Artificial Neural Networks vs. ARIMA-GARCH in Stock Market Prediction: The Case of Tunisia and Morocco

التنبؤ بأسعار الأسهم باستخدام الشبكات العصبية الاصطناعية ونموذج -ARIMA GARCH حالة أسواق تونس والمغرب

MOKRANI Ahlem, université Abdelhamid Mehri-Constantine 2
ahlem_mokrani@yahoo.fr
CHERABI Abdelaziz, université Abdelhamid Mehri-Constantine 2
azizcherabi@yahoo.fr

ملخص. يهدف هذا المقال إلى محاولة التنبؤ بأسعار الأسهم باستخدام الشبكات العصبية الاصطناعية وبالتحديد نموذج بيرسبترون متعدد الطبقات ذو خوارزمية الانتشار العكسي، ونموذج الانحدار الذاتي والمتوسطات المتحركة المتكاملة المشروط بعدم تجانس التباين ARIMA-GARCH. وتم تطبيقهما على أسعار الإغلاق اليومية لبورصتي المغرب وتونس من سنة 2013 إلى 2016. خلصت الدراسة إلى أن نموذج الشبكات قد قدم نتائج أفضل على مستوى البورصتين بالاعتماد على أقل متوسط للأخطاء المربعة مقابل النموذج الآخر. ومنه يمكن القول بأن الشبكات تعتبر الأفضل عندما يتعلق الأمر بالتنبؤ بالسلاسل المالية، إلا أن قدرتها التنبئية مرتبطة إلى درجة كبيرة بطريقة تصميمها.

الكلمات المفتاحية: الشبكات العصبية الاصطناعية، ARIMA-GARCH، التنبؤ، سوق الأسهم، المغرب وتونس.

Abstract. The objective of the present paper is to predict the future evolution of stock markets using Artificial Neural Networks namely, the Multilayer Perceptron with Back-propagation, and the Auto Regressive Integrated Moving Average with Conditional Heteroskedasticity (ARIMA-GARCH). Data consisted of daily closing stock prices from 2013 to 2016. Results showed that artificial neural networks have produced a much lower prediction error compared to ARIMA-GARCH. It was concluded that ANNs are much more powerful. However, their predictive ability is closely related to how well they are designed.

Keywords: Artificial Neural Networks, ARIMA-GARCH, Prediction, Stock Markets, Morocco and Tunisia.

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1. Introduction

From a practical perspective, it is possible to distinguish between two types of financial time series, those who have a random character and those who do not. Time series that do have a random character are unpredictable no matter the accuracy of the model in question. Our focus is redirected towards non-random time series. A time series that does not have a random character means that there is a relationship in the data. This relationship can be linear or non-linear (more complex). These types of data can be captured using conventional models such as the autoregressive integrated moving average (ARIMA).

However, when this relationship becomes more complicated, more powerful models are needed, and this is where Artificial Neural Networks have proven to be more performing compared to traditional models (Foster, Collopy, and Ungar, 1992)[1], (Kohzadi, Boyd, Kermanshahi, and Kaastra, 1996)[2] and (Tang & Fishwick, 1993)[3]. This is mainly due to the fact that ANNs are able to (i) Learn from past data; (ii) Capture hard-to-describe relationships among data; (iii) Generalize and correctly produce inferences; and (iv) Tolerate errors[4].

Research has shown that Artificial Neural Networks (ANNs) outperform traditional models like ARIMA and GARCH and can generate better predictions when applied to financial time series. In that sense, (Yao et al, 1999)[5] compared the forecasting ability of both ARIMA and ANNs when applied to the Kuala Lumpur Stock Exchange. Results showed that ANNs have outperformed ARIMA models. Similarly, (Darrat & Zhong, 2000)[6] compared the forecasting performance of several models like the Naïve model, ARIMA, GARCH, and ANNs in forecasting the Chinese stock exchange. Results have provided a strong support for ANNs as a potentially useful technique for stock market prediction. (Kumar, 2009)[7] showed that ANNs do work better than ARIMA and that it delivers consistent results across the tested periods. (Wijaya et al, 2010)[8] also compared the stock forecasting result of Indonesia using ANNs and ARIMA, and showed that forecasting using ANNs has produced smaller errors than ARIMA. (Derbal, 2014)[9] tried to predict the future evolution of Dubai Financial Market using various models namely, Box-Jenkins, ARCH models and ANNs. Results showed that ANNs are more robust than both ARCH models and the Box-Jenkins method. (Adebiyi et al, 2014)[10] also compared the forecasting performance of ARIMA and ANNs when applied to the New York Stock Exchange. They showed that ANNs do generally provide more accurate forecasts than ARIMA. (Charef & Ayachi 2016)[11] presented a comparison between ANNs and GARCH models for exchange rate forecasting. Results indicated that ANNs are more accurate than GARCH models.

