Using Climate Temporal Series in Statistic and Neural Network Integrated Techniques

Luciano Heitor Gallegos Marin
Computer Science Departament
Aeronautics Institute of Technology
São José dos Campos - Brazil
marin@ita.br

Paulo Marcelo Tasinaffo
Computer Science Departament
Aeronautics Institute of Technology
São José dos Campos - Brazil
tasinaffo@ita.br

Abstract — The most part of climate events are known as nonstationary temporal data series with high difficult to identification and forecasting dynamic data series. This work proposes a computational method to treat, identify and forecast natural dynamic systems represented by temporal data series. In this method are used the exponential smoothing (ES) statistic techniques as data treatment, the Nonlinear Auto Regressive Moving Average with eXogenous inputs (NARMAX) statistic technique integrated to a feedforward Neural Network (NN) to identify, simulate and forecast without manual treatment or choice of analitical models. The method was validated in a practical real case study application in the Doce River basin temporal data series.

Keywords – Neural Network, Statistical Techniques, Nonstationay Temporal Data Series.

I. Introduction

The most part of actual climate events should be understood as natural dynamic systems and can be described as regular data gathered along time [1]. These systems have nonstationary attributes, increasing the attainment of good computational results [2]. Besides, sensor malfunction, wrong human data gauge and the complex choice and configuration of analytical models to simulate and forecast natural dynamic systems implicates in a reduced trustful results.

Exponential Smoothing (ES) technique is capable to treat nonstationary temporal series with unreliable collected data, helping best natural dynamic system representation [3]. To identify and represent natural dynamic systems, the Neural Network (NN) technique has been showing good results in approaching nonstationary complex systems [4], [5]. The Nonlinear Auto Regressive Moving Average with eXogenous inputs – NARMAX integrated to a NN improves nonstationary dynamic system identification [6].

This paper presents the treatment, identification, representation, simulation and forecasting of actual climate temporal series of rain fall and rive flow made by an integrated method of statistics and NN techniques.

A. Related Works

The first related work uses an analytical model to simulate and forecast hydrological events. This model uses an integration of some famous options such as the TOPMODEL method. This work was applied in the Amazon Brazilian basins with good results. However it is difficult to set up the analytical model in short time and it work just in the Amazon basin [7].

Another related work also uses some analytical methods with statistical techniques to river flow forecast in the Itajaí River of Santa Catarina, south of Brazil. This work do not uses data treatment and NN learning [21].

A combination of statistical techniques and NN, known as Group Method of Data Handling – GMDH is use by Valença [8]. This method was applied in case studies such as São Francisco Brazilian basin, bringing good results in the simulation and forecasting. However, there is no temporal data treatment before the identification and representation process, implying in bad expected results.

Wavelets and NN are use to better learn the dynamic system in Spaeth [20]. However, this work don´t treat temporal data series before NN training.

II. Used Techniques

First of all users must define the extension of each cycle inside temporal series, as shown in Fig. 1. This definition point is very important to ES work starts.

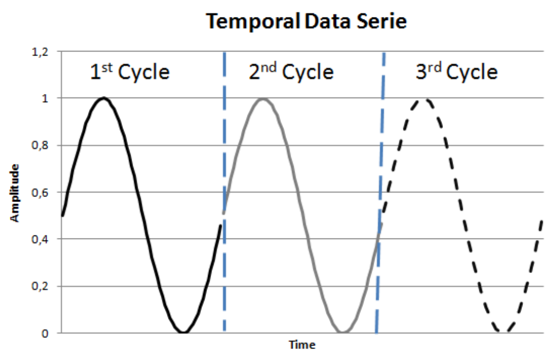

Figure 1. A temporal serie with 3 cycles.

The ES has two kind of execution:

- Double Exponential Smoothing (DES), also known as Holt technique, act in the first cycle of a temporal series, while have just tendency information [9].
- Triple Exponential Smoothing (TES), also known as Winters technique, act from the second cycle and so on. This technique uses tendency and seasonality information taken from the cycle immediately before [10].

Temporal series of rain and river flow have independent amplitude of level average. Because that was use the *Additive* TES mode, meaning that increasing and decreasing temporal series level features was respected.

The equations of DES and TES are described at Table I and their meanings at Table II. Seasonality items are used only in TES.

