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6 authors, including:


Cristian Rodriguez Rivero
National University of Cordoba, Argentina


Julian Pucheta
National University of Cordoba, Argentina


Sergio Laboret
National University of Cordoba, Argentina


Leonardo Franco
University of Malaga

Noisy Chaotic time series forecast approximated by combining Reny's entropy with Energy associated to series method: application to rainfall series

Cristian Rodriguez Rivero, Julian Pucheta, Sergio Laboret
Victor Sauchelli
Department of Electronics Engineering
Universidad Nacional de Córdoba
Córdoba, Argentina
crodriguezrivero@ieee.org
julian.pucheta.ar@ieee.org
slaboret@yahoo.com.ar
victorsauchelli@gmal.com

Alvaro David Orjuela-Cañon
Electronics and Biomedical Engineering
Universidad Antonio Nariño
Bogotá, Colombia
dorjuelac@gmail.com

Leonardo Franco,
Computer Science Department
Universidad de Málaga
Málaga, España
lfranco@lcc.uma.es

***Abstract*— This paper propose that the combination of smoothing approach taking into account the entropic information provided by Renyi' method, has an acceptable performance in term of forecasting errors. The methodology of the proposed scheme is examined through benchmark chaotic time series, such as Mackay Glass, Lorenz, Henon maps, the Lynx and rainfall from Santa Francisca series, with addition of white noise by using neural networks-based energy associated (EAS) predictor filter modified by Renyi entropy of the series. In particular, when the time series is short or long, 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 neural networks models and a higher robustness to noise seem to partially explain their better prediction performance when entropic information is extracted from the series. Then, to demonstrate that permutation entropy is computationally efficient, robust to outliers, and effective to measure complexity of time series, computational results are evaluated against several non-linear ANN predictors proposed before to show the predictability of noisy rainfall and chaotic time series reported in the literature.**

Keywords*— *neural networks, noisy chaotic time series, forecasting, energy associated to series (EAS), Renyi's entropic information.

I. INTRODUCTION

Prediction of future observations is an important problem in time series, namely in meteorology. Due to yield on agricultural production is not fair for farmers on semi-arid regions [1]; these studies have been limited to relatively smaller regions such as humid regions [2]. Since more advanced machine learning methods are now available widely for metrological modelling [3] and informatics [4], applications of such methods are needed for a better understanding of current distributions of its driving forces, as well as future predictions [5[6] for a sustainable ecosystem management [7]. 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 meteorological forecasting [8] and [9]. Since the structure of the rainfall series depends on the climatic and meteorological regime as well as the length of rainfall duration [10[11[12], static computational intelligence methods are generally unable to capture the temporal pattern of the data [13]. However, the non-Gaussian nature of the rainfall data also poses problem to statistical methods [14] that assume normal distribution, because the data has high levels of noise, uncertainties and error. The insufficient long series of probable rainfall scenarios and the misrepresentation of the actual point rainfall at specific location also create additional challenge to the problem [15]. Then, new methods have to be proposed to further improve the present tools. Neural network has shown superior performance in short-period prediction over other techniques [16], suggesting neural network is a promising tool to aid in rainfall prediction. This paper describes an alternative approach to forecasting chaotic time series based on entropy. The research builds upon an earlier statistical analysis of financial time series with entropy information published in [17] and intelligent data analysis [18]. This entropy conditional upon a model is subsequently used in place of information-theoretic entropy in the proposed multistep prediction algorithm. Usually the process may involve finding a linear or non-linear regression function that takes as arguments p past values of $x(t)$. Observations often are considered as standard statistical techniques that fail to capture sufficiently the underlying time series generator and its often non-stationary nature. This paper provides some forecast strategies when they are applied to complicated time series. Since then, hundreds, if not thousands, of strategies have been developed for a wide variety of prediction tasks including, such as electrical demand [19[20, [21], biomedical applications [22], combining forecast using genetic programming [23], wind power forecast [24], water demand [25], financial markets [26], etc. One of the reasons for the failure is that established statistical time series forecasting models, both linear regression and non-linear neural networks, do not take into account the generative cause aspect of time series. Consequently, from a physics point of view a much more attractive proposition is to try to approximate the underlying processes responsible for generating the time series or at least estimate by means of tools [27, [28]. A practice known as deterministic vs. stochastic modeling bridges the gap between local and global approaches to model-based error analysis [29]. Therefore, we propose a smoothing technique such as EAS filter [30, [31] combined with Renyi permutation entropy to provide a heuristic law for training the neural network. The objective of this paper is to select energy associated to series approach (EAS) model combined with time series entropic information to perform forecasts for future data. The interesting forecast horizon for the authors is 18 steps-ahead predictions. So, in this research effort, we have focused of computing the entropy of the time series data to modify the structure of the neural networks parameters assuming the EAS approach. The initial applications of ordinal pattern and permutation entropy demonstrate this to be very promising in quantifying and analyzing the dynamic behavior of chaotic time series and other time series. Recent studies have addressed this issue, from the original time series via ordinal pattern, in which the time series is converted to a symbolic sequence by noting the order in which the signal passes through successive windows [32]. The performance of the proposed approach is tested either to time series obtained from dynamical systems such as Mackay-Glass (MG), Logistic (LOG) and Lorenz (LOR) system equations or meteorological variables such rainfall series from Santa Francisca establishment, Cordoba. The method supports the applicability of permutation entropy in analyzing the dynamic behavior of chaotic time series, even when white noise is added for time series predictions.