However, when both ARIMA and GARCH models are combined, results may be different. This paper seeks to further clarify opinions reported in the literature on the superiority of ANNs over ARIMA-GARCH especially when it comes to stock market prediction.

2. Methods

2.1. Artificial neural networks

2.1.1 Definition

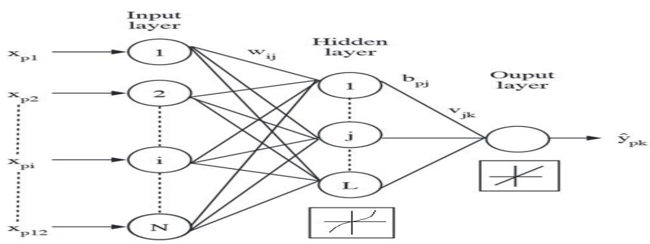
An Artificial Neural Network can be defined as: "*a mathematical model that is similar to the structure and the operating principle of mammalian cerebral cortex. It consists of a set of interconnected groups of artificial neurons that are able to learn* *from past experience and then to generalize in order to solve a problem. Artificial Neural Networks are considered as multivariate nonlinear nonparametric models. In opposite to univariate models, multivariate models are able to capture the effect of multiple variables. When their non-linear properties are added to their ability of learning, they can capture very complex relationships among data that cannot be captured by traditional non-linear models"*[12].

2.1.2 The Multilayer Perceptron with Back-propagation algorithm

There are various models of artificial neural networks. However, only very few of them can be used to make predictions on financial time series. According to (Moreno, Pol & Gracia, 2011)[13], these networks are: the Radial Base Function, the Generalized Regression Neural Network, the Recurrent Neural Network and the Multilayer Perceptron. The main focus in the present paper is on the latter model. The multilayer perceptron, known as the feed-forward with back-propagation is the most popular model in financial time series prediction. A certain number of comparative studies between these four models have shown that the multilayer perceptron performs better than the other ones when it comes to prediction. According to (Zhang et al., 1998)[14], this is due to its ability of arbitrary input-output mapping. The multilayer perceptron is equivalent to a non-linear model. In this specific case, the inputs are the previous observations $y_t, y_{t-1}, \dots y_{t-n}$ and the output is the predicted value y_{t+1}. The model's mathematical function can be expressed as: $y_{t+1} = f(y_t, y_{t-1}, \dots y_{t-n})$

Figure 1 shows the structure of a multilayer perceptron. It is composed of three layers: the input layer, the hidden layer and the output layer. For each layer, there are a certain number of settings. These settings can be adapted to better fit the studied problem. The optimal configuration of the network can be obtained using the following methods: the pruning algorithm, the polynomial time algorithm, the canonical decomposition technique and the network information criterion (Zhang et al., 1998). However, these procedures are not fully reliable and the user is always advised to test a wide set of networks in order to select the most appropriate network configuration.

Figure 1. The structure of the multilayer perceptron.



Source: Moreno, Pol, and Gracia, "Artificial Neural Networks Applied to Forecasting Time Series," 326.

While the input layer is responsible of relaying the values from their single input to their multiple outputs, the hidden layer is responsible of detecting data features and finding the existing patterns through the adjustment of weights. This operation is repeated as many times as needed until the network reaches its highest performance. (Zhang et al., 1998)[15] defined training as: *"An unconstrained nonlinear minimization problem in which arc weights of a network are iteratively modified to minimize the overall mean or total error between the desired and the actual output"*. Finally, the output layer is responsible of producing a response. In the present context, the output response is the predicted value.

2.2. ARIMA and GARCH models

2.2.1 ARIMA model

The Box-Jenkins approach to modelling ARIMA processes was introduced for the first time by (George Box and Gwilym Jenkins, 1970)[16]. An ARIMA process is considered as a mathematical model used for forecasting. The Box-Jenkins modeling seeks to: (i) identify the most appropriate ARIMA(*p,d,q*) process; (ii) fit it to the data; and then (iii) use the fitted model for forecasting. One of the most attractive features of the Box-Jenkins approach is that ARIMA processes are a very rich class of possible models and it is usually possible to find a process which provides an adequate description of the data[17].

