Archives of Business Research – Vol.7, No.8
Publication Date: Aug. 25, 2019
DOI: 10.14738/abr.78.6804.
Flifel, K. (2019). Contribution of the neural networks in the forecasting of financial markets with memory. *Archives of Business Research, 7(8),* 18-33.

Contribution of the neural networks in the forecasting of financial markets with memory

Kaouther Flifel
Doctor in Management Sciences
Institut des Hautes Etudes Commerciales de Carthage - Tunisie

ABSTRACT
The method of the neural networks is beginning to have an impressive range of applications in various fields. Faced with the hope attached by these neural methods by piercing the mysteries of the stock market, appears the notion of long memory and his "conflict" with the efficient market hypothesis. In this article we will try to see the contribution made by this method to beat the old prediction methods such as that of technical analysis in forecasting the financial markets different in terms of their economic development.

Keywords: Forecasting, long memory, Neural Networks, technical analysis.
Jel classification: G170

INTRODUCTION

Since the beginning of the 1990s the artificial neural networks, commonly used in applied physics, make their entries in management science as quantitative prediction method next to so-called conventional methods.

Since the seventies, the efficiency theory dominated the context of analyzing the determinants of stock prices in particular and financial markets in general. But with the frequency of bubbles, crashes and financial crises leading to excessive market volatility, research has expanded its scope to include some of the contributions of statistical methods in the prediction as those derived from artificial intelligence.

The efficient market hypothesis implies that the series of returns are characterized by a lack of memory. However, the predictability of returns in the short term seems to be accepted by the supporters of efficiency. This explains the interest of a study on the phenomena of memory present in the dynamics of financial markets. In conjunction with the forecasting methods, the estimate of the Hurst exponent can help to determine what assets can be expected, and which ones to ignore.

Hoping to get a better prediction of financial markets, the modelisation has to take into account the most important features of profitability (Campbell, Lo and MacKinlay [1997]) and especially that most of the models developed to this neglect the presence of long memory. This concept, introduced by Hurst [1951] while trying to model the Nile floods, characterizes a long-term persistence of the autocorrelations of a time series. This is called hyperbolic decrease. In finance, the series of daily returns exhibit long memory.

In time series forecasting, the first question to answer is whether the time series under study is predictable. If the time series is random, all methods are expected to fail. We want to identify and study those time series having at least some degree of predictability. We know that a time series with a large Hurst exponent has strong trend, thus it’s natural to believe that such time series are more predictable than those having a Hurst exponent close to 0.5. In this paper we use neural networks to test this hypothesis.

There are basically three different basic approaches to analyze stock prices, either with technical analysis, fundamental analysis or artificial intelligence tools especially neural networks.

In practice, many market players use technical analysis in conjunction with fundamental analysis to determine their trading strategy. One major advantage of technical analysis is that experienced analysts can follow many markets and market instruments, whereas the fundamental analyst needs to know closely a particular market.

Thus, the subject of this article encompasses a wide range of issues on which multiple lines of research ranging from the detection of long memory to the test of the contribution of new forecasting methods derived from artificial intelligence and especially networks neural.

LITERATURE REVIEW

Investors in stock market primarily traded stocks based on intuition before the advent of computers. The continuous growth level of investing and trading necessitate a search forbetter tools to accurately predict the market in order toincrease profits and reduce losses. Statistics, technical analysis, fundamental analysis, time series analysis, chaos theory and linear regression are some of the techniques thathave been adopted to predict the market direction (see K.S. Ravichandran, P. Thirunavukarasu, R. Nallaswamy, and R. Babu, (2005)).

The early results from the literature about the profitability of technical trading was overwhelmingly negative. For example Larson (1960), Osborne (1962), Alexander (1964), Granger and Morgenstern (1963), Mandelbrot (1963), Fama (1965), Fama and Blume (1966), Van Horn and Parker (1967), Jensen and Benington (1970) all had shown that the stock market is weak form efficient. By early 1990s, it was concluded that it was not possible to outperform the market using technical trading rules.

However, none of these techniques has been able to consistently produce correct prediction of the stock market, and many analysts remain doubtful of the usefulness of manyof these approaches. However, these methods represented a base-level standard which neural networks must outperform tocommand relevance in stock market prediction.

Although the concept of artificial neural networks (ANN) has been around for almost half a century, only in the late1980s could one ascertain that it gained significant use inscientific and technical presentations. There are quite a lot of research works on the application of neural networks ineconomics and finance (see S. A. Hamid, (2004)).

According to H. White (1988), published the first significant study on the application of the neural network models forstock market forecasting. Following White’s study, several research efforts were carried out to examine the forecastingeffectiveness of the neural network models in stock markets.

E. Avci (2007), it was stated that the study of stock prediction can be broadly divided into two schools of thought. One focuses on computer experiments in virtual/artificial markets. This is often the case when researchers model the complex movements in the market economics (see H. Matsui, Y. Koyama, and K. Ishiuyama (2005)). The other school focuses on stock prediction based on real-life financial data asexemplified in the articles of D. Zhora (2005) and T. Yamashita, K. Hirasawa, and J. Hu (2005).

According to the work ofE. Avci (2007),different studies examined the stock market forecasting applications of neural network modelsfrom different perspective. Some studies considered the effects of modelling preferences on one type of neural networkmodels. In our view, taking into account the long memory is a key point for better risk assessment action.

