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A Comparison between Neural Networks and GARCH Models in Exchange Rate Forecasting

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Abstract *Modeling and forecasting of dynamics nominal exchange rate has long been a focus of financial and economic research. Artificial Intelligence (IA) modeling has recently attracted much attention as a new technique in economic and financial forecasting. This paper proposes an alternative approach based on artificial neural network (ANN) to predict the daily exchange rates. Our empirical study is based on a series of daily data in Tunisia. In order to evaluate this approach, we compare it with a generalized autoregressive conditional heteroskedasticity (GARCH) model in terms of their performance. Results indicate that the proposed nonlinear autoregressive (NAR) model is an accurate and a quick prediction method. This finding helps businesses and policymakers to plan more appropriately.*

Key words Nominal exchange rate, Neural Networks, GARCH model, Forecasting, Tunisia

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1. Introduction

During the latest years economists have shown a great interest in exchange rate forecasting. Therefore, a new notion appeared lately in the scientific literature that is the artificial neural network. It aims to improve prediction that helps achieve accurate results and go beyond traditional linear approaches.

Neural networks started to be a forecasting tool that appeals to time series thanks to its modelling of noisy and incomplete time series. Dhamija and Bhalla (2010) have compared the predicting performance of the neural network model to other heteroscedastic models namely ARCH, GARCH, GARCH-M, EGARCH et IGACH for the exchange rate series such as BP/USD, DEM/USD, JPY/USD, et EUR/USD. Results show a great forecasting performance of the neural network model at the expense of heteroscedastic models. Indeed, it is commonly stated that the neural network model remains the most performant compared to heteroscedastic models.

Deniz and Akkoc (2013) have compared GARCH model to neural network model in terms of forecasting stock index volatility ISE30 of Turkey. They finally agreed that neural network is highly superior compared to other traditional models such as Arch and GARCH and this was clearly seen in different fields of finance namely investment decision, stock prices and risk management. The nonlinear model, specifically ARIMA model, was compared to neuronal technique. The latter was claimed to be the best technique in time series forecasting (Zhang, 2001).

Bildirici and Ersin (2012) studied nonlinear models, support vector regression and GARCH model in which they combined GARCH model and neural network to finally get MLP-GARCH and SVR-GARCH model in an attempt to improve the forecasting performance of GARCH model.

In their study which was applied on the daily yields of the stock index of Istanbul ISE100. They compared the different techniques using the error values MSE and RMSE to prove that artificial models are more robust than classical econometric models (GARCH). This study results are based on a comparison between linear models MA and ARIMA and neural network model (Mitrea *et al*., 2009) in an attempt to achieve a modeling capital structure (Hsiao, 2008).

2. Data presentation

Our study has drawn on a sample of three series of daily frequency. We applied three parities of exchange rate on the Tunisian market. They are: the US dollar, the Euro and the Japanese Yen opposed to the Tunisian dinar which corresponds to average interbank course that was extending on the period from 4th of January 1999 to the 30th of October 2014. The following data was provided by the Tunisian central bank including observations of respectively 3964, 3967 and 3286 for the dollar, the euro and the Japanese yen.

Table 1 shows the descriptive statistics of the three exchange rate parities respectively usd/tnd, eur/tnd and yen/tnd.

Table 1. Data descriptive statistics

	USD	**EUR**	**YEN**
Obs	3965	3967	3287
Mean	1.380160	1.690870	13.82220
Médian	1.357500	1.701300	12.32850
Maximum	1.813555	2.334195	20.93577
Minimum	1.090000	1.236700	9.472000
Std-Dev	0.140605	0.306289	2.916549
Skewness	0.637564	0.092028	0.561847
Kurtosis	2.883010	1.930633	2.012421
Jarque-Bera	270.8819	194.6182	306.5130
Prob	0.00000	0.00000	0.00000

Source: Statistic supplied by *Eviews* (version 7.0)

3. Modelling

3.1. Neural network model

In order to determine an adequate architecture, we choose training process in which we vary each time the number of neurons of the hidden layer. Thus we avoid any over fitting or unsuitable architecture. Training is applied until we get a network convergence. Thereafter, we can assume that good network architecture is achieved if only error and test values are getting lower and closer to each other.