Each ARIMA process has three parts: the autoregressive (AR) part; the integrated (I) part; and the moving average (MA) part. The models are often written in shorthand as ARIMA (*p,d,q*) where *p* describes the AR part, *d* describes the integrated part and *q* describes the MA part[18]. The general form for ARIMA(*p,d,q*) that generates the time series with the mean μ can be expressed as[19]:

$$\varphi_p(B)(1-B)^d(y_t-\mu)=\theta_q(B)\varepsilon_t$$

Where $\varphi_p(B)=1-\sum_{i=1}^{p}\varphi_i B^i, \theta_q(B)=1-\sum_{j=1}^{q}\theta_j B^j$ are polynomials in terms of B of degree p and q, $\nabla = (1-B)$, and B is the backward shift operator.

The original (Box & Jenkins, 1970) modelling (ARIMA) procedure involved an iterative three-stage process of model selection, parameter estimation and model checking[20]. Recent explanations of the process (Makridakis, Wheelwright and Hyndman, 1998)[21] often added a preliminary stage of data preparation and a final stage of model application.

- **Data preparation:** This step involves transformation and differencing. Transformation of the data can help stabilize the variance in a series where the variation changes with each level. This often happens with economic data. Then, the data is differenced until there are no obvious patterns such as trend or seasonality. The differenced data is often easier to model than the original data.

- **Model selection:** The Box-Jenkins framework uses various patterns based on the transformed and differenced data to try to identify potential ARIMA processes which might provide a good fit to the data. Later developments have led to other model selection tools such as Akaike's Information Criterion (Akaike 1969)[22].
- **Parameter estimation:** In this step, the values of the model will be defined.
- **Model checking:** This step involves testing the assumptions of the model to identify any areas where the model is inadequate. If the model is found to be inadequate, it is necessary to go back to step 2 and try to identify a better model.
- **Forecasting:** This is what the whole procedure is designed to accomplish. Once the model has been selected, estimated and checked, it is usually a straight forward task to compute forecasts.

2.2.2 GARCH model

The ARCH process was introduced for the first time by (Engle, 1982)[23]. It is able to recognize the difference between the unconditional and the conditional variance allowing the latter to change over time as a function of past errors. The statistical properties of this class of models have been studied in (Weiss, 1982)[24] and in a recent paper by (Milhoj, 1984)[25] (Bollerslev 1986)[26].

The most suggested models to test the existence of ARCH effect is (Engle's 1982) ARCH-LM test and (McLeod and Li's 1983)[27] Q test. Therefore, we apply

ARCH-LM test (Lagrange Multiplier, LM) to investigate the presence of Autoregressive Conditional Heteroscedasticity effect in residuals of ARIMA model under the null hypothesis of no ARCH effects[28].

The GARCH (*r,s*) process which is the generalized version of ARCH models are introduced by (Bollersev, 1986), namely the Generalized Autoregressive Conditional Heteroskedasticity is then given by:

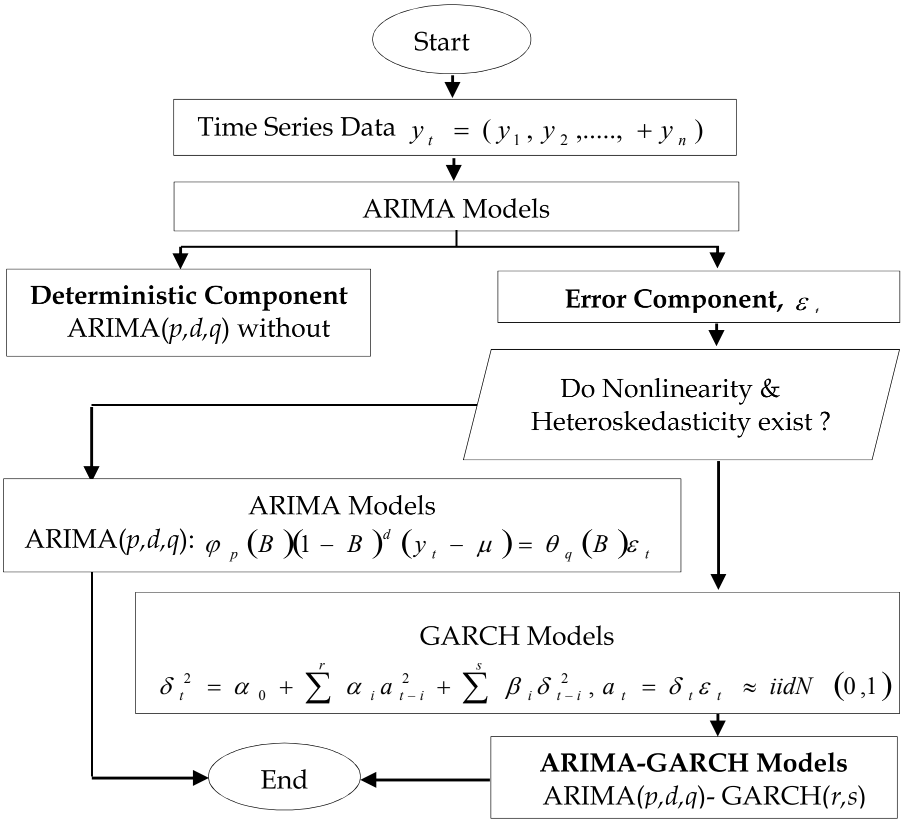
$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{r} \alpha_i a_{t-i}^2 + \sum_{i=1}^{s} \beta_i \delta_{t-i}^2$$

