Article

An Approach Using Multiple MLP Neural Networks for Predicting the Brazilian Stock Market

Paulo Tasinaffo[1] and Luiz Dias

[1] Instituto Tecnológico de Aeronáutica (ITA), São José dos Campos/SP, Brazil; tasinaffo@ita.br

Abstract: The Brazilian stock market undergoes many fluctuations over time. This makes it highly unpredictable. To make matters worse, the 2020 pandemic and financial speculation made the Brazilian stock market even more unpredictable. Therefore, in this article, an approach based on Artificial Intelligence (AI) is proposed to carry out this prediction. For this purpose, multiple MLP neural networks will be coupled, using supervised learning with input/output training patterns through the NARMAX (Nonlinear Auto Regressive Moving Average with eXogenous input) method. A case study, using the actions of the three main companies in Brazil (PETROBRAS, EMBRAER and Vale do Rio Doce) are considered for the validation of the presented methodology. A numerical and computational comparison between the proposed multiple method and the method using only one neural network is also presented.

Keywords: Universal Numerical Integrator (UNI); Nonlinear Auto Regressive Moving Average with eXogenous input (NARMAX); neural differential equations; Euler-Type Universal Numerical Integrator (E-TUNI); Runge-Kutta Neural Network (RKNN); Adams-Bashforth Neural Network (ABNN)

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1. Introduction

Artificial Neural networks (ANNs) have become very popular in recent decades, as they are complex and efficient mathematical models that try to imitate, on a computer, the behaviour of the human brain. There are basically two types of artificial neural networks: Shallow Neural Networks (SNNs) and Deep Neural Networks (DNNs). Shallow neural networks were the major contributions of this area of knowledge during the last half of the 20th century. On the other hand, deep neural networks are the most current contributions on the subject in this 21st century.

Therefore, this article presents the NARMAX model using Multiple Artificial Neural Networks (MANN) with Multi-Layer Perceptron (MLP) architecture for forecasting time series of the Brazilian stock market. The training approach employed is supervised learning using input/output training patterns. Therefore, several computational experiments will be carried out, to verify if the proposed approach, using multiple neural networks, is more efficient or not than the approach using only an artificial neural network.

This work is divided into five sections. In Section 2, a bibliographic review of the main references related to the proposed theme is carried out. In Section 3, the detailed mathematical model of the proposed multiple neural algorithm is developed. Still in Section 3, a detailed description of the operation of the stock market in the Brazilian businesses is also presented. In Section 4, computational experiments, based on real-world data, compare the performance of the proposed model with that obtained with a single neural network. Finally, Section 5 presents the main conclusions of the proposed work.

2. Related Works

In [1] and [2], it is formally demonstrated that Multi-Layer Perceptrons (MLP) neural networks with an inner layer are universal approximators of functions. This means that they can, at least theoretically, solve any important problem in Artificial Intelligence (e.g., time series prediction, neurocontrol, medical diagnosis, pattern classification, image processing, among others). In [3], a summary of the main shallow neural architectures of the 20th century are discussed in some depth.

However, among all the possible applications of artificial neural networks, in this article, only the time series forecasting problem is considered. In this case, the artificial neural network can be seen as an empirical model of autonomous non-linear differential equations [4]. Still in [4], a classification of tractable dynamic systems is carried out, through artificial neural networks, which use the supervised learning approach through input/output training patterns. According to these authors, there are three types of methodologies for empirical modelling of non-linear dynamic systems, namely:(i) NARMAX method (Auto Regressive Moving Average with eXogenous input) [5] and [6], (ii) methodology of mean derivatives [7,8], and [**?**], and (iii) methodology of instantaneous derivatives [10–13], and [14]. An overview of the use of artificial neural networks and fuzzy logic in the modelling of dynamic systems and subsequent application in control can also be found in [15].

Therefore, this article intends to simulate the Brazilian stock market, through the NARMAX method, using multiple artificial neural networks with MLP architecture. The training algorithm that will be used, in the examples presented here, will be the Levenberg-Marquardt [16] algorithm from 1994 and that is available in the Toolbox of Artificial Neural Networks (ANN) of Matlab.

3. Mathematical Development

Section 3 goes here.

