Using ANN in Financial Markets Micro-structure Analysis

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Abstract: *The present document presents/displays a model of Neuronal Networks Artificial RNA for the prognosis of the rate of nominal change in Colombia, including flow orders and the differential of the interest rates like variables of entrance to the model. Additionally methodological conclusions from the traditional treatment of the series of time were extracted.*

Keywords- Type of Nominal Change, Artificial Prognosis, Not-Linear model, Neuronal Networks, Micro-structure of the financial markets**.**

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1. Introduction

The analysis for modeling and forecasting the exchange rate of one currency against other has had several important stages. In this sense, the first models developed have, as its starting point, the balance of flows between countries, the raised of the rate could be determined by supply and demand functions for foreign exchange each of the countries, including models are part of this line of development are those of Meade (1951) and Mundell - Fleming (1963) mentioned by Manrique (2001).

Subsequently with the dynamic acquired by the financial markets and the collapse of the Bretton Woods, several models appeared in which the international trade, international flows of trade, the price of exports, domestic goods and international portfolio of assets, were taken as variables relevant to the determination of the exchange rate. This approach is called the balance of stocks or asset market, which is divided into monetary models (flexible price, sticky prices) and balance models, which attempt to explain the fluctuations in the exchange rate using a process similar to that Prices are subject to other financial assets. Currently in Colombia the literature dealing with microeconomic models and the exchange rate is not very wide, in contrast to the literature on real rates, Cárdenas (1997) mentioned the work of Wiesner (1978), Urrutia (1981), Lopez (1987) and Steiner (1987) on the process of crawling peg in Colombia's crawling peg system. The work of Cardenas (1997), analyzes the determinants of nominal exchange rate in the period 1985-1986, under the two regimes, crawling peg and bandas[65] system, through: a simple monetary model, the fixed-price monetary model and portfolio balance model, the conclusion about the determinants suggests that the monetary model with flexible prices is set in a good way the behavior of the Colombian exchange rate. According to the exchange rate model responds to changes in the money supply and interest rates. In this context, based on the microstructure and RNA, and taking into account the criticism entirely macro models of Evans and Lyons (1999) and expressed by Barkoulas, Baum, Caglayan and

Chakraborty (2001) on the processes and martingale type long-term memory, this paper examines the behavior of a forecasting model of the TCN of the peso For against the U.S. introduce a variable dollar of market microstructure (order flow) in a system of daily observations with macroeconomic variables (interest rates), under a non-linear modeling of RNA, daily time-series of one (1) year seeking to measure the predictive power and behavior modeling using the root mean square error (RMSE) and absolute average percentage error (MAPE) [67].

For this item is divided into four sections: The first section covered the introduction. Section 2 reviews the related to the RNA and the microstructure of financial markets. Section 3 describes the data, analyzes and presents the results. Section 4 is for conclusions and recommendations.

2. Artificial Neural Networks -ANN- And Financial Markets Micro-Structure

2.1. Artificial Neural Networks

An Artificial Neural Network (ANN) is an attempt to perform a computer simulation of the behavior of the human brain through small-scale replica of the patterns that it plays in shaping results from the events received. More formally the ANN is nonlinear statistical models used mainly for classification and prediction of data and variables, inspired by biological nervous systems, which try to simulate the human learning process in the belief that having been created by the selection process natural mechanism to be efficient. (Montenegro, 2001).

The structure of an artificial neuron is an emulation of a biological neuron so that it could do the following parallel with the biological neuron:

The inputs X_i represent discrete pulses from other neurons and are absorbed by the dendrites (UTP, 2000).

The weights W_i represent the intensity of the synapse connecting two neurons. 0, is the threshold value the neuron must overcome, to produce the biological process within the cell when activated, analogy can be seen in Figure 1.

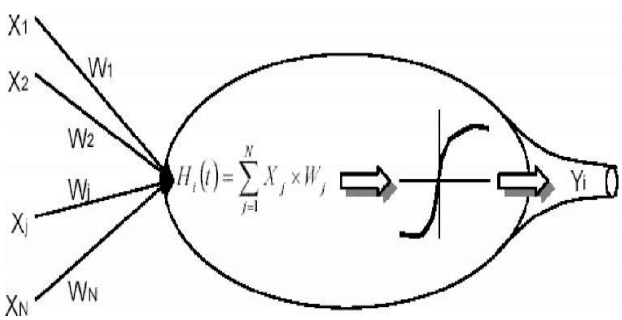

Figure 1.ANN structure

Where

***H* (*t*):** Potential synaptic neuron *i* at time *t*.

X_j: input data from the information source *j*.