Where δ_t^2 is the conditional variance of y_t, $\alpha_0 \succ 0$ and $\sum_{i=1}^{(r,s)} (\alpha_i + \beta_i) \prec 1$. Note that α_i and β_i are the coefficient of the parameters ARCH and GARCH, respectively.

2.2.3 ARIMA-GARCH model

ARIMA can in fact be combined with ARCH/GARCH. The latter is a method to measure volatility of the time series, or more specifically, to model the noise term of ARIMA. It incorporates new information and analyzes the series based on conditional variances where users can forecast future values with up-to-date information. The forecast interval for the hybridized model is closer than that of ARIMA[29]. The methodology of this hybrid procedure is shown in Figure 2.

Figure 2. Flowchart of the procedure for ARIMA-GARCH models



Source: Yaziz et al 2013, 1204.

3. Results and Discussion

3.1. Data presentation

Data was provided by MSCI Inc. It consists of daily closing values of the MSCI stock market index for both Morocco and Tunisia. Data covers the period from December 30, 2013 until December 30, 2016. (785 observations). Figure 3 and Figure 4 show that the two price series are very irregular with varied degrees of fluctuation. The two time series plots clearly show that the mean and variance are not constant, showing non-stationarity of the data.

Figure 3. Morocco's Stock Prices Index

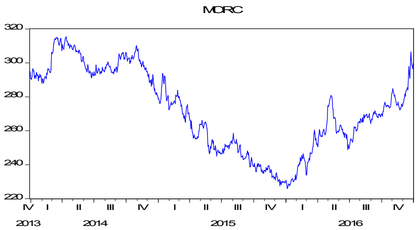
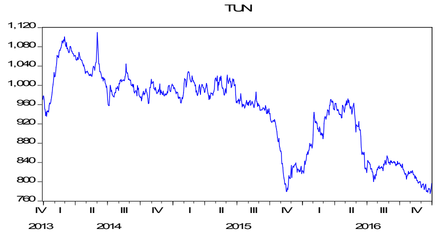


Figure 4. Tunisia's Stock Prices Index



Source: Eviews 9 outputs.

Returns were plotted using Eviews9. Figure 5 and Figure 6 show that both return series are stationary and exhibit no trend and the amplitude varies with time. Volatility clustering is also evident. We will check this with the ADF test.

Figure 5. Morocco's log returns plot.

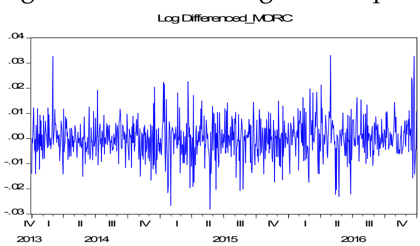
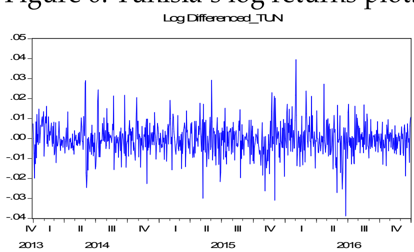


Figure 6. Tunisia's log returns plot.



Source: Eviews 9 outputs.

The Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981)[30] as given in Table 1 indicates that the two return series are stationary as the absolute value of statistics is greater than the critical value and thus, both the Moroccan and the Tunisian time series are suitable for modeling.

Table 1. Augmented Dickey Fuller test statistic for return series.

