SEA WATER LEVEL FORECASTING USING SOFT COMPUTING TECHNIQUES: COMPARATIVE PERFORMANCE OF NEURAL NETWORKS AND GENETIC PROGRAMMING

Daiane Gracieli Faller*

Luana Borato**

daiafaller@yahoo.com.br

borato.luana@gmail.com

*Programa de Pós-graduação em Engenharia Civil – COPPE – Universidade Federal do Rio de Janeiro (UFRJ), Centro de Tecnologia - Bloco B - Ilha do Fundão ,Caixa Postal 68506 – Zip Code: 21941-942 - Rio de Janeiro – RJ, Brasil

** Centro de Estudo do Mar (CEM) - Universidade Federal do Paraná, Av. Beira-mar, s/n, Caixa Postal / P.O.Box: 61, Zip Code: 83255-976 - Pontal do Paraná – PR – BRASIL

Adrieni Ferreira de Andrade***

Eduardo Marone**

Nelson Francisco Favilla Ebecken*

adrieniandrade1@gmail.com

edmarone@gmail.com

nelson@ntt.ufrj.br

***Programa de Pós-graduação em Engenharia Oceânica – COPPE – Universidade Federal do Rio de Janeiro (UFRJ), Centro de Tecnologia - Bloco C - Ilha do Fundão, Caixa Postal 68506 – Zip Code: 21941-942 - Rio de Janeiro – RJ, Brasil

Abstract. *Artificial neural network (ANN) and genetic programming (GP) have been applied to solve a wide range of different problems in coastal and ocean areas in order to develop estimation or forecasting of environmental, ocean and weather parameters, structural loads and responses. The purpose of this study is to experiment different ANN and GP structures to* *predict sea level variations due to a combination of astronomical and meteorological forces. Conventional tidal forecasting has been based on harmonic analysis using the least squares method to determine harmonic parameters, where a large number of them is required for the prediction of sea levels. Forecast improvements may be obtained using combination of harmonic analysis and meteorological variables. The use of tools capable to train and translate the combined influence of meteorological and astronomical forcing to predict sea level variations and reduce the margin of error can be a powerful alternative. In this work, improvement in the sea level forecasts at the Estuarine Complex of Paranaguá (Paraná State, Brazil) is expected by giving the knowledge of meteorological and calculated astronomical tide behavior (by harmonic analysis) to the ANN and GP, at the same time period, obtaining results as close to real observed values as possible. To perform this, the models was trained by using hourly time series of atmospheric pressure, wind, and harmonically derived tides for a specific year as input data and hourly time series of measured tides as output data. The dataset was obtained from Paranaguá meteorological and tide gauge stations. If missing data were found in time series, interpolation based on FFT analysis was used. For water level forecast, the meteorological time series were used as input data, and the resulting water level outputs will be compared with the water level measurements in the same period. In both methods, different configurations were tested to identify which configuration is the best one. The performance of the ANN and GP were measured in terms of the correlation coefficient (R), root mean square error (RMSE) and scatter index (SI).*

Key words: *sea level prediction, genetic programming, neural networks.*

1. INTRODUCTION

Sea level variations are determinate by a sum of components from oceanographic, meteorological and astronomical phenomena (Pugh, 1987; Douglas et al., 2000). Understanding the non-linear dynamics of these phenomena is one of the most challenging roles in the study of ocean-atmosphere interaction. Sea level fluctuations forecast and interpretation are essential for ocean dynamics comprehension, mainly at coastal environments where sea level could affect ecosystems, human navigation, or cause erosion, floods, etc.. Therefore, a reliable prediction can provide the possibility of analyse and quantify these and other impacts produced by sea level fluctuations (Pashova & Popova, 2011).

Among the techniques conventionally used for the forecast of sea level, stand out various methods of harmonic analysis (Franco & Rock, 1972; Franco, 2009; Foreman, 1977, Foreman et al., 2009), which permits forecast of tidal variations due to a locally modified response to astronomical forcing. However, these methods are not efficient to detect some fluctuations caused by meteorological events, thus the quality of their results are often not useful for extreme events prediction from atmospheric origin. As well as the harmonic analyses, other traditional sea level forecasting techniques have difficulty to predict the effects of meteorological forcings.