The rest of the paper is organized as follows. Section II presents some benchmarks chaotic time series and rainfall data. Then, white noise is added to time series dataset to be used by the proposed approach taking into account previous results on generating partitions, local modeling, and error distribution analysis in that context. Section III covers reviews permutation entropy, the technique that we use to measure in the time series dataset. Section IV shows the experimental setup and methods used to forecast the benchmark series, with application to rainfall forecasting. In Section V, we discuss the method proposed by empirical time series and compare that complexity to the accuracy of predictions produced by the forecasting methods. In Section VI some concluding remarks are drawn and their implications for future areas of research.

II. Benchmark Time Series

In long-term forecasts, the accuracy of predictions drops while uncertainty increases. On way used by forecaster is reducing the forecasting errors of predictions by averaging more than one model, so the reason is that averaging cancels out the errors of individuals and/or models and in doing so eliminates the noise from the pattern and improve accuracy. With the addition of white noise, the methodology try to prove that investigators are facing a practical problem with noisy information in the real-world situations [33] and should not neglect sources of information outside of the current data set [34].

A. *Mackay-Glass chaotic 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. The solution of the MG equation [35] is explained by the time delay differential equation defined as:

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

where α, β, and c are parameters and τ is the delay time. According as τ increases, the solution turns from periodic to chaotic. Eq. (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.

The benchmark chosen are called $MG17_{noisy}$ with τ=17 and $MG30_{noisy}$ with τ=30 in the forecasting shown in Table I. The H parameter serves to have an idea of roughness of a signal [36] and the time series are considered as a trace of fBm depending on the so-called Hurst parameter 0<H<1 [37].

TABLE I. Parameters to generate MG time series

Series No.	N	β	α	c	τ
$MG17_{noysy}$	102	1.6	30	10	100
$MG30_{noisy}$	102	0.2	0.1	10	30

B. *The Lorenz Chaotic Time Series*

Lorenz found three ordinary differential equations which closely approximate a model for thermal convection [38]. These equations have also become a popular benchmark for testing non-linear predictors. The Lorenz model is given by (2), the data is derived from the Lorenz system, which is given by three time-delay differential systems

$$\begin{cases} \dfrac{dx}{dt} = a(y-x), \\ \dfrac{dy}{dt} = bx - y - xz, \\ \dfrac{dz}{dt} = xy - cz \end{cases} \tag{2}$$

A typical choice for the parameter values are as a = 10, b = 28, and c = 8/3. In this case, the system is chaotic. The data set is constructed by using four-order Runge–Kutta method with the initial value as is shown in Table II for $LOR01_{noisy}$ and $LOR02_{noisy}$ series. The step size is chosen as 0.01, respectively. These sets of parameters are commonly used in generating the Lorenz system because exhibits deterministic chaos.

