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Comparative study between the FLANN model and the MLP model in the stock market forecast: case of S & P 500

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Abstract

This article highlights a comparative study between the MLP model with the backpropagation algorithm and the FLANN model using the trigonometric expansion function in different experiments to form the model weights for a short forecast (one day, one week) and long-term (one month, two months) closing price of the S & P 500 Index in the US market. In order to know the model that advocates the best forecast, we used appropriate combinations of technical and economic parameters as inputs. Measurement criteria such as: MSE, MAE, MAPE, DA% are used as performance indices to evaluate the quality of model prediction. The simulation and test results showed that the MLP model offers a better prediction than the FLANN model.

Keywords: MLP model, FLANN model, S & P 500 index, technical analysis, fundamental analysis.

1. INTRODUCTION

Currently, the prediction of stock market indices is considered one of the main activities of financial companies in the realization of investments. The main motivation in conducting this research is to study the prediction models of the S & P 500 Index using two different types of nonlinear models. First, the first model used multilayer perceptron architecture (MLP) using a backpropagation algorithm (BP). Second, the FLANN trigonometric functional link artificial neural network model, which has achieved excellent results in many areas of predictive models due to the characteristics that statistical models (ARIMA models) cannot solve. -linéarité. In this way, the idea of developing models of artificial neural networks to improve the accuracy of the prediction is justified.

The main objective of our study is to contribute to the improvement of forecasting models, to anticipate abrupt changes in share prices helped by different methods of anticipation and to adopt the best forecasting technique allowing to obtain the minimum of forecasts. errors. In our article, the predictive analysis focuses on studying the impact of economic variables and technical indicators on the prediction performance of neural networks and comparing the two models MLP and FLANN using performance criteria to find one that can easily predict by minimizing the error term and find the best result to provide accurate predictions.

2. Review of the literature:

Anticipating price movements on the stock market has been a major challenge for shareholders, companies, agents and common speculators. As more and more money is invested, shareholders are worried about future trends in the industry. According to Majhi, R., Panda, G., Sahoo, G. (2009), the FLANN model with least squares (LMS) algorithms as well as the FLANN model with recursive least squares (RLS) algorithms are used in different experiences for a short (one day) and long-term (one month, two months) forecast of the main stock market indices: DJIA and S & P 500. The average absolute percentage error (MAPE) versus real prices stocks is selected as a performance index to assess the quality of model prediction. The simulation and test results showed that the proposed models are structurally simple and required less computation during training and testing because the model contains only one neuron and one layer. Between the two proposed models, the FLANN-RLS requires far fewer experiments to train against the LMS-based model. This feature makes the RLS-based FLANN model more suitable for online prediction.

Mili, F., Hamdi, M. (2013), proposed a hybrid model FLANN (HFLANN), a process carried out using 3 techniques based on the known population such as genetic algorithms, PSO and differential evolution. The results show that the HFLANN model, which has been proposed on the basis of three algorithms, has the ability to converge faster and performs better than FLANN based on the backpropagation algorithm.

Anish, CM, Majhi, B. (2015), developed the FLANN model using factor analysis to improve prediction performance with the RLS algorithm that requires fewer iterations to form the weights of the comparing model. the one with the simulation of principal component analysis methods (PCA) and the discrete wavelet transform (DWT) method.

Hamdi, M., Aloui, C., Nanda, S. k. (2016), used the trigonometric FLANN model using a downshift rule to predict the spot price of US crude oil. The US dollar index, the S & P 500 equity price index, the gold spot price, the heating oil spot price and the US crude oil spot price are used as inputs of the proposed model.

Bebarta, D.K., Rout, A.K. (2016), used a FLANN-based model using the Chebyshev polynomial and the conventional method of neural networks to predict the IBM stock index data. The results show that the structure of the FLANN model is simple and has less complexity on the artificial neural network. By using appropriate combinations of technical and fundamental parameters, it also gives better results.