The development and application of new methodologies have shown improvements of up to 30% on quality of forecasts (Makarynska & Makarynskyy, 2008). Among these, particular techniques of soft computing techniques, such as Artificial Neural Networks (ANN) and Genetic Programming (GP) have great flexibility and ability to work with the non-linearity of the data and have been incorporated as a powerful alternative to traditional approaches (Recknagel, 2006; Olden et al., 2006). Nitsure et. al (2014) explained five strengths of these techniques, also called data-driven techniques, being: 1) understanding of the underlying physical processes is not a pre-requisite; 2) modelling and/or observed data need not be huge and exogenous; 3) re-calibration of the developed models can be done in comparatively less time and with less efforts; 4) a reasonable generalization is extracted from the data in spite of the complex physical processes involved in the phenomena, and; 5) the developed models are more robust since they are more data tolerant.

A way of inserting the action of meteorological forcings in the forecast process is the utilization of Artificial Neural Networks (ANN), which can translate and learn the relation between the behaviour of the meteorological and the sea level variables. ANN consists of a network that is inspired by the way that human brain processes the information. To reproduce the brain process to reach a reasonable solution to fit the input-output dataset, the network uses a number of artificial neurons, interconnected with connection links of different weight. The ANNs have been shown to be effective in improving sea level predictions (Deo and Chaudhari, 1998; Tsai and Lee, 1999; Cox et al., 2002; Lee and Jeng, 2002; Oliveira et al., 2006; Liang et al, 2008). ANNs are computational structures of nonlinear predictive modelling (Lek, et al., 1996) viable to solve numerous problems, including cases in which there is little understanding of the processes involved and the relationship between them. Make prediction for sea level is one case where ANNs can be applied (Jain, et al., 1996), because these are able to translate and learn the relationships between the meteorological phenomena and sea level variables.

Genetic programming, first proposed by Koza (1992) as a generalization of genetic algorithm (GA) (Goldberg, 1989), employs a ‘‘parse tree’’ structure for the search of its solutions. This technique has the capability for deriving a set of explicit formulations that rule the phenomenon and to describe the relationship between the independent and the dependent variables using various operators (Kisi et al., 2012). The GP methods are wide-ranging, similar to the GA, where their details may be obtained from various textbooks (e.g. Goldberg, 1989; Koza, 1992). Generally, they are robust to identify optimal solutions particularly in the large and complex search space. The techniques have the capability to derive a set of mathematical expressions to describe the relationship between independent and dependent variables. The GP use operators such as mutation, recombination (or crossover) and evolution, names inspired by the theory of evolution and adopting an evolutionary process to solve optimization problems based on the mechanism of natural selection (Holland, 1992). Some studies have applied the GP technique to the sea level forecast or similar issues and their results showed considerable improvement in comparison with other techniques (Ghorbani et al., 2010; Khu et al., 2001).

The purpose of this study is to experiment artificial neural network (ANN) and genetic programming (GP) structures to sea level forecast variations due to a combination of astronomical and meteorological forces.

2. MATERIALS AND METHODS

2.1 Study Area

The Paranaguá Estuarine Complex (PEC) is located in the central-north region of the Parana State (25°15'S, 48°25'W) with nearly 612 km^2 extension area. The estuary main area is divided in two segments, one called Laranjeiras and Guaraqueçaba Bay (with N-S orientation) and, other, Paranaguá and Antonina Bay (with E-W orientation).

The wave propagation inside the estuary is modified by its delta shape, particularly during ebb tide at the estuary mouth. Waves inside PEC are characterized by low height (Hs <0, 25 m) and small period (T < 5 s) (Rosa & Borzone, 2008), however, changes may occur during tidal regime. The tidal waves have a semi-diurnal regime, although inequalities and non-linear effects occur, with two high tides and two low tides per lunar day (24 h 50 min) (Marone et al., 1997). In the internal part of the estuary mouth, tidal current velocities reach 0.59 ms^{-1} during flood and 0.97 ms^{-1} in ebb tides. In PEC southern mouth external part the maximum tidal current velocity is 0.32 ms^{-1}, at ~3 m of depth, during flood tides and 0.87 ms^{-1} during ebb tides (Marone et al., 1997). In meteorological tide terms, sea level could reach 0.80 meters above astronomical tide (Noernberg, et al., 2008).