TABLE II. Parameters to generate LOR time series

Series No.	n	X(0)	Y(0)	Z(0)
$LOR01_{noisy}$	102	12	9	2
$LOR02_{noisy}$	102	0.1	0.1	2

C. *The Henon Chaotic Time Series*

The Henon chaotic time series is constructed by following (3) presents many aspects of dynamical behavior of more complicated chaotic systems [39].

$$x(t+1) = b + 1 - ax^2(t) \quad (3)$$

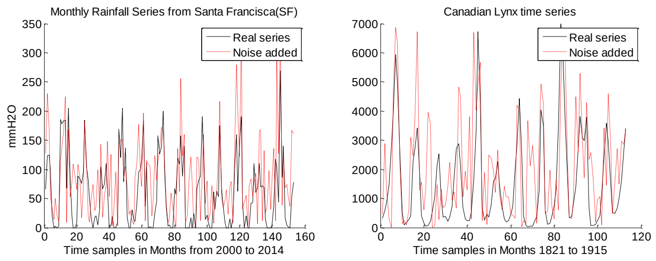
when generating data for our experiments, a and b are set as shown in Table III. These same parameters are used in both.

TABLE III. PARAMETERS TO GENERATE HEN TIME SERIES

Series No.	N	a	b	X_0	Y_0
HEN01 $_{noisy}$	102	1.4	0.3	0	0
HEN02 $_{noisy}$	102	1.3	0.22	0	0

D. *Rainfall series*

The rainfall dataset used is from Santa Francisca, Despeñaderos located at Cordoba, province of Argentina (-31.824703;-64.289692) and the collection date is from year 2000 to 2015 as shown in Fig.1 (a). The dataset has 154 observations, corresponding to the period of January 2000 – October 2014. Training set has 136 observations, corresponding to the period of 1821-1915. Test set has 18 observations, corresponding to the period of November 2014 – April 2016. Validation set has 18 observations, corresponding to the period of November 2014 –April 2016.



(a) (b)

Fig. 1 a) Monthly historical rainfall series from Santa Francisca; b) yearly lynx trapped per year in the Mackenzie River.

E. *Canadian Lynx data*

A well-known data set—the Canadian lynx data is used in this study to demonstrate the effectiveness of the neural network approach and the effectiveness of the combination method. The lynx series shown in Fig.1 (b) contains the number of lynx trapped per year in the Mackenzie River district of Northern Canada. The dataset has 114 observations, corresponding to the period of 1821-1934. Training set has 96 observations, corresponding to the period of 1821-1915. Test set has 18 observations, corresponding to the period of 1916-1934. It has been extensively analyzed in the time series literature with a focus on the nonlinear modeling [40].

III. COMBINING ENTROPY WITH ENERGY ASSOCIATED TO SERIES

Permutation entropy is computationally efficient, robust to outliers, and effective to measure complexity of time series. Bandt and Pompe [41] introduced permutation entropy as a new measure of complexity of non-linear time series, i.e. they suggested an approach to time series analysis in which they embedded a continuous time series as a symbolic sequence into another space, a process which they called “permutation entropy”. We assume that there are N observations $x_1, x_2, \ldots, x_N$ are available from some phenomenon. The goal of the analysis is to produce an estimate for the change $x_{t+\Delta T} - x_t$, where $t \in \mathbb{Z}$ denotes the current time step and $\Delta T = t_n, \ldots\ldots, t_{n+18}$ is the forecasting horizon. The proposed algorithm can be outlined in the following sequence of steps as in [5].