TABLE I. EXPONENTIAL SMOOTHING (SE) EQUATIONS

Function	Equations
Smoothing	$S_t = \alpha * (X_t - I_{t-L}) + (1 - \alpha) * (S_{t-1} + b_{t-1})$
Tendency	$B_t = \gamma * (S_t - S_{t-1}) + (1 - \gamma) * b_{t-1}$
Seasonality	$I_t = \beta * (X_t - S_t) + (1 - \beta) * I_{t-1}$

TABLE II. SE EQUATIONS MEANINGS

Symbol	Meaning
S_t	Current temporal series data smoothing
t	Time
α	Constant smoothing parameter ($0 < \alpha < 1$)
X_t	Actual temporal series values
b_t	Current tendency result
γ	Constant tendency parameter ($0 < \gamma < 1$)
I_t	Current seasonal series result
β	Constant seasonality parameter ($0 < \beta < 1$)
L	Extension of each period

A feedforward Multi-Layer Perceptron – MLP is a universal approximator function [11] and does not have cycle [12]. Cybenko [13] says that just one hidden layer approaches any continuous function. A feedfoward MLP can use the backpropagation learning algorithm to work in the descendent gradient in NN [14].

The NARMAX technique can work with a Feedforward MLP, improving identification of nonlinear dynamic systems and reducing computational processing [15], [16]. The NARMAX technique is described in Equation (1) and the meaning of each letter in shown in the Table III.

$$y_{(t)} = F^l * (y_{(t-1)}, y_{(t-2)}, \ldots, y_{(t-n_y)}, u_{(t-d)}), u_{(t-d-1)}, \ldots, u_{(t-d-nu+1)}, e_{(t-1)}, e_{(t-2)}, \ldots, e_{(t-n_e)} + e_{(t)}) \qquad (1)$$

TABLE III. NARMAX EQUATION MEANINGS

Letter	Meaning
F^l	Nonlinear function
$y_{(t)}$, $u_{(t)}$ and $e_{(t)}$	System output, input and noise, respectively
n_y, n_u and n_e	Maximum delay output, input and noise
d	System delay

A. *Computational Method Used - COMTIF*

Integrating all those techniques presented before the Computational Method to Treat, Identify and Forecast natural dynamic systems – COMTIF was designed. This method treats nonstationary temporal data series outliers, indentifying, representing and forecasting unknown natural dynamic systems [18]. The COMTIF diagram is shown in Fig. 2.

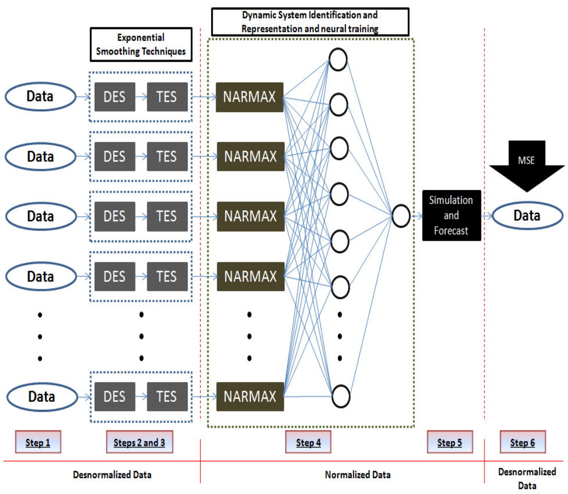

Figure 2. COMTIF: a comput. method to treat, indentify and forecast

The COMTIF has six steps of work [18]:

1. Input of one or more temporal data series;
2. Smoothing (ES) temporal data series with DES and TES;
3. Data normalization logsig between [0, +1] before neural processing;
4. Dynamic system identification, representation and neural processing;
5. Simulation and forecasting;
6. Desnormalization to the original amplitude and Mean Square Error – MSE results comparison.

Neural process cannot be done without normalization, since the computational aptness could not process original amplitude. The MSE is used to compare original temporal data series with the COMTIF forecasting results.

III. Climate Practical Application

The Doce River basin is one of most important hydrographic basins of Brazil. This basin was chosen to this practical application because it has nonstationary features due by an irregular terrain with a hot and humid climate, increasing COMTIF tests difficulty.

Two years and seven days of original Doce basin rain fall and river flow temporal data series daily average was collected from the Brazilian National Water Agency (Agência Nacional de Águas - ANA) database [19]. The original temporal data series from January/2003 up to December/2004 is shown in Fig. 3.