Local atmospheric circulation is characterized by Southeast and East winds, which have, in average, 4 ms^{-1} of intensity (Rosa & Borzone, 2008). Although, there are changes due to cold fronts occurrences. From the local climatology is possible to corroborate that frontal systems are the main responsible for sea level changes at tidal frequencies. Typical changes are common in mean sea level, especially during the winter, attributed to oceanic cold fronts passages and strong winds. They also generate large waves, and these causes piled up water into the coastline (Marone & Camargo, 1994).

2.2 Dataset and data treatment

The tidal data used in this study (sampled every 30 minutes) was obtained during 1997 at tide gauge station located in the West Pier of Paranaguá Port (25º30’10”S and 48º31’30”W). Pressure and wind times series are from the meteorological station at Pontal do Sul-PR (25º34’45”S and 48º21’04”W).

The observed mean sea level is the result of astronomical tidal forcing plus the changes over the sea surface height due to meteorological effects. In order to separate the astronomical tide from the meteorological one, two general filtering processes are applied. The first one requires tidal harmonic analysis (Franco, 2009; Marone & Mesquita, 1997) of the observed sea level heights to obtain astronomical tidal constants, which in turn are used to recalculate pure astronomical tide for a given period. Once the astronomical tide and the observed sea level are known, the difference (or residuals) between them is the meteorological tide. This was the main method used in this work to separate both tides at hourly or half-hourly time intervals. However, specialized moving average filtering is another way to “clean” the observed sea level time series, obtaining the meteorological tide without spectral analysing the data. On this work the Godin filter (Godin, 1972; Franco, 2009), consisted by two consecutive addition 24 hours length moving average filters, followed by a 25 hours length difference moving average filter (A24A24D25), was used to calculate the sea levels, ensuring that the resulting daily time series is around 99% free of astronomical signals.

Meteorological series (pressure and wind) data quality control was based on a visual inspection, which detected and corrected errors and outliers. The spurious values (outliers) have been replaced by average values between two neighbor data, or fixed with the repeated value in the hourly series. Zonal and meridional wind stress was calculated with the equations below:

$$\tau_X = \rho C_D |W| u$$

$$\tau_Y = \rho C_D |W| v$$

Where:

τ_X = zonal stress;

τ_Y = meridional stress;

ρ = air density = 1.22 kg.m^{-3};

C_D =wind drag coefficient

W = wind module

u = East-West component

v = North-South component

Spurious values were identified as the values contained among percentiles of 25% and 75% of the samples, and eliminated.

2.3 *Multilayer Perceptron* ANN network

The MLP network training was based on backpropagation algorithm principles (Rumelhart et al., 1986; Lippmann, 1987; Kung, 1993). The network is composed by three types of neuron layers: an input layer, one or more hidden (or intermediate) layers and an output layer, each layer including one or more neurons (nodes). In this network, each node in a layer is connected to all nodes of the next layer, but there is no connection between the nodes of the same layer and no connections return (feedback). Hidden layers are used to assist the network to deal with data nonlinearity.

Except for input neurons, which only connects an input value with its associated weight values, the net input of each neuron a_j is the sum of all input values x_n multiplied by their weights w_{jn}. The bias term z_j can be considered as an additional weight and usually equal to 1:

$$a_j = \sum w_{ji} x_i + z_j$$

The output values y_j can be calculated using the net input supply for the neuron transfer function:

$$y_j = f(a_j)$$

Network training consists in adjusting weights and biases using the backpropagation algorithm. For each input vector, an output vector was calculated by the network and calculated outputs for error compared to real values. This procedure is repeated until the errors become small enough or a maximum predefined number of iterations (epochs) is reached. Both weights and biases are used to decrease the error and are pre-set before the network training. Weights and biases values were initially set to be small random numbers. A more detailed description of this procedure can be found in Lek and Guégan (1999).