A. *The Proposed Learning Process*

The NN’s weights are tuned by means of the EAS approach, which assumes that the primitives of the time series are calculated as a new entrance to the ANN [42], in which the prediction attempts to even the area of the forecasted area to the primitive real area predicted. The startup of the algorithm [43] achieves the long term stochastic dependence of the Hurst parameter in order to make more precisely the prediction. The forecasted time series area is set as a new entrance to the NN and serves to be compared with the real area of the time series. We propose the entropic information provided by Renyi entropy with parameter α of the sequence to adjust the learning law. The proposed learning approach consists of changing the number of patterns, the filter’s length and the number of iterations in function of the Renyi entropy for each corresponding time series. The learning process is performed using a batch model. In this case the weight updating is performed after the presentation of all training examples, which forms an epoch. In addition, the proposed criterion to modify the pair (i_t,N_p) is given by the number of iterations performed by each epoch it is given by

$$l_x \le i_t \le R_L^{(\alpha)} \cdot l_x . \quad (4)$$

where l_x is the dimension of the input vector. Then, a heuristic adjustment for the pair (i_t,N_p) in function of $R_L^{(\alpha)}$ according to the membership functions shown in Fig.1 is proposed.

With respect to estimating entropy H_L of a given time series, a good starting point might be the Shannon n-gram (block) entropy. For more complex entropy time series one could also consider using a committee of non-linear multilayer feedforward neural networks [5] and [44].

The simulated paths are appended to the end of the original sequence $\{x_i\}$. Assuming the last available observed entropy to be H_L, for each path γ_k one can note the corresponding entropy sequence $H_L \to \mathrm{H}_{L+1}^k \to \mathrm{H}_{L+2}^k \to \ldots \to \mathrm{H}_{L+N}^k$.

The probability of the path γ_k can be linked to the probability of encountering such an entropy sequence:

$$P(\gamma_k) = \prod_{i=1}^{N} P(H_{L+i}^k / H_{L+i-1}^k, H_{L+i-2}^k, \ldots, H_{L+i-N}^k), \quad (5)$$

For prediction errors, they are bounded by $\left|\hat{H}_{L+i}^k \text{-} H_{L+i}^k\right| \le 1$.

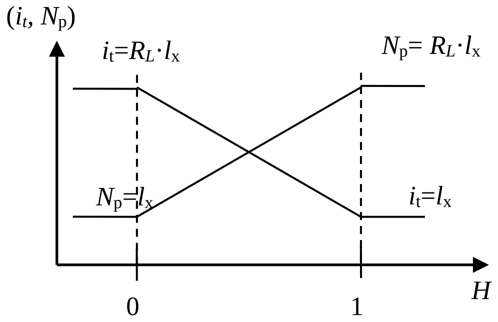


Fig.2 Heuristic adjustment of (i_t, N_p) in terms of $R_L^{(\alpha)}$ after each epoch.

IV. Computational Results

In this section, we compare our results with other method proposed in the literature, such as BEMA [5], BEA [6], BA [45], EAS [30] and NN-Mod. [46] approaches for chaotic time series prediction to demonstrate that the permutation entropy method has an acceptable and comparable performance.

A. Setup of the EAS NN algorithm

The initial conditions of the EAS-Mod. predictor filter and the learning algorithm are shown in TABLE IV. , 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 were used to forecast the primitive of the time series, whose length is 102 values.

TABLE IV. Setup of the proposed EAS Mod. approach

Variable	Initial Conditions
H_o	*19*
l_x	*17*
it	*200*
NP	l_x

The performance of the comparison is measured by the Symmetric Mean Absolute Percent Error (SMAPE) proposed in the most of metric evaluation [47], defined by,

$$SMAPE_S = \frac{1}{n}\sum_{t=1}^{n}\frac{|X_t - F_t|}{(|X_t| + |F_t|)/2}\times 100 \quad (6)$$

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 F_t, across all observations t of the test set of size n for each time series s. To perform the comparison there are three classes of data sets: one is the original time series used for the algorithm in order to give the forecast, which 102 values of MG noisy, LOR noisy and HEN noisy series, 156 for SF noisy rainfall series and 114 for Lynx noisy series, are used for training the NN weights. The other one is the forecasted and validation data obtained by the last 18 values of a total of dataset.