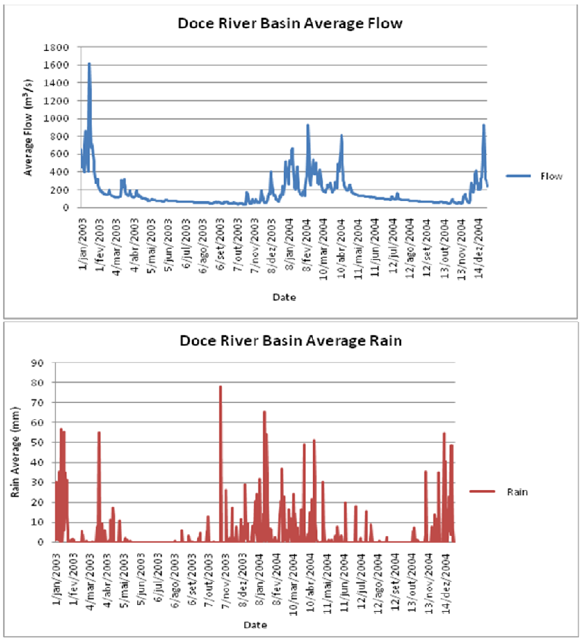

Figure 3. Doce river basin rain and flow average temporal data series

As a case study strategy the original two years rain and flow temporal data series is used in two different ways: in one the temporal series is left as original, in other is used the COMTIF to treat, indentify and represent the temporal data series. The forecast COMTIF results will be compared with original temporal series data flow.

To validate the COMTIF a computational tool was built. The development and deployment of COMTIF was made using the Matrix Laboratory (MATLAB) software version 7.6. The parameters configuration of ES is shows in the Table IV.

Some ES treatment tests were made and just average data flow has returned good results. It was decided to not treat the average data rain.

TABLE IV. Flow ES Parameters Configuration

Description	Parameter
ES (α)	0,6
Tendency (γ)	0,5
Seasonality (β)	0,4

The ES treatment results have very close features to the original data series. Those results are used in the NN input layer integrated with NARMAX technique. The treatment results are shown in Fig. 4.

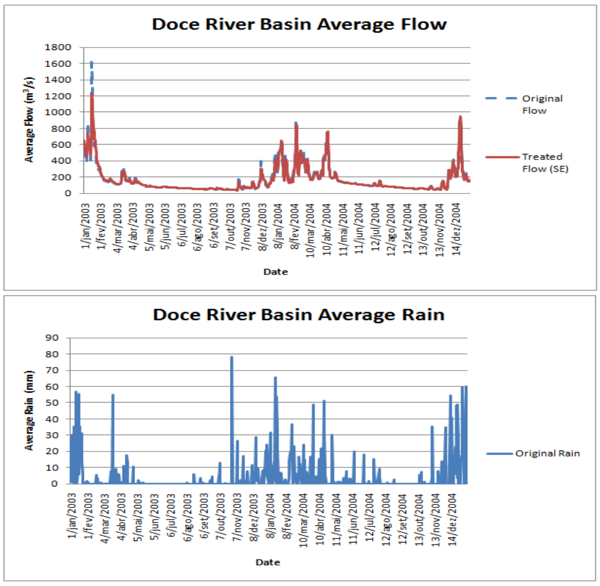

Figure 4. Doce river basin average flow ES treatment.

After the ES treatment, NN configuration is necessary. The NN configuration is chosen empirically by some initial tests and is shown in Table V.

TABLE V. NN (Flow and Rain) Configuration

Description	Parameter
Epochs	10.000.000
Learning Rate	0,1
Momentun	0,85
Imput layer	2
Hidden layer	30
Output layer	2
Activation function	Hyperbolic tangent
Output data	Linear

Almost 80 hours of neural processing was required. A decent gradient error of 3,4 * 10^{-5} was the final training result, meaning a good neural learning integrated with NARMAX technique. NN training simulation is shown in Fig. 5.

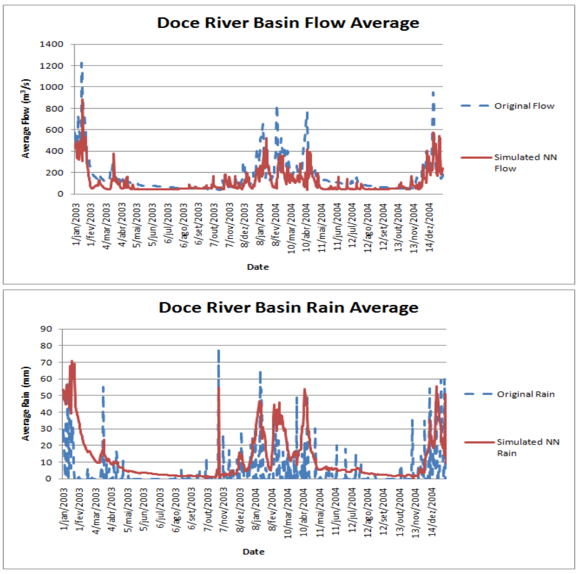

Figure 5. Doce river basin average flow and rain NN simulation.

Only seven last days of original Doce basin flow temporal data series daily average is compared with the COMTIF seven days forecast results after two years used in NN training. Moreover, a MSE is used to compare the original temporal data series and forecast results. The Fig. 6 shows original data series and forecast COMTIF results.