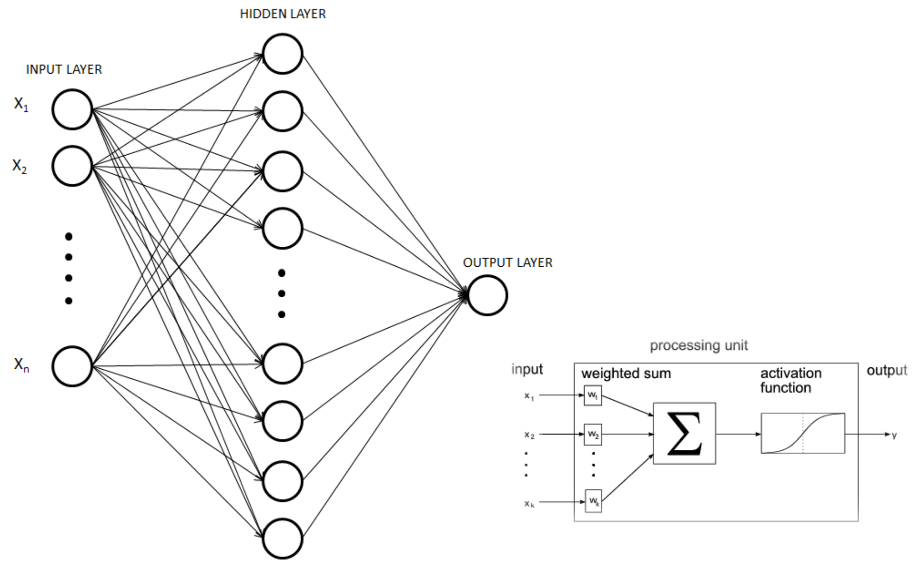

Figure 1. Schematic MLP neural network with three layers: an input layer, a hidden layer and an output layer.

For the best predictive model configuration, different network architectures were tested by modifying the number of hidden layers and their neurons. In addition, we tested the learning algorithms gradient descent with adaptive learning rate (GDA) and Levenberg-Marquardt (LM) (Hagan et al, 1996; Dedecker et al, 2002).

As the variables include different range values and in order to ensure that all variables are receiving the same degree of importance during the training process, it is recommended a standardization. Therefore, before submitting the data to the network, all the input variables have been resized to restrict their interval between -1 and 1 (Dedecker et al., 2004; 2005).

2.4 Genetic Programming

The GP is similar to Genetic Algorithm (GA) but employs a ‘‘parse tree’’ structure for the search of its solutions, whereas the GA employs bite strips (Ghorbani et al, 2010). The technique is a truly ‘‘bottom up’’ process, as there is no assumption made on the structure of the relationship between the independent and dependent variables but an appropriate relationship is identified for any given time series. The relationship can be logical statements; or it is normally a mathematical expression, which may be in some familiar mathematical format; or it may be an assemble of mathematical functions in a completely unfamiliar format.