Prediction of stock price index movement is regarded as a challenging task of financial time series prediction. An accurate prediction of stock price movement may yield profits for investors. Due to the complexity of stock market data, development of efficient models for predicting is very difficult. The study of Yakup Karaa, Melek Acar Boyacioglub(2011) for example, attempted to develop two efficient models and compared their performances in predicting the direction of movement in the daily Istanbul Stock Exchange (ISE) National 100 Index.

Inthe same way and to outperform the traditional linear and nonlinear approaches, The paper of ErkamGuresena, Gulgun Kayakutlua, Tugrul U. Daimb (2011) evaluates the effectiveness of neural network models which are known to be dynamic and effective in stock-market predictions. The models analysed are multi-layer perceptron (MLP), dynamic artificial neural network (DAN2) and the hybrid neural networks which use generalized autoregressive conditional heteroscedasticity (GARCH) to extract new input variables. The comparison for each model is done in two view points: Mean Square Error (MSE) and Mean Absolute Deviate (MAD) using real exchange daily rate values of NASDAQ Stock Exchange index.

SELECTING A NEURAL NETWORK APPROACH

To anticipate the evolution of a stock price, a trader is based on different parameters, it summarizes and draws conclusions based on what they already know and examples that come to mind. Our financial approach will determine the dominant parameters and enter them into the network so that it determines alone the price movement.

Moreover, what value to use for each indicator? As a first case, it is possible to use the value calculated with the closing price. However, traders often attach value to previous one. Thus, it seems more interesting to try to extrapolate the value of the indicator through sub neural networks. Then, an expert system would synthesize information output of each subnet and determine the networks that provide the most reliable information, that is to say those whose weight in the expert system are highest.

This ultimately leads us to propose a two-layer network:

- The first layer is an extrapolation of each indicator
- The second layer is the synthesis between the parameters from the various indicators.

Determination of the output parameter

The aim of the network is to predict the evolution of the share price. It is necessary to choose between two types of parameters:

- A "Boolean" parameter indicating an increase, decrease or constant current.
- A "digital" encoding the probability parameter and the amplitude of the variation.

It appears that the Boolean parameter has the advantage of being more easily analyzable for the investor. Yet the Boolean does not reveal whether the network is more or less confident in his estimate. The choice of the learning was done with integer values, 1, 0 and -1 since for learning, increase or decrease are known with certainty and it is expected to find real values between -1 and 1 for testing.

The input parameters

After speaking of the output parameters, a second problem, which highlights the nature and number of input variables. Indeed, stock prices can take values larger or smaller, depending on the action without the value of the share price itself has influence on its future development. It seems appropriate to consider the relative changes of the course, as it is for the output parameter. This brings the following interests: 0 plays a symmetrical role: all values are greater than 0 increase, declines are lower. In the case of a linear function, neurons will apply equally to values rise and fall.

The following formula is applied to standardization:

$$c'(t) = \frac{2(c(t) - c(t-1))}{(\left(c(t-1) + c(t)\right)V)}$$

With c (t): stock price

And V: algebraic average volatility over the entire database.

$$\text{volatility}\ (t) = \frac{2\ (\max \text{stockprice}\ (t) - \min \text{stockprice}\ (t))}{(\max \text{stockprice}\ (t) + \min \text{stockprice}\ (t))}$$

This difference was related to the volatility to prevent that the network does not give too much importance to variations in the case of very volatile indexes or otherwise stagnating around 0 for low-volatility indices. This precaution was therefore felt necessary to generalize our network for different types of action.

Furthermore, by dividing by ((c (t - 1) + c (t)), the most values are between -1 and 1, -1 indicating a drop of high amplitude while 1 indicates a strong increase.

An idea already exists on the number of input neurons. For short-term analyzes, financial usually use for their indicators, values of 5 to 15 previous courses. The choice was to use 11 inputs corresponding to the number of technical indicators which are added those of two values during the day j and j + 1.

Determination of the number of hidden layers

Each neuron further allows taking into account the specific profiles of input neurons. A larger number makes it possible to better match the data presented but decreases the generalization ability of the network. Here again there is no general rule, but rules of thumb. The size of the layer to be hidden:

- Either equal to that of the input layer (Wierenga et Kluytmans(1994)),
- Or equal to 75% of it (Baets and Venugopal, (1994)),
- Either equal to the square root of the product of the number of neurons in the input and output (Shepard, (1990)) layer.

Note that the last choice reduces the number of degrees of freedom left to the network, and therefore the ability to adapt to the training sample, to the benefit of greater generalization ability.

A path for future research would

Either to the estimation of a neural network having many then simplifies it by the analysis of multi-collinearity or a learning rule eliminating unnecessary neurons

Either define an architecture considering the structure of previously identified variables by principal component analysis. In the following, the choice will be made on a number of hidden layers that minimize the more the error.

Indicators

The indicators used here are those: Rate of Change (ROC), RSI, Moving Average (MA), Momentum (M), MACD, TRIX, Bollinger Bands (ZZ) and Zig-Zag (ZZ)[1].

EMPIRICAL EVIDENCE

Performance metrics

To evaluate the results of neural networks with their different architectures, a number of metrics related to seven different error measurements were used. Each measure interprets the results differently. These measures are:

- Graphical Comparison;
- Scattergram;
- Mean Square Error-MSE;
- Root Mean Square Error-RMSE;
- Normalized Root Mean Square Error-RMSE;
- Prediction Of Change in Directorate-POCID;
- U Theil index.

Database:

The collection, processing and preparation of data for empirical tests were made, largely, from daily data provided by Euronext and EMDB database. Our sample is composed by the indices over the 21 countries ranked by their economic power (composed of 7 economic powers, 7 emerging powers and 7 other emerging powers).