3. Development of models

3.1. The MLP model

They are organized into 3 types of layers; the first layer is the input layer whose neurons receive the input values of the network and transmit them to the hidden neurons. Each neuron usually takes as input all the nodes of the lower layer. They are an improvement of the perceptron comprising one or more intermediate layers called hidden layers, each neuron of this layer receives information from several previous layers, performs the weighted summation by the weights, then transforms it according to its activation function. Subsequently, it sends this response to the neurons of the next layer, in the sense that they have only intrinsic utility for the neural network and no direct contact with the outside. Finally, since the output layer plays the same role as the hidden layers, the only difference between these two types of layers is that the output of the neurons of the output layer is not linked to any other neuron.

Therefore, several parameters must be adjusted to select the best network topology:

- The number of hidden layers: According to Zhang et al. (1998), the ideal number of hidden layers in a neural network with the backpropagation algorithm is usually one or two layers. According to Masters (1993), the number of lying layers is calculated as follows: NHN = (N input-N output) * 1/2. On the other hand, according to Nielson (1990), the number of hidden layers is calculated by summing inputs and outputs by 2.

- The number of hidden nodes: There are no universal standards for defining the number of hidden neurons (Ögüt et al., 2009). The best procedure is to use the least units to achieve significant results, because too many nodes could deduce a problem of over-adaptation. Some could cause a problem of under-equipment (Kaastra and Boyd, 1996).

- The choice of the activation function: In the use of ANN, there are different activation functions; however, sigmoid and hyperbolic tangential functions are most commonly used in financial applications (Haykin, 1999).

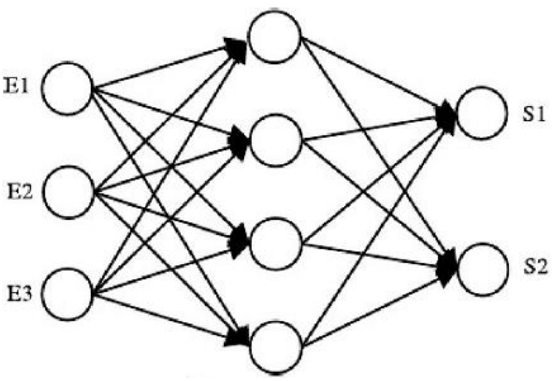

Figure 1 : *Diagram of multilayer networks (Chatelain.C, 2003)*

3.2. The FLANN model:

The functional link of artificial neural networks is a new architecture based on a unique neuron proposed for the first time by Pao (1989). It has been demonstrated that this network can be conveniently used for functional approximation and pattern classification with a faster convergence rate and a calculated lower load than a perceptron multiple layer (MLP) structure. Unlike the MLP, it performs model enhancement using a set of functional expansion functions of an element or the entire pattern. In fact, there are several conventional nonlinear functional extensions such as trigonometry, Chebyshev and power series.

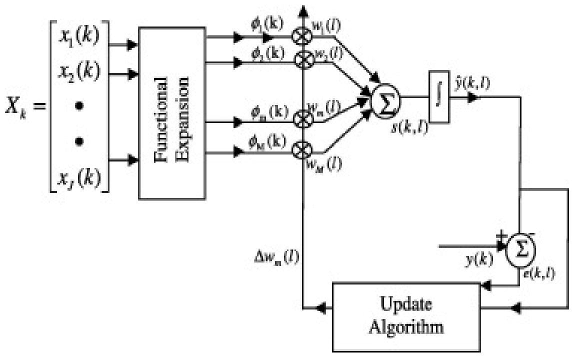

Figure 2 : *The structure of FLANN with a single exit*

4. Experimental setup

4.1. Data collection and feature extraction

The empirical validation is based on the forecast of a daily database of the S & P 500 market index relative to the US market, during the period from January of the year 2000 to October of the year 2015 for a total of 4456 observations using the MATLAB software. For our experiment, we took 33 input parameters for each pattern.