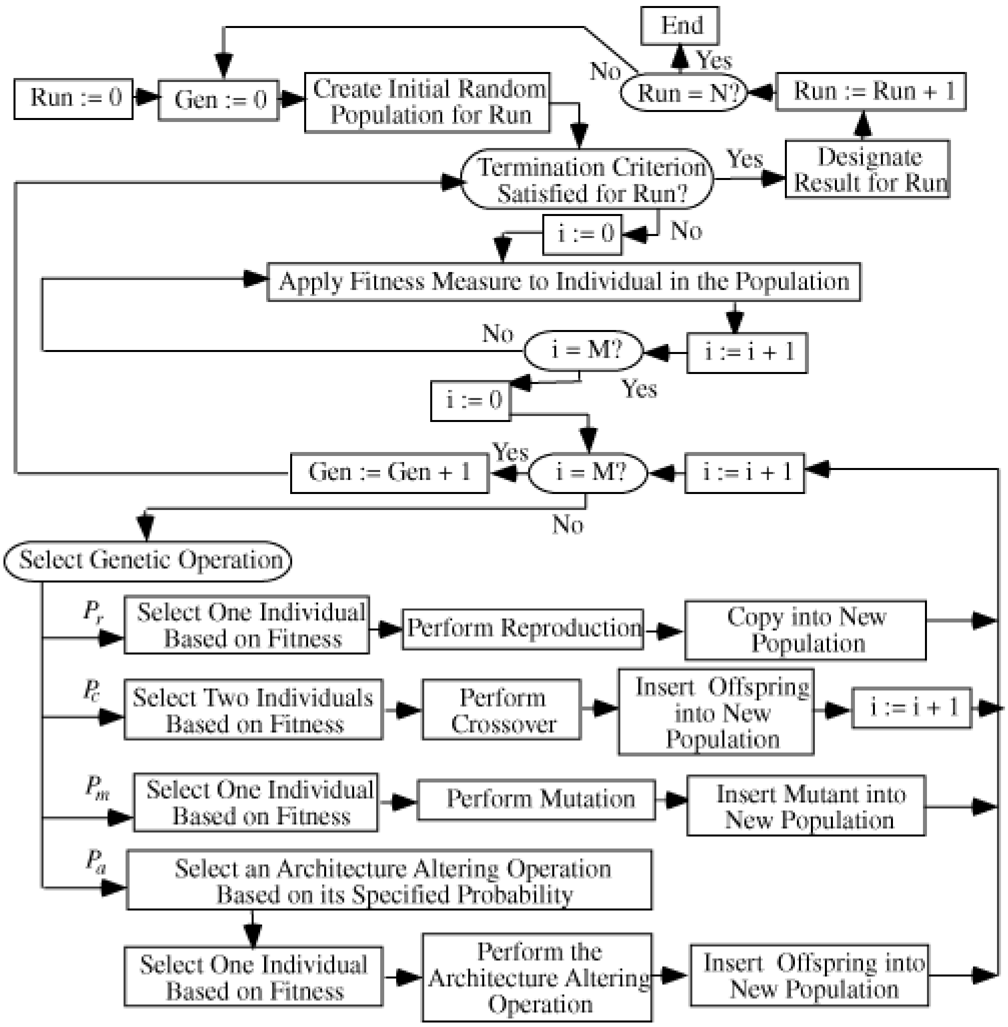

Figure 2. Flowchart of Genetic Programming (Koza, www.genetic-programming.com). Where N is the maximum number of runs and M the maximum program size.

The description and steps bellow were based on Koza (1992).

Genetic programming typically starts with a population of randomly generated computer programs composed of the available programmatic ingredients that iteratively transforms a population of computer programs into a new generation of the population by applying analogues of naturally occurring genetic operations. The iterative transformation of the population is executed inside the main generational loop of the run of genetic programming. The steps of genetic programming (Figure 2) are as follows:

(1) Randomly create an initial population of individual computer programs;

(2) Iteratively perform the following sub-steps (called a generation) on the population until the termination criterion is satisfied:

(a) Execute each program in the population and ascertain its fitness (explicitly or implicitly) using the problem's fitness measure.

(b) Select one or two individual program(s) from the population with a probability based on fitness (with reselection allowed) to participate in the genetic operations in (c).

(c) Create new individual program(s) for the population by applying the following genetic operations with specified probabilities:

(i) Reproduction: Copy the selected individual program to the new population.

(ii) Crossover: Create new offspring program(s) for the new population by recombining randomly chosen parts from two selected programs.

(iii) Mutation: Create one new offspring program for the new population by randomly mutating a randomly chosen part of one selected program.

(iv) Architecture-altering operations (AAO): Choose an architecture-altering operation from the available repertoire of such operations and create one new offspring program for the new population by applying the chosen architecture-altering operation to one selected program. GP uses AAO to automatically determine program architecture in a manner that parallels gene duplication in nature and the related operation of gene deletion in nature. These AAO quickly create an architecturally diverse population containing programs with different numbers of subroutines, arguments, iterations, loops, recursions, and memory and, also, different hierarchical arrangements of these elements. Programs with architectures that are well-suited to the problem at hand will tend to grow and prosper in the competitive evolutionary process, while programs with inadequate architectures will tend to wither away under the relentless selective pressure of the problem's fitness measure.

(3) After the termination criterion is satisfied, the single best program in the population produced during the run (the best-so-far individual) is harvested and designated as the result of the run. If the run is successful, the result may be a solution (or approximate solution) to the problem.

Table 1 shows all parameters modification:

Table 1 - Characteristics of Genetic Programming employed.

Parameter	Value
Generations without improvement	150
Generations since start	200
Maximum number of runs (N)	150
Maximum program size (M)	230
Population size	200

Mutation frequency (%)	95
Crossover frequency (%)	50
Block mutation rate (%)*	30
Instruction mutation rate (%)**	30
Instruction data mutation (%)***	40

* Parameter that set the percentage of mutation operations replace an entire block with a new randomly generated block.
** Sets the percent of mutation operations that result in a single instruction being replaced by a new, randomly chosen instruction of the same length.
*** Determines the probability that the mutation operator will change the temporary computation variable, the inputs or the constants to which an instruction refers to another temporary computation variable, input, or constant.