The study is spread over the period from January 2000 to December 2010.

Preliminary study:

To take into account the long memory in financial series, it should be the necessary calculations on the Hurst exponent.

We can estimate the Hurst exponent "H"[2] from the application of the method R/S, and therefore we can deduce the estimate (d) from the relationship: $\widehat{\mathrm{d}} = \widehat{\mathrm{H}} - \frac{1}{2}$. The table in the appendixI provides an estimate of the exponent R/S and Hurst exponent[3].

[1]See "Technical Analysis Of The Financial Markets" John J (1999).

[2]- If H = ½: therefore the process has no dependence on long-term, this type of process is called short memory.

- If ½ < H < 1, the autocorrelations are positive and decrease very rapidly when the delay increases, these are the characteristics of a long memory process.

- If 0 < H < ½, we are talking about anti-persistent process this is explained by rising phases which tend to be followed by phases of decline. This is a particular form of long memory, which was named "anti-persistence of long-term dependency."

[3]The software used is LMA

From the results of the table in annex I, we note that according to the method R/S, all series exhibit a phenomenon of persistence thus demonstrating the presence of long memory because the Hurst exponents are greater than 1/2. Nevertheless, the traditional statistic of R/S does not determine whether the estimated value of H is significantly different or not to 1/2. We can work around this problem by applying the method of R / S amended, which provides us with statistical "V"[4] that we compare it with the critical values given by Lo (1991), which in the case of one-sided test these values are 1,620 1,747 at the respective threshold of 10% and 5%, we find that only six rounds among the twenty-one exhibit long term dependence: the returns of following market indexes: LQ 45, SSE Composite, TUNINDEX, EGX, Tadawul and Merval. For the rest of the series, the memory detected from the traditional analysis of R/S seems to be short-term memory.

Work Methodology

The implementation work program simulation of neural networks is divided into two parts: the programming structure of the network itself, and programming a graphical interface. The interface makes use of the program by playing the role of intermediary between the network functions whose arguments are floating and floating tables on the one hand, and the data processed by the network on the other.

Neurons are easily represented by objects: it is similar entities, able to perform similar operations (calculation of the output of a neuron with a simple function ...) and haves different fields (output of each neuron ...).

As already stated previously, decomposition of the sample into three time series is made and is as follows:

1 A time series for the learning phase,
2 A time series for the validation phase,
3 A time series for testing.

CHOOSING THE IDEAL ARCHITECTURE

The setting values of the model parameters is carried out in the learning phase. These parameters greatly affect the simulation results. The parameters of our ANN model that will be studied later, respectively, the number of epochs (Nepoch), and the number of hidden neurons (Nhidden). The following work helps to highlight the influence of various parameters on the convergence of predicted curves to the exact solution.

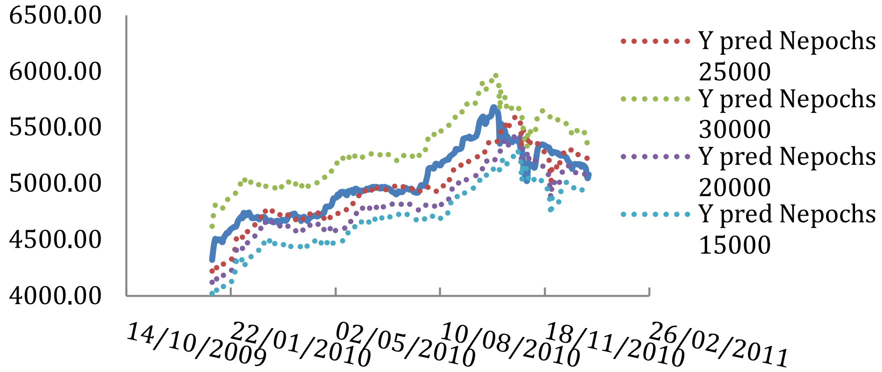
Influence of the number of epochs

In this section, extensive simulations were performed by varying the number of epochs. The other parameters are kept at constant values such as:

- The number of neurons in the hidden layer: 5;
- The structure of the network: 11-5-1.

[4]Lo (1991) defined the statistic V by $V = \frac{\tilde{Q}}{\sqrt{T}}$ where $\tilde{Q}$ is the modified R/S statistics and T the number of observations.

Graphic n°1: Comparison of the simulated response to different numbers of epochs



It can be seen from graphic n°1, that the number of epochs has a great influence on the prediction model. In effect, this should not be too small to avoid the lack of learning and should not be very high to avoid the phenomenon of over-learning. In what follows, it is retained since the 25000 number is the number which is the closest to the desired value curve.