Aqui vem o texto 3: [1],[2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15] e [16].

The Mathematical development goes here.

3.1. Relationship Between the Universal Numerical Integrator (UNI) and the NARMAX Model

Section 3.1 goes here.

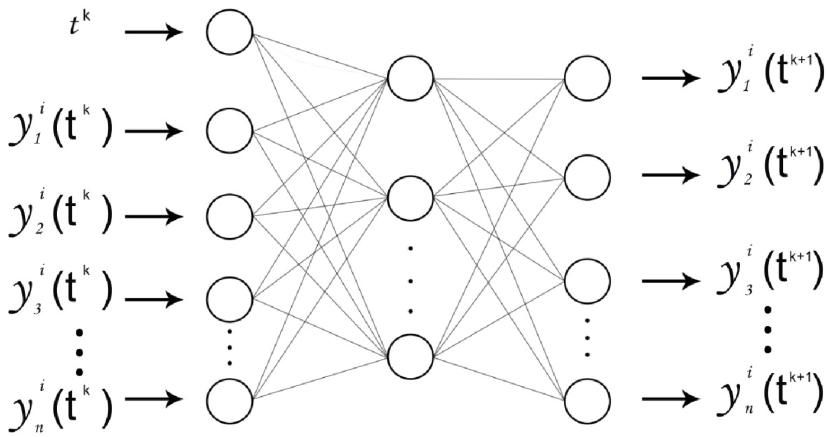

Figure 1. Basic scheme of the NARMAX methodology designed on a feed-forward neural architecture (Source: see [5,6]).

$$
\begin{cases}
\dot{y}_1 = f_1(t, y_1, y_2, \cdots y_n), & y_1(a) = \eta_1 \\
\dot{y}_2 = f_2(t, y_1, y_2, \cdots y_n), & y_2(a) = \eta_2 \\
\quad\quad\vdots & \quad\quad\vdots \\
\dot{y}_n = f_n(t, y_1, y_2, \cdots y_n), & y_n(a) = \eta_n
\end{cases}
\tag{1}
$$

Thus, a NARMAX model (no input with noise) of the Single-Input and Single-Output (SISO) type is given by [5,6]:

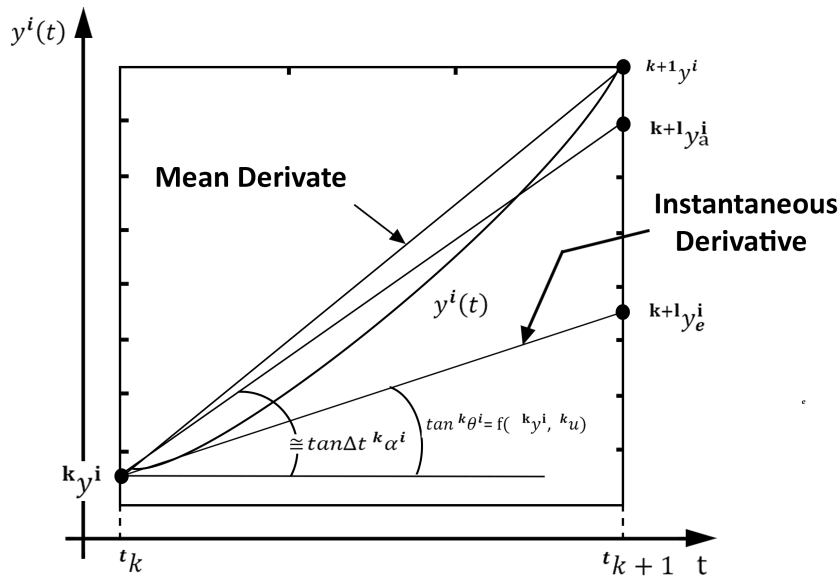

Figure 2. Difference between mean derivative and instantaneous derivative functions (Source: see [7,8]).