		Model (3)	Model (2)	Model (1)
ADF statistics	Morocco	-27,146	-27,438	-27,113
	Tunisa	-27,080	-27,068	-27,058
Critical value (5%)		-3,475	-2,903	-1,945

Source: Eviews 9 outputs.

3.2. Descriptive statistics

Table 2 shows summary statistics for both the price and the return series.

Table 2. Descriptive statistics

Statistics	Prices		Returns	
	Morocco	Tunisia	Morocco	Tunisia
Mean	271.87	943.46	2.07e-05	-0.0002
Median	270.99	965.99	8.63e-05	-0.0004
Maximum	315.48	1109.85	0.033	0.0395
Minimum	225.93	775.53	-0.028	-0.0387
Std-Dev	24.41	81.49	0.007	0.0082
Skewness	-0.04	-0.46	0.184	0.1034
Kurtosis	1.82	2.11	4.937	5.3829
Jarque-Bera	45.32	53.98	127.081	186.894

Source: Eviews 9 outputs.

The results clearly emphasize the high volatility of the studied markets since the standard deviation of both markets' returns is relatively high in comparison with the mean. Both price series have negative skewness implying that the distribution has a long left tail. On the other hand, the return series have positive skewness implying that the distribution has a long right tail. The values for kurtosis are high (above three) for both return series implying they are leptokurtic. The Jarque-Bera test (Jarque & Bera, 1987)[31] rejects normality at the 5% level for all series. We can conclude that the data sample contains volatility clustering and leptokurtosis.

3.3. Prediction by the neural networks model

3.3.1 Data segmentation

The model will be applied on two data sets, with 785 observations for each. Both data sets are divided into 3 sets: 70% for training, 15% for testing and 15% for validation. Each time the number of delays (r) and the number of neurons (n) in the hidden layer are modified.

3.3.2 Model specifications

All details about the model are displayed in Table 3. In the training phase, values are presented to the network which is expected to adjust according to its errors. In the validation phase, the network's generalization ability is tested. Training stops when generalization is no longer improving. Finally, the testing phase is specifically designed to measure the network's performance after training is over.

Table 3. Model specifications.

	Moroccan time series	Tunisian Time Series
N° input nodes	1	1
N° hidden nodes layers	3	5
N° Output nodes	One-step-ahead prediction (1)	
NN Model	Feed-forward (Multilayer Perceptron)	
Training algorithm	Levenberg-Marquardt Back-propagation	
Data segmentation	Training: 70%. Validation: 15% Test: 15%	
Type of connection between nodes	Fully connected. No direct connections between input and output.	
Performance function	Minimize MSE*: $\frac{\Sigma(e_t)^2}{N}$	
Activation function of hidden nodes	Hyperbolic Tangent (tanh): $f(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})}$	
Activation function of output nodes	Linear: $f(x) = x$	

Note: * denotes Mean Squared Errors

Source: Elaborated by the authors.

3.3.3 Multilayer perceptron with Back-propagation algorithm

The network was designed using the Neural Network Toolbox that is available on Matlab R2011a. During the training phase, the network keeps adjusting weights until it reaches the highest performance or lowest MSE at the validation phase. After several experiments with different network architectures based on our ANN algorithm, Figure 7 and Figure 8 show the evolution of MSE for both series at all three phases namely, training, validation and testing. It is clear that the convergence of errors was very smooth as the number of epochs increased. Concerning Morocco's price series, the best performance was achieved when MSE at the validation phase reached its lowest value 2.4376 after 61 epochs. Tunisia's price series however, achieved performances with an MSE at the validation phase approximating 34.1077 after 21 epochs only.

Figure 7. MSE vs epochs (Morocco)

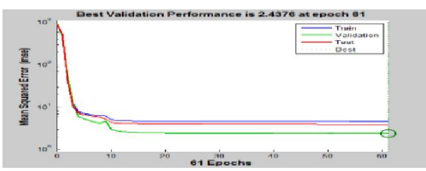
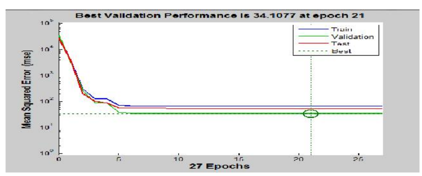


Figure 8. MSE vs epochs (Tunisia)



Source: Matlab R2011a outputs.

Weights that yielded the lowest MSE in the validation phase were saved and the prediction was carried out. Figure 9 and Figure 10 plot the predicted prices versus the real ones for both series. It is clear that the most important errors were in the training phase. However, the network performed very well with both the Moroccan index (MSE in test phase: 2.43) and the Tunisian index (MSE in test phase: 34.10).