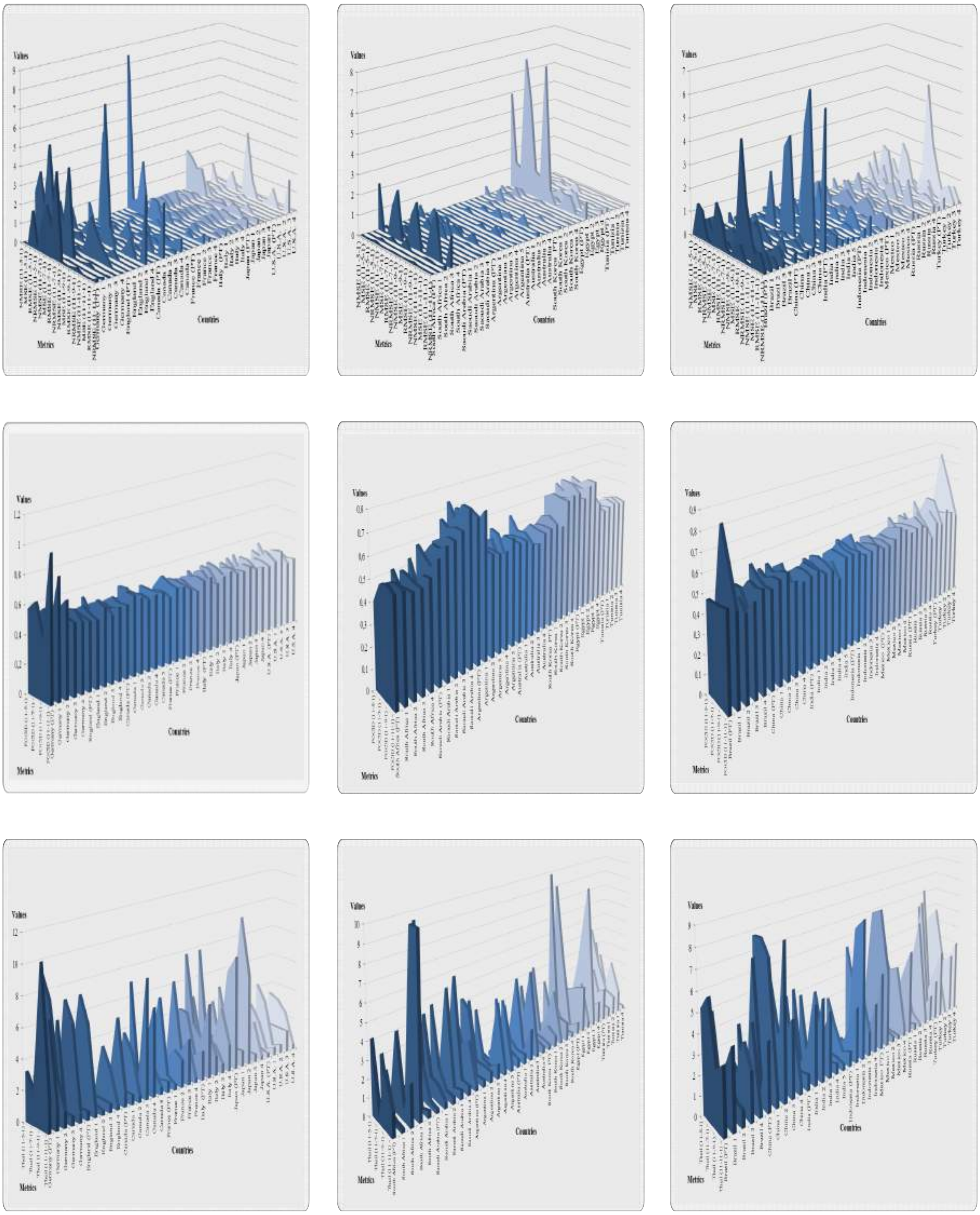
Influence of the number of hidden neurons

To study the influence of the number of hidden neurons on the performance of our model in the learning phase, four values were considered ranging from 5 to 11 with increments of two neurons. The other parameters are fixed to the following values (to achieve the desired result we had to make approximately 260 simulations):

- The number of epochs: Nepoch = 25000;
- The structure of the network: 11-5-1, 11-7-1, 11-9-1 and 11-11-1

By applying different performance metrics cited above, results in the following graphic is obtained.

Graphic n°2:Evolution of the value of four error metrics for the four architectures in the case of developed countries



Note that each metric highlights one or more characteristics. Under the following figures it should be noted, in general, for architecture 11-11-1:

- The value of MSE (as NMSE, RMSE and NRMSE) is the lowest for the majority of countries.
- The POCID metric is larger, the prediction approaches the actual curve.
- U Theil index showed the regularity of sampling. If U <1; the sampling of the database of the learning time is less than that of the database relaxation phase.

Following this remark, it should be noted that the number of neurons in the hidden layers greatly affect the prediction. Indeed, it is found that there is a definite number of neurons from which there will be no decrease in the level of error. Thus, virtual simulations are conducted to carefully stabilize the error. In these graphs, the minimum value of the mean square error is achieved for a number of neurons in the hidden layer 11 equal to (in the following this architecture will be used).

A PERFORMANCE COMPARISON OF NEURAL NETWORKS TO THOSE OF TECHNICAL ANALYSIS

Presentation of the test by the ratio of sterling

The technical analysis on the stock market is based on the principle that information on the evolution of a stock price is included in the values taken by the latter to earlier dates. However, it is difficult to determine in advance the impact of each of these values. The target system would be a "smart" to learn in a number of cases, the evolution of a stock price to infer, by imitation, the trend in the later dates. It is therefore natural that the work is oriented towards the theory of neural networks.

In the wide variety of different modeling techniques of markets, each technique has its own set of supporters and detractors. The common goal of all these methods is to predict the movements of futures markets from past information.

These methods work best when used together. The main advantage of using a neural network is to understand how to effectively use the methods of technical analysis and fundamental analysis together.

The performance obtained with the various models tested are summarized in the table in appendix II.

To make the comparison of performance between technical analysis and neural networks, the ratio of modified Sterling was used.