W_j: The synaptic weight associated with the input X_j

In this project the Multilayer Perceptron-MLP-learning ANN architecture was used, with the backpropagation technique, in which the topology can have an input layer with n neurons, for this case study, we used a layer two neurons for the first model (the order-flow-ODF and the difference between the DTF and the Libor-DDL-with the following setbacks: ODF_{t-1}, ODF_{t-2}, ODF_{t-9}, ODF_{t-13}, ODF_{t-36}, DDL_n, DDL_{t-5}, DDL_{t-6}, DDL_{t-8}, DDL_{t-9}, DDL_{t-17}), and five neurons (TRM_{t-1}, TRM_{t-2}, TRM_{t-3}; TRM_{t-4} *and* TRM_{t-6}) for the second model, at least one hidden layer (with four and eight neurons, for ANN model first and second respectively) also with n neurons and an output layer with m neurons, for these models are used only one output neuron-TRM-in RNA synthesis considered has an architecture with an input layer, a hidden layer and output layer, so it can be expressed as RNA (I, H, O).
The functional architecture of the network is:

$$Y_t = g\left(\sum_{h=1}^{H} c_h\, g\left(\sum_{i=1}^{I} x_{ti} w_{ih} + \theta_h\right) + d\right) \qquad (1)$$

Where c_h are the weights that connect the neuron h in the hidden layer neuron to the output layer and d the threshold of the neuron in the output layer, weights (w, c) and thresholds (0, d) are adjusted during the training of the network. The formula for adjusting the weights of the network depends on the position of the weights connecting layers, particularly if the weights are in the hidden layer or output layer. The base model of the artificial neural network worked is:

$$Yt = g\left(\sum_{h=1}^{H} c_h\, g\left(\sum_{i=1}^{I} x_{ti} w_{ih} + \theta_h\right) + d\right) \qquad (2)$$

2.1.Financial Market Microstructure and Exchange Rate

The microstructure of financial markets is the study of the processes and outcomes that occur in exchanging assets under explicit trading rules (Marín and Rubio, 2001).

This microstructure focuses on the interaction between the mechanisms of the negotiation process and its results in terms of prices and quantities traded. It is recognized that specific rules under which the negotiation process occurs directly affect the outcome of such processes, i.e. the behavior of agents in the game of supply and demand determine the price and transaction volumes.

The support of the microstructures for the TCN study is summarized in order flow and spread, the first concept concerns the volume of transactions and the same meaning, i.e. the volume to settle and if bought or sold, the that is treated as excess demand, any time you perform an operation does not necessarily imply a zero-sum balance, the latter in turn is conditional on the price as it enters the information asymmetries in financial markets will.

It is also important to mention that the approach of modeling TCN microstructures at the following address:

$$P_t = f(X, I, Z) + g(i) + \varepsilon_t \qquad (3)$$

3. Empirical Analysis

3.1. Available Data

The availability of detailed databases on the intraday and daily activity in financial markets has opened the possibility to econometric research on the functioning of these markets, therefore the flow volume order ODF, TRM and the differential rate DDL Libor interest from April 16, 2003 to April 16, 2004 ™.

The set of training artificial neural network is defined according to a measure of error between the data generated and the training set (actual data), this value usually varies, whereas small values.

In the training process is likely that if the RNA undergoes a process of overtraining, which causes the RNA from a loop or has a sub training process, then both processes, the RNA lose their adjustment capacity, prognosis and generalization (Buitrago and Alcala, 1998). In regard to the variable interest rate differential (DDL) was taken, the libor ninety 90 days macroeconomic component of the U.S. economy, the source of the data is the system REUTER and Colombia is ninety took the DTF 90 This data comes from the website of CORFINSURA. The foreign exchange market in the country is relatively new 1991. Finally, taking into account the definition given before order flow, this is calculated as the difference between all the purchase transactions initiated (T) and all transactions initiated on sale (P) on the same day, so if $OD > 0$ is more intent to purchase and therefore upward pressure on exchange rate - which is not necessarily explained by macro variables of the market - and when $OD < 0$ the reverse process occurs.

3.2. Results Analysis

Figure 2 shows the variables in levels. Hopefully, a high volatility characteristic of financial time series. Using the ADF and KPSS tests determined the stationary of the series.