In this present paper the network architecture consists of an input, a hidden layer with a sigmoid function of neuron activation, and an output for the activation function of linear type. The output was compared to the required values giving forecasting errors to measure the model performance. A flow chart of neural network is presented below: The data is divided into three separate sets: training, validation and test sets.

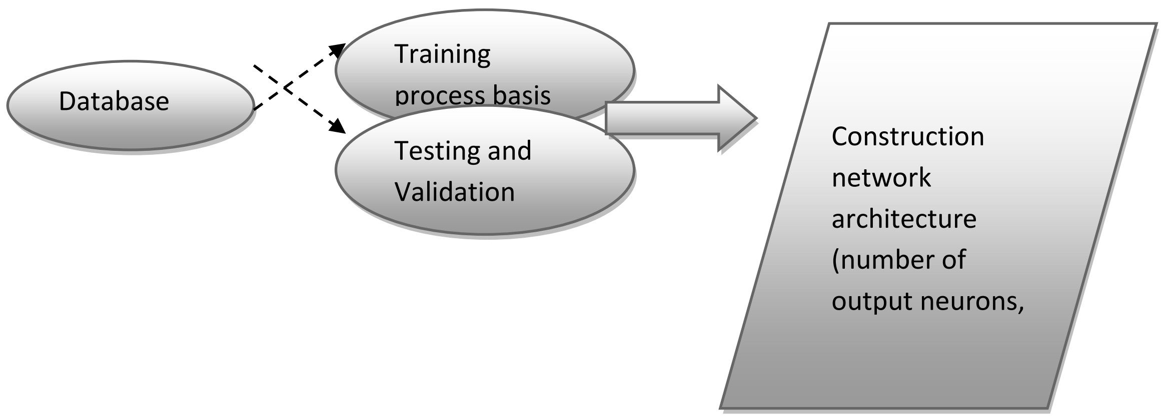


Figure 1. Illustration of the network architecture where input units are connected to hidden units which are similarly connected to the output

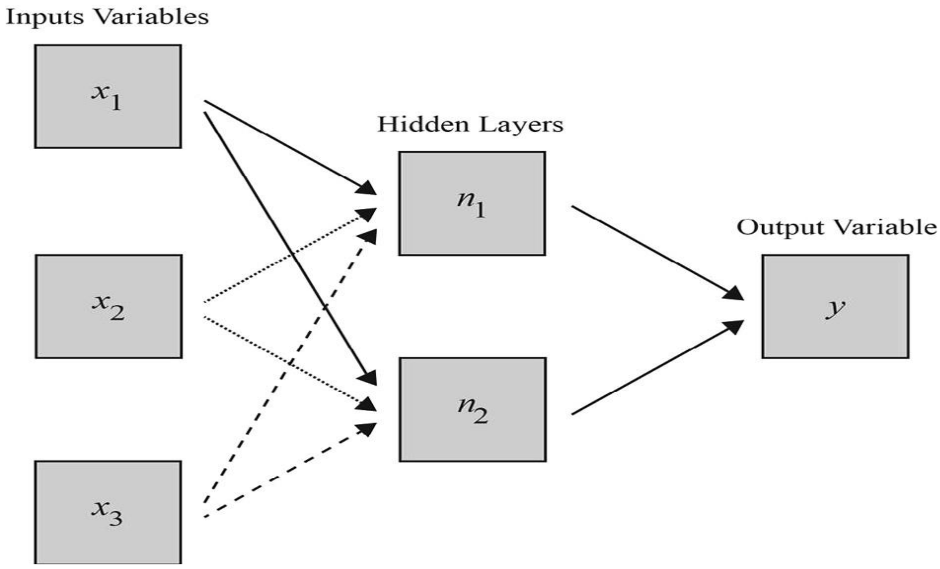


Figure 2. Neural network architecture

3.2. GARCH Model

3.2.1 Stationnarisation

In order to avoid spurious regression we resorted to ADF, PP and KPSS tests to study the stationarity of series. Table 2 illustrates the non stationarity of 3 studied at the levels 1%, 5% et 10 %.

