FORECASTING NOISY TIME SERIES APPROXIMATED BY NEURAL NETWORKS

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Abstract: in this work, a proposed methodology for univariate noisy time series prediction approximated by artificial neural networks (ANN) is applied to the problem of forecasting monthly rainfall precipitation in Cuesta El Portezuelo at Catamarca, province of Argentina (-28°28'11.26";-65°38'14.05") with addition of white noise. The feasibility of the proposed scheme is examined through dynamic modeling of the well-known chaotic time series such as Mackay Glass (MG) and one-dimensional Henon series (HEN).
In particular, when the time series is noisy, the underlying dynamical system is nonlinear and temporal dependencies span long time intervals, in which this are also called long memory process. In such cases, the inherent nonlinearity of ANN models and a higher robustness to noise seem to partially explain their better prediction performance. So, in one-step-ahead prediction tasks, the predictive models are required to estimate the next sample value of a noisy time series, without feeding back it to the model's input regressor. If the user is interested in a longer prediction horizon, a procedure known as long-term prediction, the model's output should be fed back to the input regressor for a fixed but finite number of time steps. Even though feed-forward networks can be easily adapted to process time series through an input tapped delay line, giving rise to the well-known time tagged feed-forward neural network, respectively.
The results show that the new method can improve the predictability of noisy rainfall and chaotic time series with a suitable number of hidden units compared to that of reported in the literature.

keywords: neural networks, noisy rainfall time series, time series forecasting.

1. INTRODUCTION

Prediction of future observations is an important problem in time series, namely in meteorology. All attempts to forecast future developments and to reproduce past data, a process necessary to gain understanding of relevant mechanisms, show that climate can only be interpreted as a stochastic system. Specifically, in view of the highly nonlinear relationships governing the rainfall phenomenon, long-term forecasting can be done only in a stochastic way.
Time series prediction is based on the assumption that an observable feature of a system is determined by an underlying deterministic system. If the evolution of the system can be described by a set of n ordinary differential equations in n variables, there exists a unique trajectory through every point a in R^n. Neural Networks have been widely used as time series forecasters: most often these are feed-forward networks which employ a sliding window over the input sequence. Typical examples of this approach are market predictions, meteorological and energy forecasting (Catalao *et al.*, 2007; Yang *et al.*, 2012; Vamsidhar, 2010; Valverde Ramírez *et al.*, 2005; Rodriguez Rivero and Pucheta, 2014). The advantages and disadvantages of neural networks in comparison to other statistical techniques for

pattern extraction are discussed in (Müller and Reinhardt, 1991; Atiya *et al.*, 1999).
Since the structure of the rainfall series depends on the climatic and meteorological regime as well as the length of rainfall duration, static computational intelligence methods are generally unable to capture the temporal pattern of the data (Pucheta *et al.*, 2009).
Moreover, the non-Gaussian nature of the rainfall data also poses problem to statistical methods (Alcroft and Glasbey, 2003) that assume normal distribution. The fact that the data has high levels of noise, uncertainties and error complicated the matters (Toth *et al.*, 2000). Together with the random nature of rainfall, these render the rainfall prediction challenging. The insufficient long series of probable rainfall scenarios exacerbate the situation (Gaume *et al.*, 2007). The misrepresentation of the actual point rainfall at specific location also creates additional challenge to the problem (Mikkelsen *et al.*, 2005).
Hence, new methods have to be devised to further improve the present tools. It is found that neural network can get rid of the drawbacks of statistical methods (Guhathakurta, 2006) and handle uncertainties. Neural network has shown superior performance in long-short period prediction over other techniques, suggesting neural network is a promising tool to aid in weather prediction.
In this work the Hurst's parameter is used in the learning process to modify on-line the number of patterns, the number of iterations, and the number of filter's inputs. This H serves to have an idea of roughness of a signal (Abry *et al.*, 2003; Bardet *et al.*, 2003), and to determine its stochastic dependence. The definition of the Hurst's parameter appears in the Brownian motion from generalize the integral to a fractional one. The Fractional Brownian Motion (fBm) is defined in the pioneering work by Mandelbrot through its stochastic representation (Duncan *et al.*, 2000).