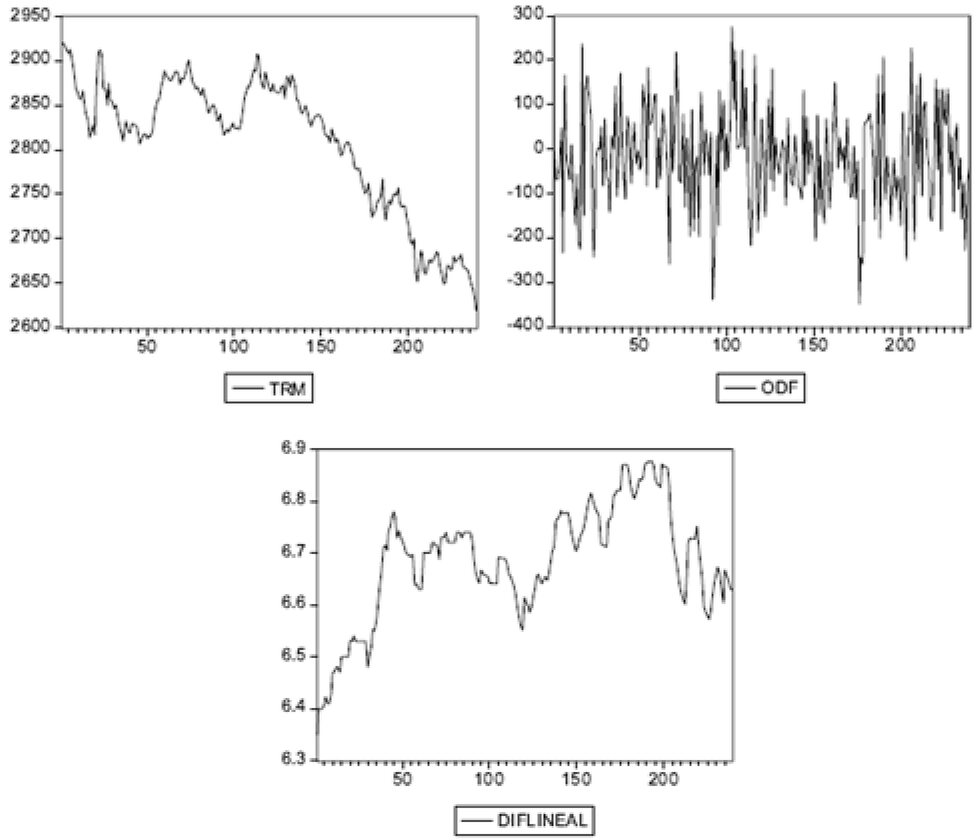

Figure 2. Level Series

	ADF	Critic Value 1%	KPSS	Critic Value 1%	Decision
TRM (1)	-1.829393	-2.574714	1.550905	0.739	KD
ODF(2)	-15.03944	-3.457747	0.173559	0.739	1 (0)
DIFERENCIAL	-2.66635	-3.457865	0.851827	0.739	KD

Table 1. Unit Root Tests

- (1) Q(36) = 44.25(0.163)
- (2) Q(36) = 43.19(0.191)
- (3) Q(36) = 22.937(0.955)

The results show that at a significance level of 1%, and TRM series of interest rate differential is not stationary. ODF Series is stationary. Additionally we present the Ljung-Box test for the residue of the auxiliary regression in each case and in brackets the p-value associated with the test.

In the case of parametric models should be considered the property of stationary. Below are the results of Johansen co integration test and univariate models for forecasting TRM worked with the first difference in natural logarithm (which is the return compounded continuously).

3.3 Artificial Neural Network Models - ARN

As explained previously, RNA did not have a specific parametric model, which was done, was to vary the input vector, independent variables, order flow, differential interest rate (DTF-Libor) at time t and lag in *t*.

For the first model to implement the 8 - test, we obtained the following most significant setbacks for the model: (ODF_{t-1}, ODF_{t-2}, ODF_{t-9}, ODF_{t-3}, ODF_{t-36}, DDL_{t-1}, DDL_{t-5}, DDL_{t-6}, DDL_{t-8}, DDL_{t-9}, DDL_{t-17})

For the second model considers the TRM behind a $t = 1$, like an $AR(p)$, in this case, gives significance to the lags TRM_{t-1}; TRM_{t-2}; TRM_{t-3}; TRM_{t-14}; TRM_{t-16}