Results extracts from the three tests are presented in this below table:

Table 2

	Cim_usd	Cim_eur	Cim_yen
Test ADF	-0.4813 (0.8924)	0.8500 (0.9949)	-1.2848 (0.6388)
Test PP	-0.6089 (0.8663)	0.7722 (0.9936)	-1.3137 (0.6253)
Test KPSS	3.3703	7.5831	5.6287

Note :p-value is between brackets, Critical values for ADF and PP tests are extracted from the tabulated values given presented by Mckinnon(1996) one sided p-values, These critical values are -3.431 ;-2.862 and -2.567 respectively at the level of significance 1%, 5% and 10%. The critical values of statistics KPSS are 0.739; 0.463 and 0.347 respectively at the level of 1%; 5% and 10% Tests are performed by EVIEWS (version 7.0).

In order to stationary the three parities of exchange rate, we distinguish between log series so as to address their heteroscedasticity by studying exchange rate yields $\mathbf{r_t}$. By the end, our study focuses on logarithmic returns of exchange rate indicated by : $r_t = \log(S_t/S_{t-1})$

In which S_t et S_{t-1} are the average interbank rates at the instants (t) et (t-1).

Aiming to determine the numbers of lags p and q based on Akaike info criterion (AIC) and Schwarz criterion (SC).

3.2.2. GARCH process

Arch model is a model for the variance of a time series which depends on a set of available information (Engle 1982). This type of model aims to meet the insufficient traditional ARMA representation which doesn't fit with the financial issues. ARCH model was then generalized to be GARCH model and became a staple tool in the field of finance useful not only for analyzing but also forecasting volatility. This consisting in introducing delay values of variance.

GARCH process (p,q) is defined by:

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}{}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}{}^2 \tag{1}$$

Where, $\alpha_0 \rangle 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, $\forall_i, \forall_j$.

4. Empirical results

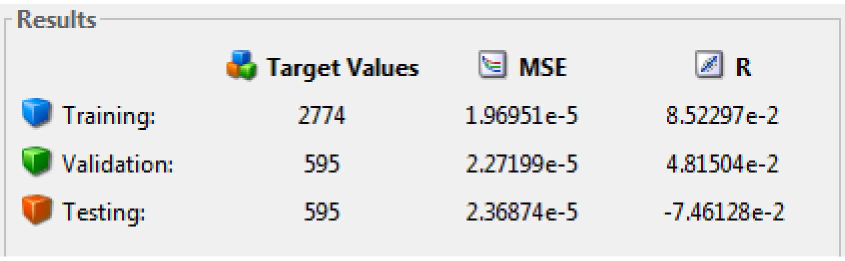
4.1. Prediction by the neural network model

The output of the three series was divided into 3 sets: 70% for training, 15% for testing and 15% for validation. Each time we vary the number of delay (r) and the number of neuron (n) in the hidden layer. The MSE measuring performance varies each time. The results obtained are displayed in the below table respectively for the dollar, the euro and the yen.

Table 3. Choice of the best architecture for the dollar

		MSE				MSE		
n	r	Training	validation	test	r	Training	validation	test
(2)	1	$2.1472.10^{-5}$	$1.9418.10^{-5}$	$1.9133.10^{-5}$	5	2.042010^{-5}	2.214710^{-5}	$2.1543\ 10^{-5}$
	2	2.0551410^{-5}	2.08210^{-5}	2.216110^{-5}	6	2.099510^{-5}	2.219510^{-5}	1.881110^{-5}
	3	1.969510^{-5}	2.271910^{-5}	2.368710^{-5}	7	2.0703710^{-5}	1.884110^{-5}	2.258410^{-5}
	4	2.136110^{-5}	1.996410^{-5}	2.125610^{-5}	-	-	-	-
(3)	1	2.0913910^{-5}	2.172510^{-5}	1.926910^{-5}	3	2.0712310^{-5}	2.188510^{-5}	2.008610^{-5}
	2	2.0501710^{-5}	2.1669610^{-5}	2.159110^{-5}	4	2.068810^{-5}	2.012710^{-5}	2.250710^{-5}
(4)	1	2.063510^{-5}	2.084110^{-5}	2.141310^{-5}	-	-	-	-
	2	2.0743310^{-5}	1.888910^{-5}	2.252410^{-5}	-	-	-	-

Mean Squared Error (MSE) in grey colour corresponds to the selected optimal architectue, RN(3,2) where 3 is the number of lags and 2 is the number of neurones in the hidden layer of dollar estimation.