Developed by Deane Sterling Jones, Sterling ratio is a ratio of return / risk adjusted, which allows investors to measure the return per unit of risk. Theoretically, a high ratio of Sterling is better because it means that the investment receives a higher return for the risk. Its formula is as:

$$\mathrm{Ster} = \begin{cases} \dfrac{\mathrm{R}}{1 + \dfrac{\%\mathrm{MDD}}{100}} & \text{if } \mathrm{R} \geq 0 \\ \mathrm{R} & \text{if } \mathrm{R} < 0 \end{cases}$$

- Where: R is the cost for a period of length "n".
- MDD: Maximum DrawDown as a percentage of initial capital.

Maximum DrawDown is a measure of extreme risk widely used by practitioners to assess capital losses that may occur over a period of investment. This maximum is defined as the greatest loss recorded in relation to the highest level reached by a portfolio over the investment period in question.

In this regard, the ratio of Sterling provides additional information that is not captured by the other measures of performance (such as the ratio of Sharp ...) when it includes the average yield in the numerator and the denominator maximum DrawDown.

RESULT

Sterling ratio seems to be useful for capturing large variations in risk-adjusted performance within each set of tests.

The values presented in annex II show that, depending on the degree of freedom and the observed values, the calculated values are mostly below the critical value. Thus the null hypothesis is rejected and the opposite hypothesis regarding the existence of significant differences between the indices is accepted. Therefore, the hypothesis of a significant difference between the performance of the indices calculated using the model of the neural networks and the market is accepted.

In addition we note that the performance of neural networks is higher in case of emerging countries and emerging powers. This comes to prove the contribution these new methods in case of financial markets with a long memory.

Determining the level of trust and the level of coverage

Evaluation of performance reporting tool is traditionally based on two measurements (confidence and cover), which can be set from the following matrix:

Table n°1:Evaluation of the performance matrix

		Realized	
		Increase	**Drop**
Intended	**Increase**	A	B
	Drop	C	D

Where A and D represent the number of good signals and B and C the number of false signals.

- Trust corresponds to the percentage increase (decrease) correctly predicted:

$$\text{Increase confidence } = \frac{\text{A}}{\text{A}+\text{D}} \text{ and } \quad \text{Lower confidence} = \frac{\text{D}}{\text{C}+\text{D}}$$

- Coverage corresponds to the percentage increase (decrease) correctly predicted:

$$\text{Increase confidence } = \frac{\text{A}}{\text{A}+\text{C}} \text{ and } \quad \text{lower confidence} = \frac{\text{D}}{\text{B}+\text{D}}$$

How then can we properly understand these two measures? For this, a model known as "coin" is used model. This means that for each country and each sub period, a coin is launched to determine if increase (decrease) will occur. This model obviously has very limited explanatory power. Its coverage is 50% (every crisis has a one in two chance of being predicted) and its confidence is equal to the probability of increase (decrease) (if the sample contains 10% increase (decrease) then 10% likely to actually have higher (lower) when a signal is issued). Thus, a model with superior coverage to 50% and a higher likelihood confidence increase (decrease) can be called "better" than the model "heads or tails".

Table 2 shows the performance obtained by the two methods (neural networks and technical analysis).

Table n°2: Comparison of the prediction by neural networks and technical analysis

			France	United States	Angland	Italy	Canada	Japan	Germany	Turkey	Indonesia	Brasil	Mexico	China	India	Russa	Tunisia	Egypt	Sowth Corea	Sowth Africa	Saudi Arabia	Argentina	Australia
Confiance in %	Increase	RN	75	55	43	44	65	66	32	34	65	66	76	78	21	43	45	55	56	88	78	78	56
		AT	23	27	35	65	33	43	23	21	55	45	34	54	55	16	34	44	46	38	47	56	48
	Drop	RN	45	55	77	67	56	55	65	76	67	78	43	45	34	43	56	65	76	79	77	67	56
		AT	11	43	45	33	43	50	24	26	39	29	13	48	35	58	36	38	47	49	35	47	38
Coverage in %	Increase	RN	54	56	46	48	49	33	54	47	32	23	29	43	58	23	21	46	55	38	46	25	39
		AT	25	21	22	40	59	38	46	23	21	23	29	59	23	21	46	55	26	21	29	23	50
	Drop	RN	43	37	59	27	36	45	35	35	26	27	39	33	51	32	44	48	34	25	37	24	32
		AT	27	36	44	34	20	36	44	48	34	25	44	37	25	33	39	40	34	25	32	24	35

The performance obtained using neural networks are excellent on all forecast horizons and confidence is about 75%. This means that when a signal is a crisis actually occurs 3 times out of 4 This high confidence is associated with significant coverage, which allows us to cover 60% to 80% of the episodes.

In technical analysis, the decrease in performance is important. In other words, the performance of the model are twice the model "heads or tails", indicating its ability to provide relevant forecasting financial crises.

The combination of these two methods allows us firstly to provide a reliable forecast of increase (decrease) due to neural networks. On the other hand, the optimized neural network model, tells us what part of this forecast can be explained by economic reasoning. The difference between the two reveals the part that escapes the expertise of the economist and shows the complexity of country risk.

CONCLUSION

A forecast is considered correct if the direction of the anticipated change is the same as the actual direction of change (-, constant, +). Tolerance is taken into account for providing a zero change, that is to say a course (or indicator) constant. For example: if the network provides an price change of 0.02 and that the actual change is -0.01, and the average price change over the period is 0.5; then to a tolerance of 10%, the absolute tolerance of 10% '0.5 = 0.05. Or 0.02 <0.05 | - 0.01 | <0.05, so the forecast and actual match (both indicate a constant current) and the prediction is considered accurate.