The data obtained for the stock index consist of the closing price, the opening price and the lowest value of the day, the highest value of the day, and the total volume of shares traded each day. Technical indicators predict future price levels or simply the general price direction of a security by examining past trends. A brief explanation of each indicator is provided here:

4.1.1. Moving Averages

The moving average is the most used measure in technical analysis. It belongs to the category of main indicators. It is calculated based on the average closing price over the last ten days. All closing prices in the last 10 days are added and the sum is divided by 10 (creating the average of the period). Then, for each day, an average of ten days is created the new day is included on average and the first is deleted. Therefore, it is called "moving average". We are interested in two most usable moving averages:

- Simple Moving Average (SMA) :

$$SMA = \frac{\sum_{i=1}^{N} CLOSE(i)}{N}$$

- Exponentialmoving average (EMA) :

$$\mathbf{EMA}(\mathbf{i}) = (\mathbf{C}(\mathbf{i}) * \mathbf{P}) + \mathbf{EMA}(\mathbf{i}-1) * (1-\mathbf{P})$$

With:

C (i): closing price for the current period;

P: percentage of use of the price

EMA (i-1): exponential moving average for the previous period.

EMA (0) = SMA.

EMAs of 5.10, 20.30 and 100 days were considered in the experiments.

4.1.2. Stochastic K% D

cThe stochastic indicator is the indicator of the technical analysis created by George Lane (1950). It belongs to the oscillators and measures the relative position of the closing prices in relation to the amplitude of the price oscillations in a given period. This indicator is therefore composed of two curves. The first curve is a simple moving average serving as a signal curve; it's called the% D. The second curve represents the essential calculation of the indicator; it's called the% K. The formulas for calculating the% K and% D lines are:

$$\%\mathrm{K} = 100 \frac{CLOSE(i) - L(n)}{H(n) - L(n)}$$

$$\%D = SMA(\%\mathrm{k}, 3)$$

L (n) is the lowest low and H (n) is the highest value in the last n samples. For n reprsent usually a value of 14 days.

4.1.3. Accumulation / Distribution Oscillator (ADO)

Is an indicator of momentum in the technical analysis created by Marc Chaikin. It measures whether investors generally buy (build) or sell (distribute) by measuring the volume of price movements. The accumulation / distribution is calculated according to the formula:

$$\mathrm{ADO}_t = \frac{(\mathrm{C}_t - \mathrm{L}_t) - (\mathrm{H}_t - \mathrm{C}_t)}{(\mathrm{H}_t - \mathrm{L}_t)} \mathrm{Volume}_t + \mathrm{ADO}_{t-1}$$

With C the closing price, H and L are ups and downs respectively for period t.

4.1.4. On Balance Volume (OBV):

The Balance Volume Indicator (OBV) is a measure of the positive and negative movement of the transaction volume. The value of the indicator is calculated as follows:

- If the current closing price is higher than the previous one: $OBV(i) = OBV(i-1) + volume(i)$
- If the current closing price is lower than the previous one: $OBV(i) = OBV(i-1) - volume(i)$
- If they are identical: OBV (i) = OBV (i-1)

4.1.5. Larry Williams %R

The% R of Larry William is an indicator in the technical analysis of the family of oscillators. Its operation is relatively similar to the RSI and Stochastic indicators. It aims to highlight the levels of over-buying and overselling. It is a bounded indicator that changes between 0 and -100.

The calculation formula is:

$$\%\mathrm{R} = 100 \frac{\mathrm{CLOSE}(\mathrm{i}) - \mathrm{H}(\mathrm{n})}{\mathrm{H}(\mathrm{n}) - \mathrm{L}(\mathrm{n})}$$

with; L (n) is the lowest low and H (n) is the highest value in the last n samples. For n is usually a value of 14 or 28 days. The indicator takes values in the range: (0, -100), which is a little unusual. This is why some analysts add 100 to the value of the indicator. However, negative values should not confuse you. Simple (-100) is the smallest and 0 is the largest value.

4.1.6. Relative Strength Index (RSI)

The Relative Strength Index (RSI) was introduced in 1978 by J. Welles Wilder in his book "New Concepts in Commercial Trading System". It belongs to a group of leading indicators. Welles Wilder, recommends using a 14-day RSI. However, it turns out that the 9-day RSI improves the visibility of signals while the 25-day RSI weights the jumps of the RSI. Analysts therefore work a lot with these two periods. The formula for calculating the relative resistance index is:

$$\mathrm{RSI} = 100 - \frac{100}{1+\mathrm{RS}}$$

Assuming that: GM = average gain; PM = Average Loss; n = number of periods

$$RS = GM / PM$$

$$GM = \frac{\left[GM\,(n-1) + GM\,(n)\right]}{n}$$

$$GM\,(1) = \left(\frac{total\ gain\ in\ the\ first\ n\ periods}{n}\right)$$

$$PM\,(1) = \left(\frac{\left[PM\,(n-1) + PM\,(n)\right]}{n}\right)$$

$$PM\,(1) = \left(\frac{total\ losses\ in\ the\ first\ n\ periods}{n}\right)$$

If the current closing price is higher than the previous one, it is considered a gain. Average earnings are the average of the closing prices. The average loss is the average over the differences where the closing price is lower than the previous one. The most common value for n is 14. Since n is an oscillator smaller than a higher amplitude.