2. SERIES DATA

2.1 Rainfall Series from Cuesta El Portezuelo

A rainfall time series can be actually regarded as an integration of stochastic (or random) and deterministic components (Pucheta *et al.*, 2012). Once the stochastic (noise) component is appropriately eliminated, the deterministic component can then be easily modeled. Rainfall is an end product of a number of complex atmospheric processes which vary both in space and time.
The standard non-parametric approaches presented in this work by means of time-series analysis, is based on stochastic techniques that assume non-linear relationship among data that reproduce the rainfall time series only in statistical sense. Then, in principle, machine learning models, such as artificial neural networks (Gencay and Liu, 1997), can improve the forecasting results obtained using models based on standard non-parametric approaches (Sorjamaa *et al.*, 2007).
The rainfall dataset used is from Cuesta El Portezuelo located at Catamarca, province of Argentina (-28°28'11.26";-65°38'14.05") and the collection date is from year 2000 to 2010 shown in Fig.1.

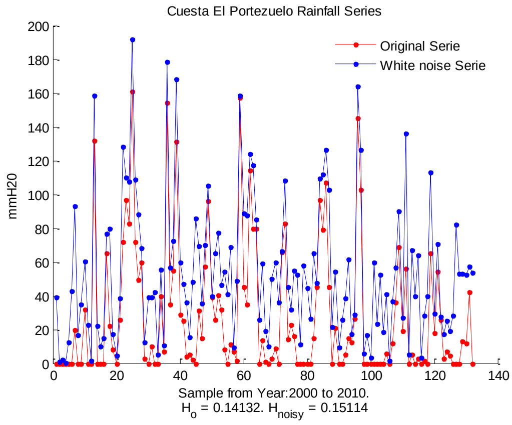

Fig. 1 Rainfall times series from Cuesta El Portezuelo, Catamarca, Argentina.

2.2 Mackay-Glass time series

This equation serves to model natural phenomena and has been used in earlier work to implement a comparison of different methods employed to make forecast (Vamsidhar, 2010; Hall, 1999; Senthil Kumar *et al.*, 2005). Here one of the proposed algorithms to predict values of time series are taken from the solution of the MG equation (Glass and Mackey, 1988), which is explained by the time delay differential equation defined as

$$\dot{y} = \frac{\alpha y(t-\tau)}{1+y^{c}(t-\tau)} - \beta y(t) \qquad (1)$$

where α, β, and c are parameters and τ is the delay time. According as τ increases, the solution turns from periodic to chaotic. Equation (1) is solved by a standard fourth order Runge-Kutta integration step, and the series to forecast is formed by sampling values with a given time interval.
Thus, a time series with a random-like behavior is obtained, and the long-term behavior changes thoroughly by changing the initial conditions. Furthermore, by setting the parameter β between 0.1 and 0.9 the stochastic dependence of the deterministic time series obtained varies according to its roughness. In Fig. 2 and Fig. 3, $MG30_{noisy}$ and $MG17_{noisy,}$ the first 102 data points are used for training and the remaining 18 points are kept for testing.

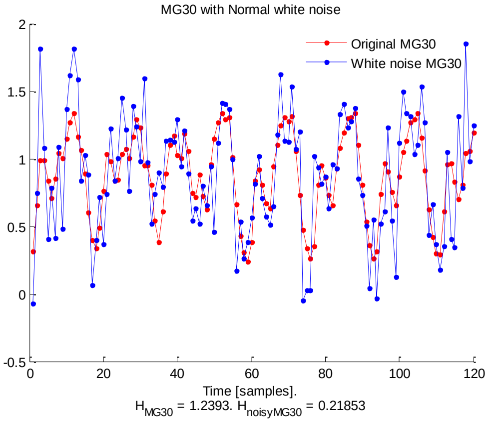

Fig. 2 $MG30_{noisy}$ series with Tau=30.

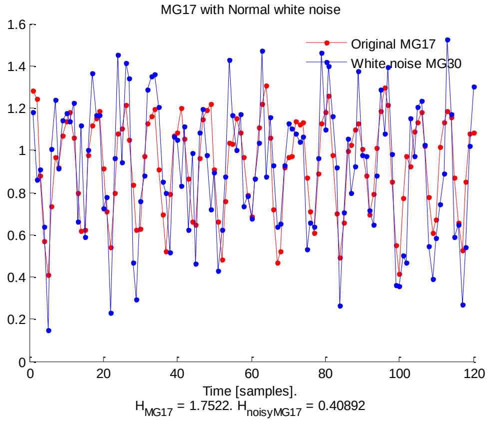

Fig. 3 $MG17_{noisy}$ series with Tau=17.