Figure 9. Predicted vs real prices (Morocco)

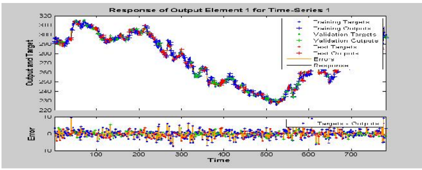
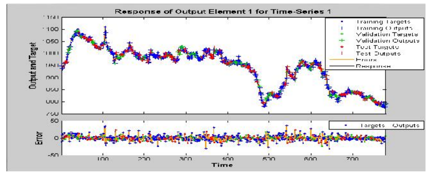


Figure 10. Predicted vs real prices (Tunisia)



Source: Matlab R2011a outputs.

Figure 11 and Figure 12 display the errors' distribution for both series. It is clear that most errors are close to zero (indicated by the orange line). However, prediction errors in the two series seemed to be much more reasonable approximating by the same way the normal distribution. This is usually a strong indication that the network is well behaving.

Figure 11. Errors' distribution (Morocco)

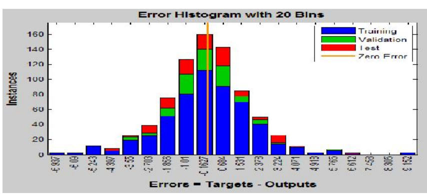
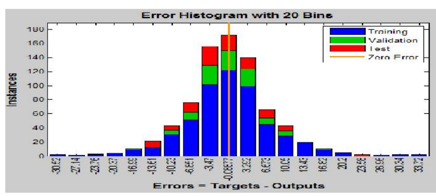


Figure 12.Errors' distribution (Tunisia)



Source: Matlab R2011a outputs.

As a conclusion, the best network architecture that could be obtained from this experiment for Morocco stock price series on the basis of the MSE is (1–3–1) i.e., one node in the input layer, three nodes in the hidden layer and one node in the output layer. The neural network model (1–3–1) provided the best fit to Morocco stock price series. The best network architecture obtained for Tunisia stock price series on the basis of the MSE is (1–5–1) i.e., one node in the input layer, five nodes in the hidden layer and one node in the output layer. The neural network model (1–5–1) provided the best fit to Tunisia stock price series.

3.4. Prediction by ARIMA-GARCH model

3.4.1 ARIMA model

The Box- Jenkins procedure (ARIMA) has been applied on the returns series and the ARIMA (p,d,q) process for both price series has been identified using AIC. Table 4 indicates that the best-fit model for Morocco is ARIMA (6,1,15), and that the best-fit model for Tunisia is ARIMA (12,1,12).

Table 4. Estimation results from ARIMA.

ARIMA(6,1,15) for Morocco	AR(6)	MA(15)
T-statistic	2,707	-1,899
ARIMA(12,1,12) for Tunisia	AR(12)	MA(12)
T-statistic	-2,583	3,078

Source: Eviews 9 outputs.

We have also tested the mean model for an ARCH effect with the ARCH-LM Test. Table 5 shows ARCH(1)-LM test results. The value of the test statistic is greater than the critical value from the distribution, the null hypothesis is rejected. This is a strong indication that there is an ARCH effect in the two models.

Table 5. ARCH(1)LM Test Results

Returns	ARCH(1)LM Stat	P
Morocco	10,600*	0,001
Tunisia	36,864*	0,000

Note: * denotes significant at 5% level.

3.4.2 ARIMA-GARCH model

The GARCH model was used to handle the existence of heteroscedasticity in the residuals. The suggested model was a hybridized ARIMA-GARCH. Table 6 shows the best-fit ARIMA-GARCH model. The best-fit model for Morocco is ARIMA-GARCH(6,1,15)(1,1), and the best-fit for Tunisia is ARIMA-GARCH(12,1,12)(1,1). From the conducted analysis in the estimation stage, both models have shown significance at the 5% level.

Table 6. Estimation Results from ARIMA-GARCH.

ARIMA-GARCH (6,1,15)(1,1) for Morocco					
	AR(6)	MA(15)	C	ARCH(1)	GARCH(1)
Z-Statistic	2,51	-2,24	3,42	3,94	9,37
Coefficient	0,09	-0,08	1,15E-05	0,10	0,69
ARIMA-GARCH (12,1,12)(1,1) for Tunisia					
	AR(12)	MA(12)	C	ARCH(1)	GARCH(1)
Z-Statistic	4,91	-5,69	6,87	8,33	25,66
Coefficient	0,66	-0,70	1,27E-05	0,16	0,71

Source: Eviews 9 outputs.