TABLE V. Comparison Results by SMAPE index through the proposed approaches

Series No.	Method	SMAPE
MG30 noisy	EAS-Mod	0.025
	BEMA	0.026
	BEA	0.031
	BA	0.085
	EAS	0.101
	NN-Mod.	0.292
MG17 noisy	EAS-Mod	0.033
	BEMA	0.040
	BEA	0.045
	BA	0.078
	EAS	0.156
	NN-Mod.	0.920
HEN01 noisy	EAS-Mod.	0.0035
	BEMA	0.004
	BEA	0.002
	BA	0.0025
	EAS	0.0063
	NN-Mod.	0.018
HEN02 noisy	EAS-Mod.	0.0053
	BEMA	0.0006
	BEA	0.0001
	BA	0.0019
	EAS	0.003
	NN-Mod.	0.009
LOR01 noisy	EAS-Mod.	0.22
	BEMA	0.31
	BEA	0.12
	BA	1.42
	EAS	6.54
	NN-Mod.	5.06
LOR02 noisy	EAS-Mod.	3.2
	BEMA	2.69
	BEA	2.84
	BA	3.15
	EAS	3.6
	NN-Mod.	4.95
Lynx noisy	EAS-Mod.	19.98
	BEMA	42.89
	BEA	44.63
	BA	36.25
	EAS	20.30
	NN-Mod.	56.72
Rainfall SF noisy	EAS-Mod.	19.28
	BEMA	9.55
	BEA	15.42
	BA	48.63
	EAS	35.36
	NN-Mod.	52.12

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 noisy rainfall, Lynx, MG, LOR and HEN series.

Results in TABLE V show that EAS-Mod was not superior against competitors for issuing time series prediction, with a SMAPE average of 5.34 over all-time series.

V. DISCUSSION

In this work, noisy chaotic time series prediction approximated by combining EAS neural networks based forecasting method with permutation entropy was compared by other prediction approaches and applied to real life chaotic time series, mainly rainfall series. Fig.4 shows the evolution of the SMAPE average for EAS-Mod., BEMA, BEA, BA, EAS and NN-Mod filter predictors.

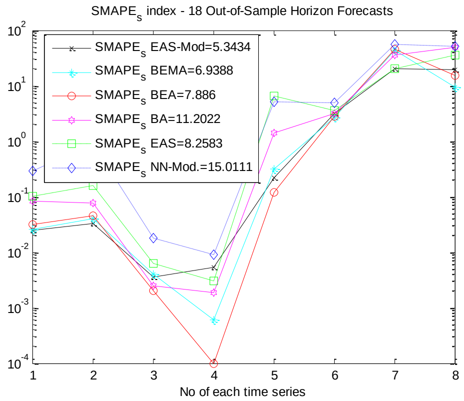


Fig. 4 The SMAPE average applied over the 8 time series.

The study analyzed and compared the relative advantages and limitations of each time-series predictor filter technique in term of SMAPE metric. The discussion appear of how feed-forward networks can successfully approximate the quantitative changes in the dynamics of the time series data due to changes in the parameter values of the exogenous variables remains open for study, which results from the use of a stochastic characteristic to generate a deterministic result. Although the comparison was performed by ANN-based filters, the experimental results confirm that these forecasting methods method can predict chaotic time series fairly in terms of SMAPE metric. However, the wish to preserve the stochastic dependencies constrains all the horizons to be forecasted with the same model structure.

VI. CONCLUSIONS

The study shows the relative advantages and disadvantages of the NAR time-series predictor filter techniques used for issuing rainfall and chaotic time series forecast. This paper presents a methodology for the combination of EAS predictor filter taking into account the entropic information provided by Renyi method, which has an acceptable performance in term of forecasting errors. The experimental results confirm that the method proposed can predict the noisy chaotic time series more effectively in terms of SMAPE indices when compared with other existing forecasting methods in the literature [50].

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