The benchmark chosen for MG solutions are called $MG17_{noisy}$ and $MG30_{noisy}$ in the forecasting

2.3 Henon time series

The Henon equation was first introduced by Henon in 1976. The Henon equation has a simple format; however, it presents many aspects of dynamical behavior of more complicated chaotic systems (Davies, 1999). Henon equation is described by Eq. (2), which generates the benchmark chosen called HEN_{noisy},

$$x_{(t+1)} = b + 1 - a x_t^2 \qquad (2)$$

In order to compare the results of the proposed technique with the results published in the literature, the parameters are selected according to (Fanzi and Zhengding, 2003), where the constants are taken to be A = 1.3, B = 0.3, x(0) = 0 and x(1) = 0. A chaotic time series with 120 samples is generated by Eq. (2). In Fig. 4, the first 102 data points of HEN_{noisy} are used for training and the remaining 18 points are kept for testing.

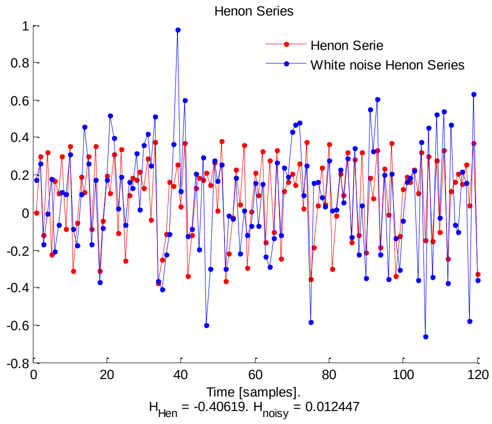

Fig. 4 HEN_{noisy} series with b=0.3 and a=1.3.

3. PROPOSED LEARNING APPROACH

Once a model is selected and data are collected, the work is to find parameter values that best fit the historical data. We can only hope that the resulting model will provide good predictions of future observations. Statisticians usually assume that all values in a given sample are equally valid. For time series, however, most methods recognize that recent data are more accurate than aged data. Influences governing the data are likely to change with time so a method should have the ability of deemphasizing old data while favoring new. A model estimate should be designed to reflect changing conditions.

Some results had been obtained from a linear autorregresive approach, which are detailed on (Pucheta *et al.*, 2009).

The proposed criterion in this work to modify the pair (i_t, N_p) is given by the statistical dependence of the time series $\{x_n\}$, supposing that is an fBm. The dependence is evaluated by the Hurst's parameter H, which is computed using a wavelet-based method (Abry *et al.*, 2003). Then, a heuristic adjustment for the pair (i_t, N_p) in function of H according to the membership functions shown in Fig. 5 is proposed.

The feed-forward neural network architecture is selected and trained. The number of the hidden layer nodes is selected via heuristic law via. The weights and biases of the neural networks are kept to forecast the unknown phase space points.

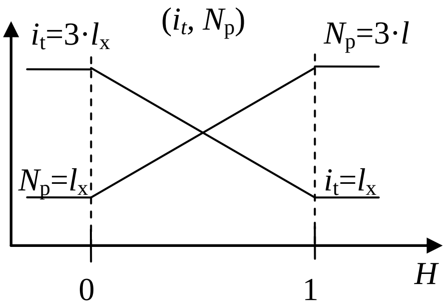

Fig. 5 Heurist adjustment proposed.

4. TIME SERIES PREDICTION RESULTS

The initial conditions of the ANN filter and the learning algorithm are shown in Table 1, in which it can be noted that the number of neurons in the hidden layer and iterations are adjusted depending on the number of inputs. These initiatory conditions of the learning algorithm are used for rainfall series, which consists of a 132 samples dataset. However, the dataset solutions of the MG and Henon equations have 120 samples.

Table 1. Initial conditions of the parameters

Variable	Initial Conditions
H_o	19
l_x	$1.5H_o$
i_t	200
N_P	$3l_x$

The last 18 values can be used to validate the performance of the prediction system and to compare if the forecast is acceptable or not.

The Monte Carlo method was used to forecast the next 18 values from MG time series and Henon time series. Such outcomes are shown from Fig. 6 to Fig. 13.