4.1.7. Rate of price change (PROC)

The price change indicator ("ROC") displays the difference between the current price and the price N-periods of elapsed time. The difference can be displayed in points or in percentage. When the rate of change displays the price change in points, it subtracts the N-time price from the current price:

$$\left(Closing\ price\ today - closing\ price\ \text{of}\ \mathrm{N}_{period}\ elapsed\ time\right)$$

When the rate of change displays the percentage change in price, it divides the price change by the N-time elapsed price:

$$\left(\frac{\left(closing\ price - closing\ price\ N_{period}\ of\ elapsed\ time\right)}{\left(closing\ price\ N_{period} of\ elapsed\ time\right)}\right)$$

4.1.8. Acceleration of high prices (HPACC)

It is the acceleration of high prices in the given period.

$$\left(\frac{\text{High Price} - \text{High price N\_periode ago}}{\text{High price N\_periode ago}}\right)*100$$

4.1.9. Average True Range (ATR)

The ATR tries to detect the volatile phases which are often preludes to major changes of trend. It is a measure of volatility presented by Wells Wilder in his book, "New Concept in Technical Trading System". The first step in calculating ATR is the calculation of True Range (TR). The true range is based on the high and low values of the current period (H and L) and the value close to the previous period (C). Second step is the calculation of the ATR using the values of TR. This measure is usually considered a 14-day moving average.

$$TR_t = MAC\left(\left|H_t - L_t\right|, \left|H_t - C_{t-1}\right|, \left|L_t - C_{t-1}\right|\right)$$

$$ATR_0 = TR_0$$

$$ATR_t = \frac{(n-1)ATR_{t-1} + TR_t}{n}$$

4.1.10. Commodity Channel Index (CCI)

Is a technical indicator of the family of oscillators, developed by the American Donald Lambert, in the early 80s. Originally designed to study commodity markets. The higher the ICC, the more there is an overbought situation on the price. Conversely, a very weak ICC indicates an oversold title. First, it will be a question of calculating the average price for each day, according to the following formula:

$$CoursM = \frac{H + B + C}{3}$$

Where H = highest of the session, B = lowest of the session and C = closing price. Then, the moving average of this data series is calculated for each day. The period retained classically is 14 days. Let's call CMM this moving average. Using the preceding data, the "average deviation" is calculated according to this formula:

$$DM\ (i) = \frac{1}{p} * \sum_{n=1}^{14} \left| CoursM\ (i-n) - CMM\ (i-n) \right|$$

Finally, the ICC for each day will be given using the formula below:

$$CCI\ (i) = \frac{CoursM\ (i) - CMM\ (i)}{DM\ (i) * 0.015}$$

4.1.11. TRIX indicator

TRIX is a triple exponential moving average indicator. He would be able to be used a swing indicator. TRIX can be used to anticipate turning points within a trend, when there is a discrepancy between the indicator and prices. TRIX is calculated by the following formula:

$$TRIX = \frac{EMA3_t - EMA3_{t-1}}{EMA3_{t-1}}$$

The calculation of TRIX is based on EMA3 = triple exponential moving average (EMA of EMA of EMA). For the EMA period, the value usually used is 15 days.

Fundamental analysis is the study of the economic, industrial and enterprise conditions in order to determine the value of the course of a company. Four fundamental factors used including gold price, oil price, inflation rate and federal funds rate per day.