Figure 13 and figure 14 present the real versus the predicted values for both Tunisia and Morocco using the previously specified ARIMA-GARCH models. For Tunisia, the MSE was equal to 59.37 and for Morocco the MSE was equal to 4.15.

Figure13. Predicted vs real prices (Morocco)

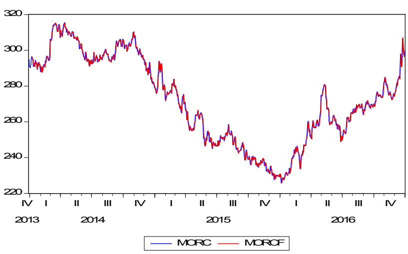
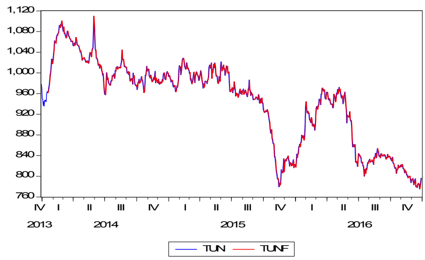


Figure14. Predicted vs real prices (Tunisia)



Source: Eviews 9 outputs.

3.5. Comparison of Neural Networks model and ARIMA-GARCH model

The present study uses the mean squared errors in order to compare between the applied models. Table 7 clearly shows that the multilayer perceptron had a higher predictive ability compared to ARIMA-GARCH. The former was able to produce an MSE equal to 2.43 for Morocco and 34.10 for Tunisia while the latter was only able to produce an MSE equal to 4.15 for Morocco and 59.37 for Tunisia.

Table 7. MSE results for MLP and ARIMA-GARCH

Models	Morocco	Tunisia
MLP	2,43	34,10
ARIMA-GARCH	4,15	59,37

Source: Eviews 9 & Matlab R2011a outputs.

4. Summary and Conclusion

The present study has tried to compare the predictive ability of both the multilayer perceptron and the ARIMA-GARCH model when applied to financial time series and precisely to the stock indices of both Tunisia and Morocco. Results have clearly suggested that the multilayer perceptron with Back-propagation algorithm was able to outperform the ARIMA-GARCH model in terms of MSE. This was the case for both Tunisia and Morocco.

These results are in line with the findings of (Darrat & Zhong, 2000), (Derbal, 2014), (Charef & Ayachi 2016) and many other researchers who found that artificial neural networks have a superior predictive ability not only compared to ARIMA and GARCH models but to any other conventional prediction model. In addition, results from the current paper constitute a significant added value especially when it comes to comparing the predictive ability of artificial neural networks and any other kind of hybridization based on conventional models.

The findings of the present paper have major implications for: (i) the advancement of science in the field of financial prediction as it has clarified the debate regarding two recent prediction models, namely artificial neural networks and ARIMA-GARCH; and (ii) Finance professionals who will be aware about the most efficient prediction models, which will mainly help them make more accurate investment decisions.

Finally, the application of the latest prediction models significantly contributes in making stock markets more efficient. These improvements can be observed in developed markets but more importantly in emerging markets. Even stock markets that are still in an embryonic phase like it is the case for Algeria will benefit from these advancements as soon as the trading volume becomes important enough.

References

1. Foster, W. R., Collopy, F., &Ungar, L. H. (1992). Neural network forecasting of short, noisy time series. *Computers & Chemical Engineering, 16(4)*, 293–297.
2. Kohzadi, N., Boyd, M. S., Kermanshahi, B., & Kaastra, I. (1996). A comparison of artificial neural network and time series models for forecasting commodity prices. *Neurocomputing, 10(2),* 169–181.
3. Tang, Z., &Fishwick, P. A. (1993), Feedforward neural nets as models for time series forecasting, *ORSA Journal on Computing, 5(4)*, 374–385.
4. Zhang, G., Eddy Patuwo, B., & Y. Hu, M. (1998). Forecasting with artificial neural networks: The state of the art, *International Journal of Forecasting, 14(1)*, p 35.
5. J. Yao, C. L. Tan, H. L. Poh, (1999), Neural Networks for technical analysis: a study on KLCI, International Journal of Theoretical and Applied Finance, Vol. 2, No. 2, pp.221–241.
6. Ali F. Darrat, Maosen Zhong. (2000), On Testing the Random-Walk Hypothesis: A Model-Comparison Approach, *The Financial Review 35,* pp 105-124.