Results

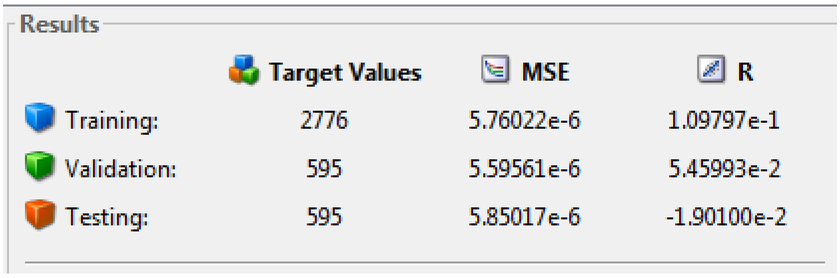
	Target Values	MSE	R
Training:	2774	1.96951e-5	8.52297e-2
Validation:	595	2.27199e-5	4.81504e-2
Testing:	595	2.36874e-5	-7.46128e-2

Figure 3. Usd/tnd yield estimation by the neural model with 3 lags and 2 neurons in the hidden layer

Table 4. Choice of the best architecture for the Euro

		MSE				MSE		
n	r	Training	validation	test	r	Training	validation	test
(2)	1	$5.8861.10^{-6}$	$6.0856.10\text{-}^{6}$	$4.8867.10^{-6}$	4	5.753410^{-6}	5.54710^{-6}	$5.8687\ 10^{-6}$
	2	$5.9373.10^{-6}$	$5.7562.10^{-6}$	$4.9571.10^{-6}$	5	5.876110^{-5}	5.988810^{-6}	5.211010^{-6}
	3	$5.8291.10^{-6}$	$5.7562.10^{-6}$	$6.2384.10^{-6}$	6	5.896910^{-6}	5.556710^{-6}	5.236910^{-6}
	1	$5.7333.10^{-6}$	$5.4197.10^{-6}$	$6.3892.10^{-6}$	-	-	-	-
(3)	2	$6.6093.10^{-6}$	$6.3612.10^{-6}$	$5.7091.10^{-6}$	-	-	-	-
	3	$5.8026.10^{-6}$	$5.5396.10^{-6}$	$6.0068.10^{-6}$	-	-	-	-
(4)	1	$5.7602.10^{-6}$	$5.5956.10^{-6}$	$5.8501.10^{-6}$	-	-	-	-
	2	$6.0354.10^{-6}$	$5.0501.10^{-6}$	$5.4154.10^{-6}$	-	-	-	-

Mean Squared Error (MSE) in grey colour corresponds to the selected optimal architectue, RN(1,4) where 1 is the number of lag and 4 is the number of neurones in the hidden layer of Euro estimation.



Results

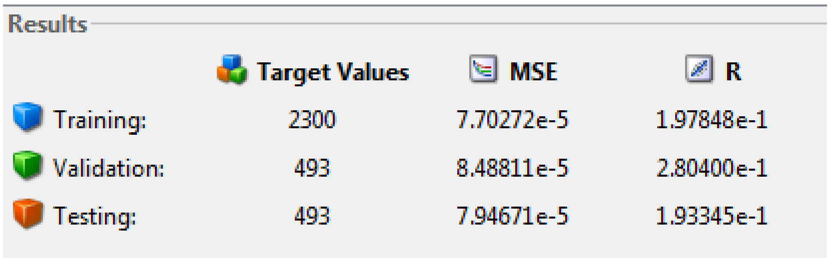
	Target Values	MSE	R
Training:	2776	5.76022e-6	1.09797e-1
Validation:	595	5.59561e-6	5.45993e-2
Testing:	595	5.85017e-6	-1.90100e-2