The results are summarized in Table 2 and the performance can be noted form Fig. 6 for PORTEZUELO series, Fig. 8 and Fig. 10 the MG17 $_{noisy}$ and MG30$_{noisy}$ series and Fig. 12 for HEN $_{noisy}$ series and their forecast horizons in Fig. 7, Fig. 9, Fig. 11 and Fig. 13, respectively. The measure of performance is defined as the Symmetric Mean Absolute Percent Error (SMAPE) proposed in the most of metric evaluation, defined by

$$\mathrm{SMAPE}_s = \frac{1}{n}\sum_{t=1}^{n}\frac{|X_t - F_t|}{(X_t + F_t)/2}\cdot 100 \qquad (3)$$

where **t** is the observation time, n is the size of the test set, s is each time series, X_t and F_t are the actual and the forecasted time series values at time t respectively. The SMAPE of each series s calculates the symmetric absolute error in percent between the actual X_t and its corresponding forecast value Ft, across all observations t of the test set of size n for each time series s.

The assessments of the obtained results adding white noise to the series is compared with the performance of an earlier work (Rodriguez Rivero *et al.*, 2012; Rodriguez Rivero *et al.*, 2013), both are based on ANN.

Although the difference between filters resides only in the adjustment algorithm, the coefficients that each filter has, each ones performs different behaviors, in which it can be noted from short rainfall series (Rodriguez Rivero *et al.*, 2012; Rodriguez Rivero *et al.*, 2013) have more roughness than MG solutions and rainfall series. So, the proposal of considering white noise addition applied to the time series demonstrate a level improvement when refers to stochastic series. The SMAPE INDEX decreases an adequate prior distribution model was chosen in order for tuning the parameters and outputs of the predictor filter.

The main results shows that the addition of white noise outperform a similar performance to predict rainfall time series where the roughness of the series is assessed by the Hurst parameter, which is calculated in the real and forecasted series.

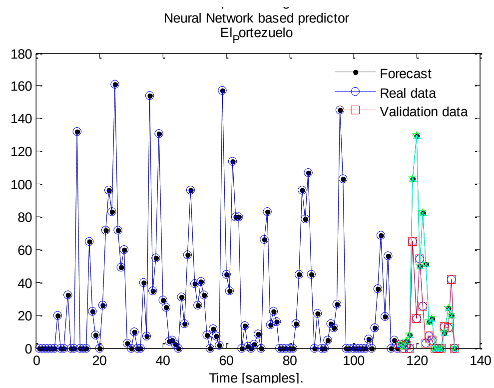

Fig. 6 PORTEZUELO rainfall times series from Catamarca, Argentina.

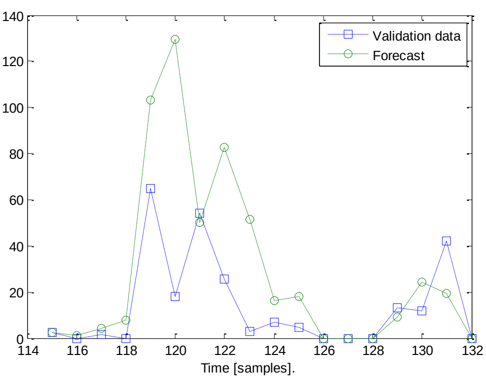

Fig. 7 Forecast horizon of the PORTEZUELO series.

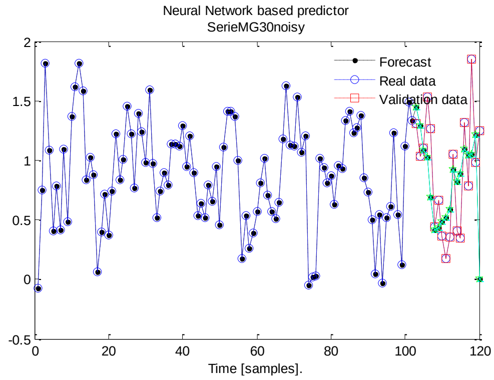

Fig. 8 $MG30_{noisy}$ with Tau=30 series forecast.

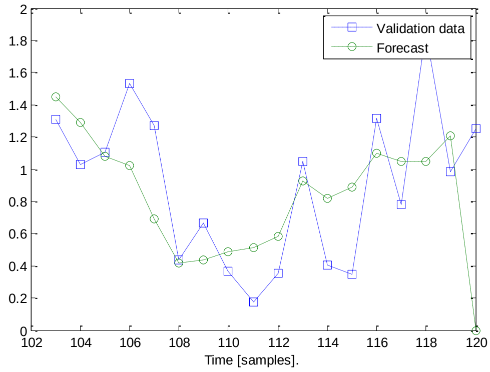

Fig. 9 Forecast horizon of the $MG30_{noisy}$ series.