4.2. Experimental conditions:

For the FLANN model, each input function is extended to five values, four of which are trigonometric extensions and the fifth is the input itself. The trigonometric functions used are cos πx, sin πx, cos2πx, sin 2πx where x is an input characteristic. For 33 parameters, different statistics of the lag values of the stock index, the total input for the single neuron FLANN is 165 plus a bias. This gives us 166 weights to train using a proper Backpropagation algorithm for our S & P 500 stock index. The linearly weighted sum at the output of the neuron is then applied to the sigmoid-type nonlinear activation function for the MLP model and type (tanh) for all the experiments of the FLANN model. The convergence coefficient is fixed at a constant value of 10-3 for all simulations. Similarly, the initialization constant for the BP algorithm is taken in 1000. The inputs are normalized between + 1 and -1 for the good functioning of the FLANN model and between 0 and 1 for the MLP model.

4.3. Learning and testing process

During the learning process, the weights are updated after they are initialized to random values between 1 and + 1. The weights remain unchanged until the entire set of learning data is applied. sequentially in the network, compared to the desired output, their respective error stored and the weight change in each channel is calculated. The cost function for the training process considered in the article is the mean absolute error (MAE). This average is nothing other than the residual variance that one seeks to minimize. The learning of the network is completed when the minimum level of the cost function is obtained. At the end of the network learning process, the weights are frozen to test the network on inputs that are set apart from the learning set. The performance criterion, to judge the quality of the prediction shown by the model, is the average of all the absolute errors of the test data set. The mean absolute error (MAE) is used to evaluate the performance of the prediction model formed for the test data. The idea is to minimize the EAW to test the models in the search for a better model for predicting price movements of the stock index. The EAW is calculated as follows:

$$MAE = 1/\mathrm{n} \sum_k \left| r_k - y_k \right|$$

5. Simulation study:

- Experiment 1: Data filtering phase with a yield greater than 3% in absolute value, with more than one week before and after.

- Experiment 2: Sensitivity analysis of other technical indicators using price history, simple moving averages and ADO, Williams% R and RSI9 technical indicators as inputs.

- Experiment 3: The 10% test prediction using the FLANN model and the MLP model after choosing the variables.

- Experiment 4: The forecast in advance of a day, a week, a month and two months using the 2 models. Experience5: choice of models.

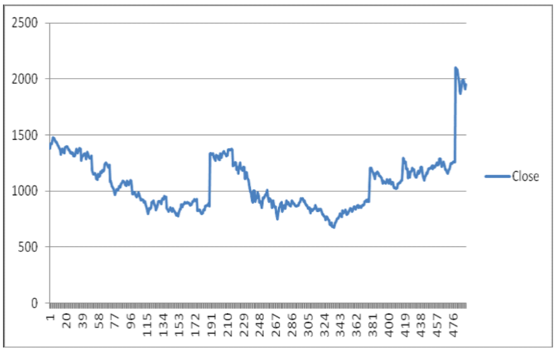

Figure 3 : *The closing price curve before filtering*

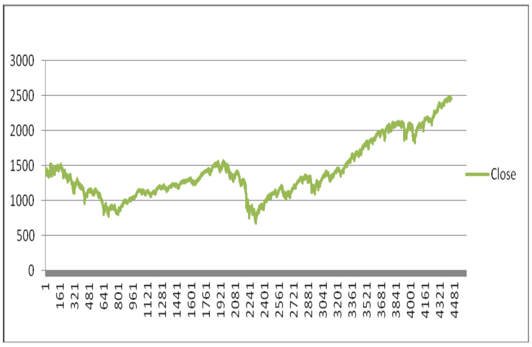

Figure 4 :*The closing price curve after filtering*

Table1: *The impact of the explanatory variables on the price history*

	Price History	**Price History + SMA**	**Price History + EMA**	**Price History + Economic variables**	**Price History + SMA + Economic variables**	**Price History + Other technical indicators**
MSE	0,0055	0,0008	0.0007	0.0038	0.001	0.0029
MAE	0,0599	0,0173	0,0178	0,0512	0,025	0,0448
MAPE	6,6577	2,0630	2.1236	5.9142	3.0865	4.9759

Table2 : *Sensitivity analysis of other technical indicators*

Technical indicators	Part of sensitivity	Percent of sensitivity
ADO	0,3144	36,1379
STO%K14	0,0072	0,8276
STO%D3	0,006	0,6897
OBV	0,0196	2,2529
William's%R14	0,0723	8,3103
RSI9	0,2692	30,9425
RSI14	0,0717	8,2414
PROC12	0,0087	1

