and 0.4669 ; respectively for MSE, RMSE and NMSE. However, the most important for business practitioners and traders is the accuracy of price directions which can help them to improve their decisions and therefore to get more profit. Directional change statistic D_{stat}[1] is the main used indicator to judge the model ability in predicting the movement direction of prices (Yu et al., 2007). In reality and for business practitioners, the D_{stat} indicator is more important than RMSE ; as a smaller value of RMSE does not necessarily imply that there is a high D_{stat} (Wang et al., 2005 ; Yu et al., 2008). According to this new metric, hybrid FIAPARCH-NNBP model can predict the trend of returns with 81.49% of accuracy, whereas 79.27% for FIAPARCH, 79.11% for GARCH and only 24.27% for FIGARCH. Therefore, and based on this empirical forecasting study, we can conclude that an artificial neutral network augmented FIAPARCH model predictions can help investors to hedge their trading risks on Islamic stock market by making, in advance, adequate trading decisions.

To note, the forecasting task assessment is based on 890 observations as the total observations of the test sample (20% from the total sample), the remain (80% of sample) is used in learning phase, in our study.

6. Conclusion

In this paper, we investigate the volatility and forecast accuracy of Islamic stock market during the period 1999-2016. From the in-sample results, we found strong evidence of asymmetry and long memory in the conditional volatility of the Islamic market. Then, we propose a hybrid strategy by combining GARCH model family with NNBP to forecast accuracy of the Islamic stock market. According to the empirical forecasting study, we conclude that an artificial neutral network augmented FIAPARCH model outperforms all other single models such as GARCH, FIGARCH and FIAPARCH. This significant forecasting accuracy of returns as well as their directions implies an evidence of Islamic stock market predictability for short time horizons. Therefore, profitable business opportunities may exist.

[1] $D_{stat} = \frac{1}{N}\sum_{i=1}^{n} B_i$; $B_i = 1$ *if* $(d_{i+1} - d_i)(o_{i+1} - d_i) \geq 0$ *and* $B_i = 0$ *otherwise.*

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