With this work, it is easy, finally, to build a network specialized in predicting stock prices better than the method of technical analysis. The prediction results exceed in many cases the success of 55%, up to 65% under the expert systems.

This work was an opportunity to delve into the financial theories of stock market mechanisms. Programming a tool for building networks and its graphic interface allowed to learn and master the Matlab ® software.

One can also note that the network (11-11-1) was almost able to learn by heart a database of over 1000 values. Nevertheless, the results so far are positive and show that the neural network model has mechanisms that may have anticipated with reasonable probability.

The results presented in this work, they are very positive and encouraging, are certainly a real success, but not the end. It would be interesting to test other network structures, to compare different ways of assembling them, see to use other learning algorithms such as radial basis function.

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ANNEXI

Calculating the Hurst coefficients with R/S analysis

	The analysis R / S			The modified R / S			
	Hurst	d of ARFIMA	C_m	Hurst	d of ARFIMA	C_m	V V
CAC 40	**0.835**	0.335	0.592	0.442	-0.058	-0.077	0.630
SP500	**0.544**	0.044	0.063	**0.538**	0.038	0.054	1.350
FTSE100	**0.535**	0.035	0.050	**0.541**	0.041	0.059	1.390
MIBTEL	**0.599**	0.099	0.147	**0.561**	0.061	0.089	1.610
S$P/TSX	**0.577**	0.077	0.113	**0.555**	0.055	0.080	1.550
NIKKEI225	**0.553**	0.053	0.077	**0.534**	0.034	0.049	1.310
DAX	**0.555**	0.055	0.079	**0.555**	0.055	0.080	1.550
ISE-100	**0.548**	0.048	0.069	**0.529**	0.029	0.041	1.270
LQ-45	**0.604**	0.104	0.155	**0.578**	0.078	0.114	**1.850**
BOVESPA	**0.575**	0.075	0.110	**0.531**	0.031	0.043	1.280
IPC	**0.561**	0.061	0.089	**0.547**	0.047	0.067	1.450
SSE	**0.619**	0.119	0.180	**0.566**	0.066	0.096	**1.690**
NIFTY	**0.582**	0.082	0.121	**0.553**	0.053	0.076	1.520
MICEX	**0.573**	0.073	0.107	**0.537**	0.037	0.053	1.340
TUNINDEX	**0.654**	0.154	0.237	**0.600**	0.100	0.149	**2.210**
EGX 30	**0.590**	0.090	0.133	**0.573**	0.073	0.106	**1.770**
KOSPI	**0.565**	0.065	0.094	**0.528**	0.028	0.040	1.250
FTSE JSE	**0.546**	0.046	0.066	**0.511**	0.011	0.015	1.090
TADAWUL	**0.649**	0.149	0.229	**0.575**	0.075	0.109	**1.820**
MERVAL	**0.600**	0.100	0.149	**0.565**	0.065	0.094	**1.670**
SP/ASX50	**0.539**	0.039	0.055	**0.542**	0.042	0.060	1.400

With :

France : CAC 40, **United States** : SP 500, **Angland** : FTSE 100, **Italy**: Mibtel, **Canada**: S&P/TSX, **Japan**: NIKKEI 225, **Germany**: DAX, **Turkey**: ISE-100, **Indonesia**: LQ-45, **Brezil**: Bovespa, **Mexico**: IPC, **China**: SSE Composite, **India**: NIFTY, **Russia**: MICEX, **Tunisia**: TUNINDEX, **Egypt**: EGX , **Sowth Corea**: KOSPI , **Sowth Africa**: FTSE/JSE Afrique, **Saudi Arabia**: Tadawul, **Argentina**: Merval , **Australia**:S&P/ASX 50.

ANNEX II

Performance comparison of the selected network model neuron with that of technical analysis using the ratio of Sterling