PROC27	0,0025	0,2874
CPACC10	0,0097	1,1149
HPACC10	0,0199	2,2874
ATR	0,0201	2,3103
CCI	0,0251	2,8851
TRIX	0,0236	2,7126

Table 3: *Comparison between performance before and after variable selection*

	Results before variables selection	Results after variables selection	Percent of improvement
MSE	0,0009	0,0006	54,4937
MAE	0,0242	0,0164	47,4197
MAPE	2,6863	1,8273	47,01
CORRELATION	0,985	0,9908	0,6095
DA	92	96	4,167
TIME	1532	615	149

Table4 :*The final results of the comparison*

	MLP						FLANN					
Echantillon prévisionnel	MSE	MAE	MAPE	CORR	DA	TEMPS	MSE	MAE	MAPE	CORR	DA	TEMPS
10%	0,0006	**0,0164**	1,8273	0,9908	96	615	0,0066	**0,0540**	6,0048	0,8841	78	192
Un jour	0,0007	**0,0169**	1,8539	0,9981	100	1110	0,0045	**0,0512**	5,6212	0,9125	100	271
Une semaine	0,0006	**0,0174**	1,9339	0,9980	100	1110	0,0054	**0,0545**	6,0572	0,8601	80	327
Un mois	0,0005	**0,0160**	1,7746	0,9939	100	997	0,0032	**0,0417**	4,6286	0,9535	100	255
Deux mois	0,0007	**0,0207**	2,3200	0,9911	90	940	0,0041	**0,0457**	4,6798	0,9355	90	226

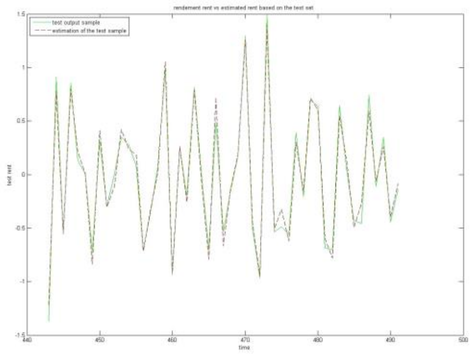

Figure 5 : *Actual yield vs estimated yield with model*

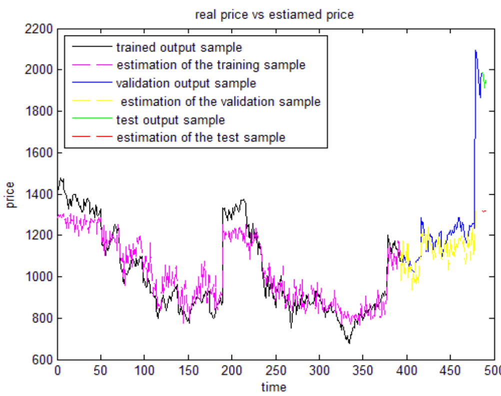

Figure 6 : *Prediction of data with FLANN model*

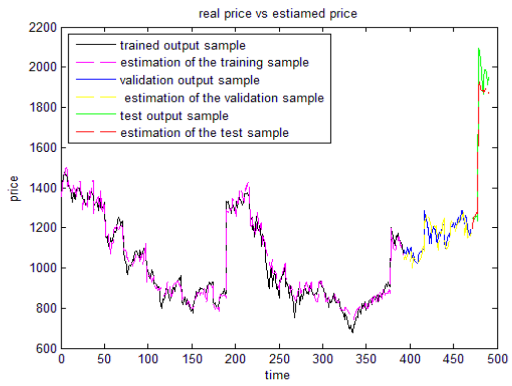

Figure 7: *Prediction of data with MLP model*

Conclusion:

The interest of this article is therefore to compare two non-parametric models of neural networks in the prediction of the abrupt evolution of the US stock market price S & P 500 most representative of the entire stock market of the United States. It is important to note that six performance measures such as: MSE, MAE, MAPE, DA%, linear correlation and run time are used to measure the prediction performance of the two models used in this study. In terms of comparison, it appears that the MLP model demonstrates better prediction accuracy over the entire forecast sample.

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