Figure 4. Eur /tnd yield estimation by the neural network with 1 lag and 4 neurons in the hidden layer

Table 5. Choice of the best architecture for the Yen

	MSE				MSE			
n	r	Training	validation	test	r	Training	validation	test
(2)	1	$7.8634.10^{-5}$	$7.5121.10^{-5}$	$8.6910.10^{-5}$	5	7.987210^{-5}	7.455410^{-5}	$8.1126\ 10^{-5}$
	2	$8.1260.10^{-5}$	$8.8741.10^{-5}$	$7.6085.10^{-5}$	6	7.918210^{-5}	8.738810^{-5}	8.416210^{-5}
	3	$8.4229.10^{-5}$	5.8397.10-5	$7.4529.10^{-5}$	7	7.893310^{-5}	$8.089.10^{-5}$	7.48810^{-5}
	4	$8.1616.10^{-5}$	$7.0339.10^{-5}$	$7.7616.10^{-5}$		-	-	-
(3)	1	$7.9914.10^{-5}$	$8.0718.10^{-5}$	$7.2322.10^{-5}$		-	-	-
	2	$7.9694.10^{-5}$	7.284510^{-5}	$7.7493.10^{-5}$		-	-	-
	3	$7.7027.10^{-5}$	$8.4881.10^{-5}$	$7.9467.10^{-5}$		-	-	-
(4)	1	$7.9259.10^{-5}$	$8.6205.10^{-5}$	$7.6758.10^{-5}$		-	-	-
	2	$8.2746.10^{-5}$	$7.0129.10^{-5}$	$6.4446.10^{-5}$		-	-	-
	3	$8.0581.10^{-5}$	$7.5765.10^{-5}$	$8.0267.10^{-5}$		-	-	-

sMean Squared Error (MSE) in grey colour corresponds to the selected optimal architecture, RN(3,3) where 3 is the number of lags and the other 3 is the number of neurones in the hidden layer in the Yen estimation.



Results

	Target Values	MSE	R
Training:	2300	7.70272e-5	1.97848e-1
Validation:	493	8.48811e-5	2.80400e-1
Testing:	493	7.94671e-5	1.93345e-1

Figure 5. Yen/tnd yields estimation by the the neural network with 3 lags and 3 neurons in the hidden layer

4.2. Forecasting by GARCH model

According to the Akaike and Schwarz criterion which determines the number of delay p =1 and q=1, GARCH process is defined as follows:

$$\sigma^2{}_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}{}^2 + \beta_1 \sigma_{t-1}{}^2 \qquad (2)$$

The forecast of the three yields is provided in the table below:

Table 6. Forecasting yields of exchange rates

Criterion	r -dol_-di	_r -eur_-di	r_-yen-_di
RMSE	0.004564	0.002405	0.009058
MAE	0.003422	0.001803	0.006581
Thell	0.9654	0.9424	0.9951

4.3. Comparing the neural network to the GARCH model

Root mean square error (RMSE), is the most popular criterion forecasting. We resort to RMSE in this paper to compare the quality of the models.

models	r_dol_di	r_eur_di	r_yen_di
RN(r,n)	0.004437	0.002400	0.008776
GARCH(1,1)	0.004564	0.002405	0.009058

Source: Table 6. RMSE criterion

The above given results show clearly that the neural network model is more robust and the more efficient in forecasting exchange rates compared to heteroscedastic models. Hence, it is agreed upon that this technique remains the most superior one in different empirical research fields.

5. Conclusions

In this paper, we found that the neural network, robust as it is, remains undoubtedly the most efficient model in forecasting time series as claimed by different participants in the exchange market who used these techniques instead of traditional statistic models so to forecast the evolution of exchange rate which helps reduce the risk of exchange rate market. However, new other new techniques such as the hybrid model could be used to get more accurate results when dealing with economic or social problems.

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