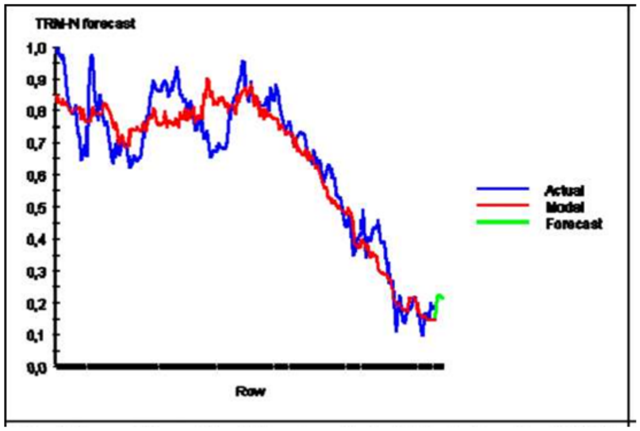

Figure 3. ANN Model 1 Forecast $h = 10$

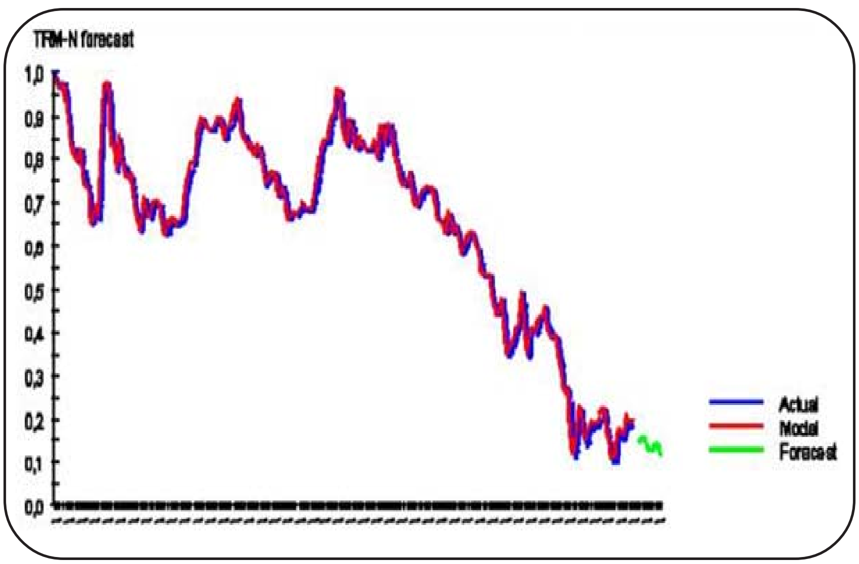

Figure 4. ANN Model 2 Forecast $h = 10$

Finally it is needed to mention, that forecast, we see that as time goes by (days) in model 2 of RNA loses predictability, however, their test statistics (MAPE, RMSE and approximately R2) behave appropriate and acceptable values, which makes RNA techniques to forecast the TRM a viable tool in the manner presented.

	RMSE	**MAPE**	**R^2**
	Forecast 10 datos		
RNA Model 1	0.0775	10.54870	93.54
RNA Model 2	0,036	5.671	97.3662

Table 2. Statistical Models AR (p) and RNA - One year

3.4 Time Series Model Multivariate Analysis

The following table presents the johansen cointegration test. In all cases occur in the trace test. Results were obtained using 2 lags

In all cases there is one co integrating vector. However, as discussed above, one of the variables is 1 (0), which may affect this conclusion, in particular, this variable may be the one that forms the co integrating vector. Using the schwartz criterion, the model was first considered appropriate. In estimating the vec was obtained the following results:

Vectors	Modelo 1	Valor Crítico 1%	Modelo 2	Valor Crítico 1%	Modelo 3	Valor Crítico 1%	Modelo 4	Valor Crítico 1%
None	99.38	29.75	104.03	41.07	100.82	35.65	106.29	48.45
At least 1	7.90(*)	16.31	12.36(*)	24.6	9.59(*)	20.04	14.94(*)	30.45
At least 2	2.42	6.51	2.54	12.97	0.00	6.65	3.52	16.26

Table 3. Johansen Cointegration Test

	TRM	ODF	DIFERENTIAL
Coefficient	1	32.33773	446.6811
Statistical t		[10.4216]	[16.9962]
	Alpha Matrix		
Coefficient	-0.00268	0.024488	-4.18E-07
Statistical t	[-9.72161]	[5.37546]	[-0.61896]

Table 4. Alpha Matrix and Co Integration Vector

	Caused: TRM	
Exelude	**Test**	**P-value**
D(ODF)	96.86	0.00
D(DIFLINEAL)	2.43	0.30
	Caused: ODF	
D(TRM)	2.32	0.31
D(DIFLINEAL)	1.04	0.59
	Caused: DIFERENTIAL	
D(TRM)	1.120	0.571
D(ODF)	1.163	0.559
Portamentau(40)	6.99439	0.6377

Table 5. Granger causality and Portmanteau Test

3.5 Time Series Model Univariate Analysis

It was considered an alternative model of the first difference in the rate of cambio.Un GARCH (1.1).