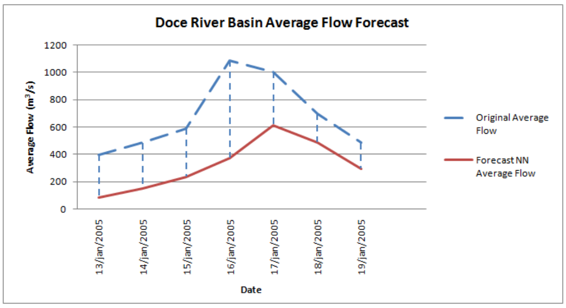

Figure 6. Doce river basin average flow forecast.

The forecast made for 7 days had a MSE of 3,93 * 10^2, comparing original data (dashed) and forecast data (bold line). The most important features of tendency were similar with the original temporal data series, showing how close the forecast result was presented.

IV. CONCLUSIONS

The COMTIF has worked satisfactorily with nonstationary temporal series, even with short range data as the practical application.

When analytical model is not available or does not work well to present good results the COMTIF appears as a good alternative for this kind of work.

This method is also a good alternative to people that needs temporal data forecasting answer without previous temporal series or knowledge.

REFERENCES

[1] A. Lencastre and F. M. Franco, “Lições de Hidrologia”, 2nd ed. Lisboa: Serviços Editoriais da Universidade Nova Lisboa, 1992.

[2] L. A. Aguirre and E. M. A. M. Mendes, “Global nonlinear polynomial models”, International Journal of Bifurcation and Chaos, vol. 6, no. 2, pp. 279-294, 1996.

[3] S. Makridakis, S. C. Wheelweight, and V. E. McGee. “Forecasting: methods and applications”, 2nd ed. Canada: John Wiley & Sons, Inc., 1983.

[4] P. M Tasinaffo, “Estrutural de integração neural feedfoward testadas em problemas de controle preditivo”, Engineering and space technology doctorate thesis, Spatial Research National Institute, São José dos Campos, 2003, (INPE-10475-TDI/945).

[5] P. M. Tasinaffo and A. Rios Neto, “Modelagem de sistemas dinâmicos com integrador neural de Euler baseado em derivadas médias”, Congresso Brasileiro de Automática. Gramado: CBA, 2004.

[6] F. M. de Azevedo, L. M. Brasil, and R. C. L. Oliveira, “Redes neurais com aplicações em controle e sistemas especialistas”, Florianópolis: Bookstore, 2000.

[7] W. Collischonn, “Simulação hidrológica de grandes bacias”, Doctorate thesis, Federal University of Rio Grande do Sul, Porto Alegre: 2001.

[8] M. J. S. Valença, “Aplicado redes neurais: um guia completo”, Olinda: Livro Rápido – Elógica, 2005.

[9] C. C. Holt, “Forecasting seazonal and trend by esponentially weighted moving averages”, International Journal of Forecasting, 2004.

[10] P. R. Winters, “Forecasting sales by exponentially weight moving average ”, Journal of Management Science, 1960.

[11] K. Hornik, M. Stinchcombe, and H. White, “Multilayer feedforward networks are universal aproximators”, Neural Network, vol. 2, no. 5, pp. 359-366, 1989.

[12] S. Haykin, “Neural networks”, New York: Macmillan College, 1994.

[13] G. Cybenko. “Continuous valved neural networks with two hidden layers are sufficient”, Medford: Tufts University, 1988.

[14] A. P. Braga, T. B. Ludemir, and A. C. P. L. F. Carvalho, “Redes neurais artificiais”, Rio de Janeiro: LTC, 2000.

[15] J. Sjoberg, “Nonlinear system identifiaton with neural networks”, DSc thesis in electrical engineering, Linkoping University, Linkoping, 1995.

[16] R. Guarize, “Uso de redes neurais na análise de resposta dinâmica de estruturas”, Master thesis, Federal University of Rio de Janeiro, 2004.

[17] S. A. Billing and S. Chen, “Representation of nonlinear systems”, International Journal of Control, vol. 49, pp. 1012-1032, 1989.

[18] L. H. G. Marin and P. M. Tasinaffo, “Um método computacional para tratamento, identificação e previsão aplicado a rios da bacia amazônica”, The 3rd Southern Conference on Computational Modeling. Rio Grande: MCSUL, 2009.

[19] HIDROWEB, “Hidrological information system”, 2009. [Online]. Avaliable: http://hidroweb.ana.gov.br

[20] F. Spaeth, “Modelo para previsão de vazão fluvial baseado em wavelets e redes neurais”, Master thesis, Federal University of Santa Catarina, Santa Catarina, 2008.

[21] A. A. Olivo, “Modelos matemáticos para previsão de cheias”, PhD thesis, Aeronautics Institute of Technology, São José dos Campos, 2004.