		Neural networks	Technical analysis								Buy and Hold
			BB	MACD	M	MM	ROC	RSI	TRIX	ZZ	
germany	(PT)	0,49	0,012	-0,077	0,215	0,052	0,440	-0,046	0,072	-0,022	-0,031
	1	1,231	-0,024	0,113	0,862	0,146	0,284	-0,038	0,299	-0,074	-0,146
	2	0,111	-0,015	-0,085	-0,105	-0,013	-0,016	-0,185	-0,043	-0,043	0,088
	3	**0,288**	0,064	-0,095	0,220	0,073	1,597	0,027	0,159	0,159	-0,260
	4	0,122	0,022	-0,243	-0,117	0,001	-0,105	0,010	-0,129	-0,129	**0,111**
Angland	(PT)	0,250	0,001	0,113	0,028	-0,001	0,245	-0,068	-0,013	-0,013	-0,024
	1	1,550	-0,007	0,180	0,072	0,004	0,405	0,084	-0,026	-0,026	-0,094
	2	0,191	-0,003	0,008	-0,049	-0,014	-0,100	0,091	-0,001	-0,001	0,050
	3	1,260	0,018	0,319	0,198	0,033	1,250	-0,107	-0,007	-0,007	-0,279
	4	1,000	0,000	-0,050	-0,106	-0,022	-0,573	-0,336	-0,016	-0,016	0,090
Canada	(PT)	1,390	0,030	0,371	0,035	0,011	0,195	0,009	0,020	0,020	0,050
	1	0,200	0,019	0,044	-0,155	-0,014	0,025	-0,562	0,012	0,012	0,160
	2	0,980	0,063	0,647	0,146	0,069	0,096	0,456	0,043	0,043	-0,142
	3	0,760	-0,001	-0,017	-0,032	-0,003	0,138	0,291	-0,002	-0,002	0,043
	4	1,750	0,065	1,462	0,338	0,022	1,157	0,224	0,040	0,040	-0,373
	5	**0,109**	0,009	-0,276	-0,122	-0,018	-0,436	-0,360	0,007	0,007	0,115
France	(PT)	0,470	0,017	-0,180	0,033	0,013	0,191	0,024	0,011	0,011	-0,027
	1	0,840	0,032	-0,540	0,140	0,022	0,387	-0,361	0,027	0,027	-0,107
	2	0,101	0,006	-0,183	-0,081	0,001	-0,209	-0,115	0,008	0,008	0,063
	3	0,980	0,039	0,458	0,144	0,024	0,695	0,980	0,022	0,022	-0,184
	4	**0,007**	-0,008	-0,453	-0,069	0,007	-0,105	-0,408	-0,009	-0,009	0,039
Italy	(PT)	0,450	0,018	0,204	0,032	0,008	0,288	0,450	0,016	0,016	-0,173
	1	0,377	-0,004	0,158	-0,056	-0,002	0,377	-0,026	0,002	0,002	0,066
	2	1,218	0,026	0,629	0,194	0,035	0,741	1,218	0,016	0,016	-0,237
	3	**0,026**	0,026	-0,313	-0,199	0,000	-0,132	-0,600	0,019	0,019	0,202
	4	1,201	0,018	0,336	0,184	-0,009	0,159	1,201	0,020	0,020	-0,173
Japan	(PT)	0,410	0,017	-0,058	0,041	0,010	0,307	-0,006	0,013	0,013	0,049
	1	0,450	0,007	-0,531	0,102	0,002	-0,134	-0,353	0,003	0,003	-0,095
	2	0,415	0,007	-0,174	-0,082	0,007	0,356	-0,312	0,009	0,009	0,086
	3	1,100	0,049	0,575	0,196	0,028	0,897	0,789	0,031	0,031	-0,240
	4	0,330	0,006	-0,102	-0,051	0,006	0,113	-0,147	0,011	0,011	0,049
USA	(PT)	0,640	0,014	-0,060	0,028	0,011	0,243	-0,044	0,009	0,009	-0,015
	1	0,530	0,011	-0,580	0,083	0,022	0,285	-0,331	0,000	0,000	-0,081
	2	0,130	0,000	-0,022	-0,030	-0,005	0,061	-0,016	0,001	0,001	0,047
	3	1,440	0,044	0,636	0,205	0,051	1,224	0,482	0,029	0,029	-0,238
	4	1,010	0,005	-0,268	-0,142	-0,022	-0,597	-0,309	0,010	0,010	0,117

Neural **Technical analysis** **Buy**

		networks	BB	MACD	M	MM	ROC	RSI	TRIX	ZZ	and Hold
Sowth Africa	**(PT)**	1,655	0,027	-0,300	0,021	0,024	0,056	-0,037	0,027	0,027	0,054
	1	0,569	0,010	0,092	-0,088	-0,014	-0,036	-0,035	0,028	0,028	0,091
	2	0,956	-0,006	0,025	0,257	-0,038	0,826	0,611	0,030	0,030	-0,230
	3	0,227	0,035	-1,707	-0,034	0,089	-0,593	-0,763	0,008	0,008	0,050
	4	0,948	0,076	0,289	0,033	0,080	0,343	0,276	0,040	0,040	-0,079
	5	1,203	0,024	-0,195	-0,062	0,006	-0,258	-0,274	0,030	0,030	0,054
Saudia Arabia	**(PT)**	0,989	0,015	0,367	0,013	0,024	0,442	0,780	0,017	0,017	0,069
	1	0,687	0,013	0,037	-0,285	0,003	-0,369	-0,182	0,017	0,017	0,281
	2	1,810	0,062	-0,184	0,352	0,075	0,247	1,049	0,041	0,041	-0,345
	3	3,701	-0,055	1,612	-0,135	-0,074	1,309	2,701	0,008	0,008	0,244
	4	1,211	0,060	0,078	0,203	0,123	0,843	0,086	0,024	0,024	-0,265
	5	0,685	0,000	0,297	-0,067	-0,001	0,182	0,249	0,001	0,001	0,069
Argentina	**(PT)**	0,751	0,024	0,291	0,007	0,036	0,143	0,613	0,015	0,015	0,234
	1	1,820	0,022	-0,198	-0,064	0,003	-0,260	-0,276	0,028	0,028	0,056
	2	2,937	0,054	0,984	0,332	0,104	1,062	2,253	0,032	0,032	-0,345
	3	1,184	0,002	0,094	-0,240	0,009	-0,366	-0,132	-0,009	-0,009	0,234
Australia	**(PT)**	0,967	0,020	0,038	0,022	0,011	0,790	-0,042	0,014	0,014	0,051
	1	0,867	0,007	0,095	-0,065	-0,005	0,294	0,071	0,010	0,010	0,074
	2	2,885	0,044	0,231	0,190	0,026	2,389	0,091	0,022	0,022	-0,230
	3	1,715	0,010	-0,209	-0,058	0,014	-0,312	-0,287	0,011	0,011	0,051
Sowth Corea	**(PT)**	0,791	0,048	0,560	0,012	0,058	0,730	0,230	0,009	0,009	0,105
	1	1,456	-0,001	0,475	-0,072	-0,009	0,130	-0,038	0,001	0,001	0,101
	2	2,880	0,141	1,058	0,199	0,170	2,382	0,713	0,022	0,022	-0,330
	3	0,774	0,008	0,150	-0,088	0,016	-0,320	0,019	0,007	0,007	0,105
Egypt	**(PT)**	1,364	0,191	0,626	0,110	0,203	0,984	0,458	0,151	0,151	0,322
	1	0,950	0,074	-0,452	0,151	0,075	-0,207	0,001	0,068	0,068	-0,139
	2	0,880	0,067	0,303	-0,286	0,053	0,079	-0,133	0,079	0,079	0,315
	3	2,840	0,247	1,176	0,285	0,363	2,289	0,471	0,037	0,037	-0,564
	4	1,139	0,642	0,878	0,288	0,627	0,654	0,441	0,653	0,653	-0,260
	5	3,740	0,096	1,816	0,435	0,084	3,522	2,006	0,042	0,042	-0,610
Tunisia	**6**	0,470	0,043	0,053	-0,192	0,034	-0,413	-0,020	0,047	0,047	0,180
	(PT)	0,480	-0,003	0,190	-0,027	0,005	0,161	0,173	-0,007	-0,007	0,112
	1	0,755	-0,004	-0,004	0,062	0,003	-0,247	0,468	-0,009	-0,009	-0,052
	2	0,912	0,000	0,386	-0,114	0,010	0,571	-0,120	-0,003	-0,003	0,112