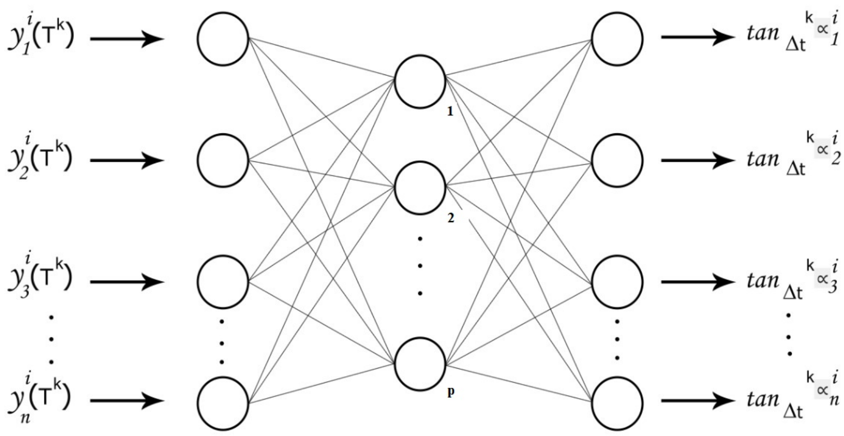

Figure 3. A feed-forward neural network project with the concept of mean derivative functions.

$$\hat{y}(k+1) = H[\varphi(k)] =$$

$$\hat{f}_{NN}\left[y(k) \quad \cdots \quad y(k-n_y) \quad u(k) \quad \cdots \quad u(k-n_u)\right] \tag{2}$$

Furthermore, the NARMAX model can also be easily extended to the Multiple-Input and Multiple-Output (MIMO) case. For example, if $\vec{y}(k-i) = [y_1(k-i)\ y_2(k-i) \cdots y_n(k-i)]^T$ e $\vec{u}(k-j) = [u_1(k-j)\ u_2(k-j) \cdots u_n(k-j)]^T$ then one would have the following:

$$[\hat{\vec{y}}(k+1)\ \hat{\vec{y}}(k+2) \cdots \hat{\vec{y}}(k+n_{y_{out}})] =$$

$$\hat{f}_{NN}[\quad \vec{y}(k) \quad \vec{y}(k-1) \quad \cdots \quad \vec{y}(k-n_{y_{in}}) \quad \vec{u}(k) \quad \vec{u}(k-1) \quad \cdots \quad \vec{u}(k-n_u)]^T \tag{3}$$

There is also the mean derivatives methodology, which is an alternative to the NARMAX model [7–9]. This type of integrator couples a feed-forward neural network to the first-order Euler integrator and as schematized by equations (4) and (5).

$$^{k+1}y^i = tan_{\Delta t}{}^k\alpha^i \cdot \Delta t + {}^ky^i \tag{4}$$

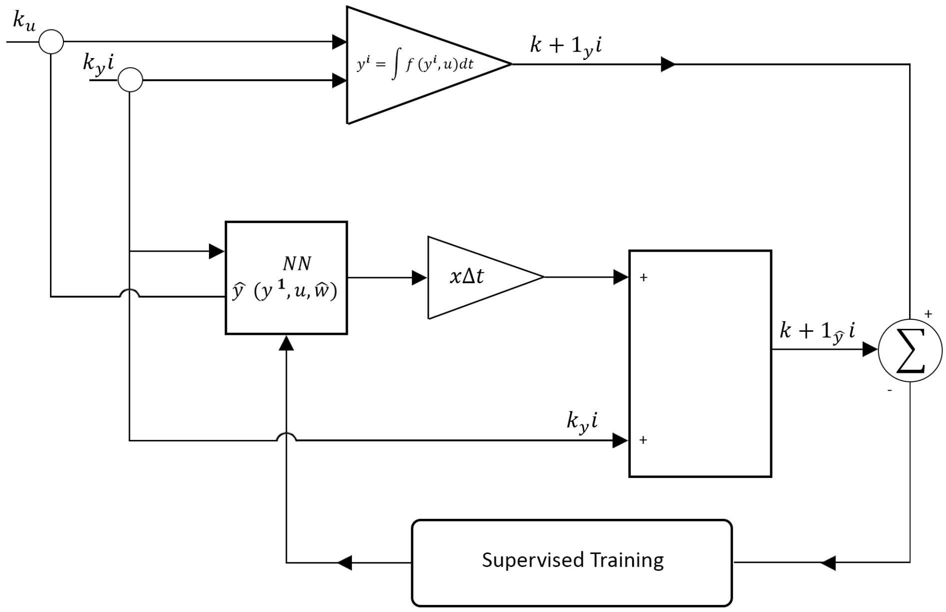

Figure 4. Basic scheme of a feed-forward network designed internally in the Runge-Kutta 4-5 integrator (Source: see [11]).