	COEFFICIENT	z-	P-
c	-0.05	-2.05	0.04
D21	1.52	9.95	0
D25	-1.48	-3.9.4	0
D203	0.87	6.13	0
AR(1)	-0.34	-1.9.3	0.22
MA(1)	0.55	2.31	0.02
	Variance		
C	0.03	1.68	0.09
ARC(1)	0.27	2.97	0
GARCH(1,1)	0.45	2.19	0.02
	Test	P-	
Ljung-Box	34.74	0.17	
Jarque-Bera	0.31	0.85	
Arch(4) Model	1.62	0.80	

Table 6. Garch(L, L) Model.

	Garch(1,1)	Vec	Model 1 ANN	Model 2 ANN
Rmse	22.90	20.66	31.98	17.24
Mape	17.94	15.72	26.93	12.78

Table 7. Forecast Evaluation With Models

The forecast evaluation results show that the neural network model 2 has a better prognosis than the parametric models introduced.

4. Conclusions and Recommendations

This work moves in the direction of the recent work of Evans and Lyons of the microstructure and exchange rate, making a first approach to the case of Colombia, together with a new non-linear approach to model-ANN-raised in the case of Mass inflation, Lopez and Cherub (2002). This approach allows the analysis of how signals are perceived differently by actors and somehow reflected in the microstructure of the information, being, however, asymmetries of the forex market.

The use of ANN, which is typically non-linear statistical models, which can be expressed as a generic model forecasts allowed approximation of functions acceptably good for a model of TRM according to the RMSE, with the inclusion of the variable microeconomic order flow.

The explanatory power of macroeconomic variables, as mentioned by Evans and Lyons (1999), behavior exchange rate in the short term, daily-is very significant, since for the developed models behave as non-significant in this sense the financial market with speculative behavior, explained largely by the order flow is a determinant dollar price in the short term, as the daily trading volume far exceeds the volume of bids and actual demand of the economy, which largely explains the power of financial markets in determining price them.

The structure of the market is in itself is a determinant of prices and the determination of the nominal exchange rate, specifically the order flow as an indicator of the mechanisms of negotiation, agreement and settlement, it affects the price behavior.

As a recommendation on methodology, it would be appropriate to initiate the study of research that merging different techniques of bio-inspired computing such as genetic algorithms and fuzzy logic in order to thus obtain predictive and optimization methods more effective and powerful as they try to simulate human behavior in ways different from the traditional linear models and computational.

References

[1] Baillie, R., Bollerslev, T. (1989). Common stochastic trends in a system of exchange rates, *Journal of Finance*, 44,167-181.

[2] Barkoulas, T., Baum, C., Caglayan, M., Chakraborty, A. (2000). Persistent dependence in foreign exchange rates? A reexamination. Department of Economics and Accounting. University of Liverpool

[3] Buitrago, A., Alcalá, J. (1998). Análisis, Diseño e Implementación de un Prototipo de Sistema Neuronal Para Pronóstico de Series de Tiempo Económicas. Departamento de Ingeniería de Sistemas. Universidad nacional

[4] Cárdenas, M. (1997). La tasa de cambio en Colombia, Editores Tercer Mundo S.A. Primera Edición. Bogotá

[5] Diebold, F. J. Nason. (1990). Nonparametric exchange rate prediction?, *Journal of International Economics*, 28, 315-332

[6] Dominguez, K., (1986). Are foreign exchange forecasts rational? New evidence from survey data, Economic Letters, 21: 277-281.

[7] Dornbusch, R., (1982). Equilibrium and disequilibrium exchange rates, Zeitschrift fur Wirtschafts und Sozialwissenschaften, 102: 573-799; reprinted in R. Dornbusch,Dollars, Debts and Déficits, MIT Press: Cambridge, MA

[8] Grossman., Rogoff, K., (eds.). Handbook of International Economics, Elsevier Science: Amsterdam, 1689-1729.

[9] Flood, R., Rose, A. (1995). Fixing exchange rates: A virtual quest for fundamentáis, *Journal of Monetary Economics* 36, 3-37

[10] Gradojevic, N., Yang, J. (2000). The Application Of Artificial Networks To Exchange Rate Forecasting: The Role Of Market Microstructure Variables, Bank of Cañada December, working paper 2000-23

[11] Kuan, C-M., Liu, T. (1995). Forecastíng exchange rates using feedforward and recurrent neural networks, *Journal ofApplied Econometrics*, 10, 347-364

[12] National Center for Biotechnology Information, http://www.ncbi.nlm.nih.gov

[13] Jalil, M. y Meló, L.F. (1999). Una relación no lineal entre la inflación y los medios de pago". Borradores de Economía Banco de la República