7. Manish Kumar. (2009), Nonlinear Prediction of the Standard & poor's 500 and the Hang Deng Index under a dynamic increase sample, Asian Academy of Management *Journal of Accounting and Finance,* Vol 5, N 2, pp 101-118.

8. Y. B. Wijaya, S. Kom, T. A. Napitupulu. (2010), Stock price prediction: comparison of Arima and artificial neural network Methods - an Indonesia stock's Case, *in proceeding of second International Conference on Advances in Computing, Control, and Telecommunication Technologies*, pp. 176–179, Jakarta, Indonesia.
9. Derbal, A. (2014). *An attempt to predict financial time series using various models: the case of Dubai Finacial Market (PhD)*. Abu BekrBelkaid, Tlemcen Algeria.
10. A. A. Adebiyi, A. O. Adewumi, C. K. Ayo, (2014). Comparison of ARIMA and Artificial Neural Networks Models for Stock Price Prediction, *Journal of Applied Mathematics Volume, Hindawi Publishing Corporation.*
11. Fahima Charef, Fethi Ayachi. (2016), *A Comparison between Neural Networks and GARCH Models in Exchange Rate Forecasting*, International Journal of Academic Research in Accounting, Finance and Management Sciences Vol. 6, No.1, pp. 94-99.
12. Cherabi, I. (2014). *On the Behaviorof Financial Markets in the GCC Countries From Market Efficiency to Behavioral Finance (PhD)*. Abu BekrBelkaid, Tlemcen Algeria, p. 94.
13. Moreno, J. J. M., Pol, A. P., &Gracia, P. M. (2011). Artificial neural networks applied to forecasting time series, *Psicothema, 23(2)*, pp. 322–329.
14. Zhang, G., Eddy Patuwo, B., & Y. Hu, M. (1998), p. 37.
15. Ibid, p. 47.
16. Box, G.E.P. and G.M. Jenkins (1970). Time series analysis: Forecasting and control, *San Francisco: Holden-Day.*

17. Hyndman, R. J. (2002). Box-Jenkins modelling. In: The Informed Student Guide to Management Science. *Ed. by H. Daellenbach and R. Flood. Cengage Learning Business Press,* p. 42.
18. Hyndman, R. J. (2002). ARIMA process. In: The Informed Student Guide to Management Science. *Ed. by H. Daellenbach and R. Flood. Cengage Learning Business Press,* p. 27.
19. S.R. Yaziz, N.A. Azizan, R. Zakaria, M.H. Ahmad. (2013), *The performance of hybrid ARIMA-GARCH modeling in forecasting gold price*, 20th International Congress on Modelling and Simulation, Adelaide, Australia, p. 1203.
20. Box, G.E.P. and G.M. Jenkins (1970), p. 19.
21. Makridakis, S., S.C. WheelWright, and R.J. Hyndman. (1998). Forecasting: methods and applications, *New York: John Wiley & Sons.*
22. Akaike, H. (1974), A new look at the statistical model identification, *IEEE Transactions on automatic Control, Vol. 19.*
23. Engle, Robert F (1982). Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation, *Econometrica*, Vol 50, 987-1008.
24. Weiss, A.A., (1982), Asymptotic theory for ARCH models: Stability, estimation and testing, *Discussion paper 82-36 (University of California, San Diego, CA).*
25. Milhoj, A. (1984), The moment structure of ARCH process, *Research report 94 (Institute of Statistics, University of Copenhagen).*
26. Bollerslev Tim (1986). Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics 31*, North-Holland, p. 308.

27. McLeod, A. I. & Li, W. K. (1983). Diagnostic Checking ARMA Time Series Models Using Squared residual Autocorrelations. *Journal of Time Series Analysis, 4*, 269–273.

28. Yasemin Deniz Akarim, Soner Akkoc, (2013), *A Comparison of Linear and Nonlinear Models in Forecasting Market Risk : The Evidence from Turkish Derivative Exchange*, Journal of Economics and Behavioral Studies, Vol 5, N 3, ISSN 2220-6140, p. 165.

29. Ly Pham. (2013), Time Series Analysis with ARIMA-ARCH/GARCH model in R, *L-Stren Group,* p. 18.

30. Dickey, D., Fuller, W. (1981), Likelihood ratio statistics for autoregressive time series with unit root, *Econometrica*, Vol. 49, No. 4.

31. Jarque C. M, A. K. Bera, (1987), A Test for Normality of Observations and Regression Residuals, *International Statistical Review, 55, 2,* pp 163-172, Great Britain.