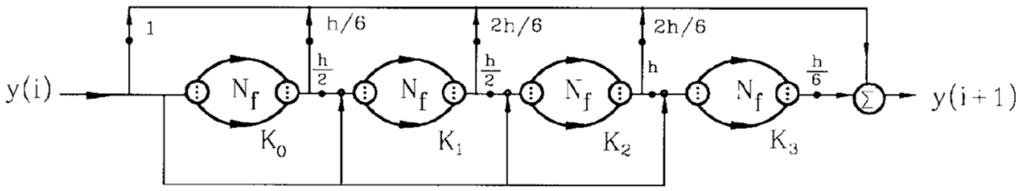

Figure 5. Basic scheme of a feed-forward network designed internally in the Adams-Bashforth 4 integrator (Source: see [12]).

where ${}^{k+1}y^i = [\,{}^{k+1}y_1^i\ {}^{k+2}y_2^i \cdots {}^{k+1}y_n^i\,]^T$, $tan_{\Delta t}{}^{k+1}\alpha^i = [\,tan_{\Delta t}{}^{k+1}\alpha_1^i\ tan_{\Delta t}{}^{k+1}\alpha_2^i \cdots tan_{\Delta t}{}^{k+1}\alpha_n^i$ $]^T$ and ${}^k y^i = [\,{}^k y_1^i\ {}^k y_2^i \cdots {}^k y_n^i\,]^T$.

$$tan_{\Delta t}{}^k\alpha_j^i = \frac{{}^{k+1}y_j^i - {}^k y_j^i}{\Delta t} \tag{5}$$

The only Runge-Kutta Neural Network (RKNN) that is available in the literature is the order 4-5 [11]:

$$y_{n+1} = y_n + \frac{h}{6} \cdot (k_1 + 2 \cdot k_2 + 2 \cdot k_3 + k_4) \tag{6}$$

where,

$$k_1 = N_f(y_n; w)$$

$$k_2 = N_f(y_n + \frac{h}{2} \cdot k_1; w)$$

$$k_3 = N_f(y_n + \frac{h}{2} \cdot k_2; w)$$

$$k_3 = N_f(t_n + h, y_n + h \cdot k_3; w)$$

$$N_f(\cdot, \cdot; w) \cong \dot{y} = f(y(t))$$

Alternatively, there is also the Adams-Bashforth Neural Network (ABNN) which is also available in the literature and is given by [12]:

$$y(t_{n+1}) = y(t_n) + \frac{h}{24} \cdot (55 \cdot f_n - 59 \cdot f_{n-1} + 37 \cdot f_{n-2} - 9 \cdot f_{n-3}) \tag{7}$$

3.2. Detailed Description of the Brazilian Financial Stock Market

Section 3.2 goes here.

3.3. Methodology Using Only One MLP Neural Network

Section 3.3 goes here.

3.4. The Proposed Method Using Multiple Neural Networks with MLP Architecture

Section 3.4 goes here.

4. Results and Analysis

Here goes the Results and Experiments Section.

4.1. Simple Method

Section 4.1 goes here.

4.2. Compound Method

Section 4.2 goes here.

4.3. Numerical and Computational Comparisons Between the Two Proposed Methodologies

Section 4.3 goes here.

5. Conclusion

Here goes the Conclusion.

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Abbreviations

The following abbreviations are used in this manuscript:

ABNN	Adams-Bashforth Neural Network
E-TUNI	Euler-Type Universal Numerical Integrator
NARMAX	Nonlinear Auto Regressive Moving Average with eXogenous input
MLP	Multi-Layer Perceptron
PCNN	Predictive-Corrector Neural Network
RBF	Radial Basis Function
RKNN	Runge-Kutta Neural Network
SVM	Support Vector Machine
UNI	Universal Numerical Integrator

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