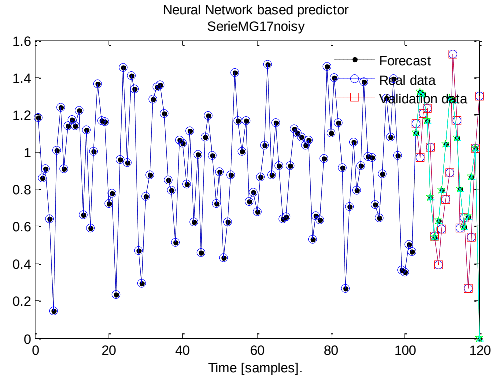

Fig. 10 $MG17_{noisy}$ with Tau=17 series forecast.

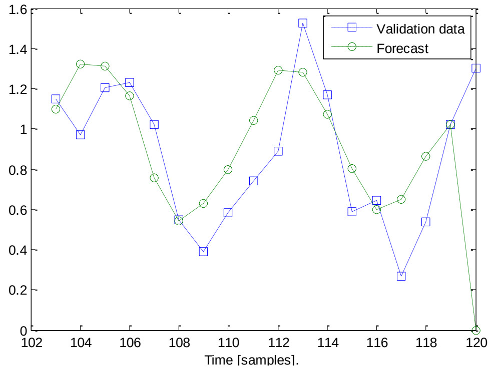

Fig. 11 Forecast horizon of the $MG17_{noisy}$ series.

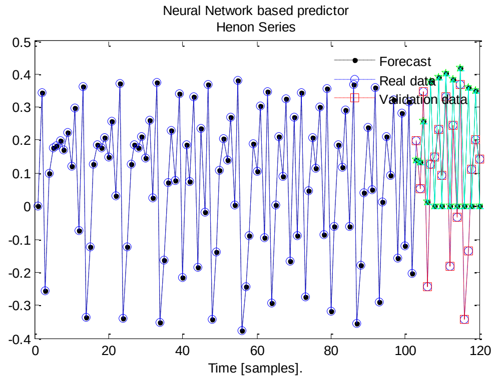

Fig. 12 HEN_{noisy} series forecast

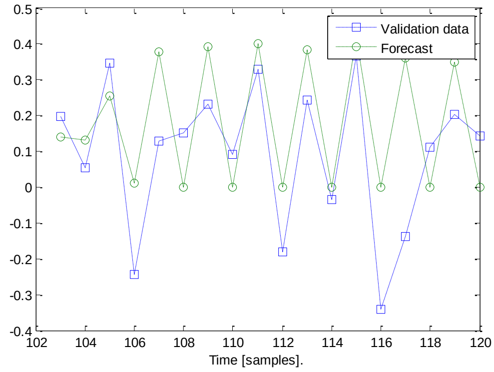

Fig. 13 Forecast horizon of the HEN_{noisy} series.

Table 2 Results prediction of time series

Series No.	H	He	Real mean	Mean Forecasted	SMAPE
PORTEZUELO	0.621	0.665	0.181	0.194	$5.63\ 10^{-7}$
MG17noisy	0.719	0.679	0.150	0.142	$6.8\ 10^{-4}$
MG30noisy	0.47	0.339	0.152	0.18	$4\ 10^{-5}$
HENnoisy	0.262	0.258	0.15	0.123	$2{,}34\ 10^{-7}$

5. CONCLUSIONES

En In this study, the proposed methodology for univariate noisy time series approximated by artificial neural networks (ANN) forecasting method was applied to some benchmarking and real life chaotic time series. The learning rule proposed to adjust the ANN weights is based on the Levenberg-Marquardt method. Likewise, in function of the long or short term stochastic dependence of the time series evaluated by the Hurst parameter H, an on-line heuristic adaptive law was proposed to update the ANN topology at each time-stage.

Results are presented for prediction of nonlinear, chaotic and non-stationary chaotic time series using computational intelligence techniques. In fact, the proposed approach to meteorological time series such as rainfall, when observations are taken from a single standpoint, shows a good performance measured by the SMAPE index shown in Table 2 compared with earlier works (Rodriguez Rivero *et al.*, 2012; Rodriguez Rivero *et al.*, 2013). Thus, the ANN filter proposed and its higher robustness to noise seem to partially explain their better prediction performance in time series prediction illustrated using two well-known chaotic benchmark datasets, MG and Henon solutions.

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