		Neural networks	Technical analysis								Buy and Hold
			BB	MACD	M	MM	ROC	RSI	TRIX	ZZ	
Brezil	**(PT)**	0,943	0,035	0,630	0,145	0,087	0,432	0,538	0,017	0,017	0,110
	1	0,206	-0,015	0,000	-0,085	-0,002	-0,169	-0,149	-0,014	-0,014	0,126
	2	2,801	0,119	1,633	0,633	0,249	1,781	2,039	0,065	0,065	-0,746
	3	0,643	0,003	0,261	-0,111	0,017	-0,312	-0,271	0,005	0,005	0,110
China	**(PT)**	0,942	0,034	0,355	0,004	0,046	0,519	0,109	0,012	0,012	0,066
	1	0,801	0,071	0,532	-0,083	0,084	-0,321	-0,371	0,013	0,013	0,091
	2	0,887	0,006	0,204	0,062	0,017	0,082	0,619	0,004	0,004	-0,063
	3	0,850	-0,001	0,341	-0,317	0,004	0,241	-0,182	0,006	0,006	0,334
	4	3,004	0,085	0,504	0,414	0,116	2,853	0,727	0,042	0,042	-0,509
	5	0,544	0,013	0,198	-0,054	0,014	-0,255	-0,243	-0,001	-0,001	0,066
India	**(PT)**	2,482	0,004	0,446	0,016	0,006	0,774	2,219	0,022	0,022	-0,003
	1	0,300	0,015	0,066	-0,158	-0,014	-0,181	-0,058	0,029	0,029	0,157
	2	3,368	0,044	1,184	0,309	0,062	3,288	0,970	0,038	0,038	-0,343
	3	0,381	-0,006	0,341	-0,219	-0,002	-0,410	-0,120	0,016	0,016	0,174
	4	9,024	-0,036	0,195	0,134	-0,022	0,398	8,086	0,006	0,006	-0,003
Indonesia	**(PT)**	1,721	0,032	0,910	-0,040	0,064	-0,058	0,058	0,015	0,015	0,172
	1	0,247	0,009	-0,119	-0,177	0,007	-0,608	-0,499	0,020	0,020	0,165
	2	2,600	0,091	2,297	0,283	0,170	1,343	1,173	0,026	0,026	-0,396
	3	1,504	0,003	0,557	-0,221	0,020	-0,905	-0,493	0,004	0,004	0,203
Mexico	**(PT)**	0,299	0,022	-0,048	-0,051	0,019	0,006	0,015	0,011	0,011	0,152
	1	0,230	0,006	0,007	-0,153	0,009	-0,064	0,109	0,008	0,008	0,157
	2	0,631	0,045	0,051	0,157	0,060	0,302	0,385	0,022	0,022	-0,167
	3	0,685	0,019	-0,196	-0,153	-0,009	-0,216	-0,445	0,008	0,008	0,152
Russia	**(PT)**	1,934	0,088	1,138	0,146	0,125	1,441	1,111	0,036	0,036	0,169
	1	**-0,029**	-0,041	-0,168	-0,029	-0,035	-0,074	-0,065	-0,048	-0,048	0,091
	2	7,954	0,277	3,702	0,623	0,389	4,979	3,699	0,130	0,130	-1,172
	3	0,400	0,034	-0,115	-0,150	0,026	-0,578	-0,297	0,031	0,031	0,172
Turkey	**(PT)**	0,832	0,062	0,656	0,073	0,095	0,762	0,826	0,041	0,041	0,069
	1	0,590	0,107	0,385	0,394	0,121	0,423	0,349	0,114	0,114	-0,465
	2	0,831	0,015	0,148	-0,149	0,009	-0,185	0,235	0,029	0,029	0,146
	3	3,855	0,110	2,326	0,420	0,231	1,808	3,804	0,041	0,041	-0,479
	4	1,684	0,039	0,256	-0,315	0,018	-0,271	-0,160	0,049	0,049	0,318
	5	2,940	0,100	1,000	0,278	0,165	2,938	1,123	0,033	0,033	-0,383
	6	0,379	0,003	-0,172	-0,190	0,029	-0,139	-0,389	-0,017	-0,017	0,187