2.5 Analysis of Results

Basic statistics were performed with the observed sea level data and used for the formation of the network (mean value, standard deviation, minimum and maximum values) and the respective estimated value. The models performance were measured in terms of the correlation coefficient (R), root mean square error (RMSE) and scatter index (SI), expressions for which are presented below:

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 (y_i - \bar{y})^2}}$$

$$RSME = \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}}$$

$$SI = \frac{RMSE}{\bar{x}}$$

where x_i is the value observed at the *i*th time step, y_i the corresponding simulated value, **N** the number of time steps, $\bar{x}$ the mean of observational values and $\bar{y}$ the mean value of the simulations.

3. RESULTS AND DISCUSSION

The data division and input sequence were identical for both methods, where the standard data division of 70:30 is adopted for training and testing the models. The input data were the atmospheric pressure, T_x and T_y wind stress components data series, and the calculated astronomical tide. The output data were sea level (observed level) measurements.

Throughout the year of 1997, the largest observed tidal range was 335 cm, in May, 24 at 12pm and July, 7 at 2am. The observed average was 179,4 cm and a minimum of 30 cm in December, 15 at 12pm.

During the design step, several neural networks (ANN) and genetic programming (GP) were tested. For ANN were performed 108 different network architectures by modifying the amount of hidden layers and their neurons ([5 5], [5 10], [10 5], [10 15], [10 10], [5], [10], [15], [20] with two types of sigmoid functions: logarithmic and tangential transfer function. In addition, two variations of backpropagation algorithm were used in this study: the gradient descent algorithms with adaptive learning and the Levenberg-Marquardt (Hagan et al., 1996; Dedecker et al., 2002). Were tested 200, 500, 1000 training epochs. After tests, the ANN was chosen with Levenberg-Marquardt algorithm with a hidden layer with 20 neurons and transfer functions log-sigmoid and linear for hidden layer and output layer respectively. A stopping criteria was set at 500 training epochs or mean squared error (*MSE*) value equal to 0.01.

For GP were performed 96 different by were modifying the number of generations without improvement (100, 150, 200), maximum number of runs (100, 150, 200, 250), population size (100 and 200), mutation frequency (90 and 95) and crossover frequency (50 and 75). For GP, the Table 1 shows all parameters values.

The results of sea level prediction for all periods considered (1h, 6h, 12h and 24h) were similar when considering the different metrics adopted (R, RMSE and SI) for both models adopted (Table 2). Figure 3 shows the correlation between the observed and predicted data for ANN (a) and GP (b) and the correlation between the predicted values for the two networks (c). The correlation between observed and estimated were similar in all times considered for both models, with ANN performance being marginally better for 1h and 6h and GP for 24 hours averaging.

Table 2 - Statistical analysis of forecasted values for ANN and GP.

	ANN										
	S.L. Observed				S.L. Estimate						
	min	Max	Mean	std	min	Max	mean	std	R	RMSE	SI
1hour	30.00	335.00	179.44	50.93	0.83	295.65	181.09	43.82	0.85	27.29	0.152
6hours	104.58	244.58	179.44	21.16	121.32	238.96	178.98	17.60	0.84	11.61	0.065
12hours	138.33	228.54	179.44	15.63	139.11	228.92	179.77	13.59	0.83	8.79	0.049
24hours	142.00	212.92	179.44	11.93	133.32	197.72	175.47	9.99	0.82	6.87	0.038
	GP										
	S.L. Observed				S.L. Estimate						
	min	Max	Mean	std	min	Max	mean	std	R	RMSE	SI
1hour	30.00	335.00	179.44	50.93	30.00	335.00	179.44	50.93	0.84	27.38	0.153
6hours	104.58	244.58	179.44	21.16	128.96	239.04	179.46	17.27	0.83	11.70	0.065
12hours	138.33	228.54	179.44	15.63	144.55	217.45	180.09	12.01	0.83	8.80	0.049
24hours	142.00	212.92	179.44	11.93	149.29	198.55	179.54	9.59	0.83	6.60	0.037

The estimated values for both models were highly correlated at all times considered, which suggests that both were able to predict the tide observed values with the same precision. The results of Nitsure et al. (2014) also showed a similar correlation values between both models for different tide gauge stations in the United States, but with a marginally more accurate prediction using GP to predict the water level. Ghorbani et al. (2010) showed significant improvements with GP results compared with the results of ANN from Makarynska and Makarynskyy (2008) work.

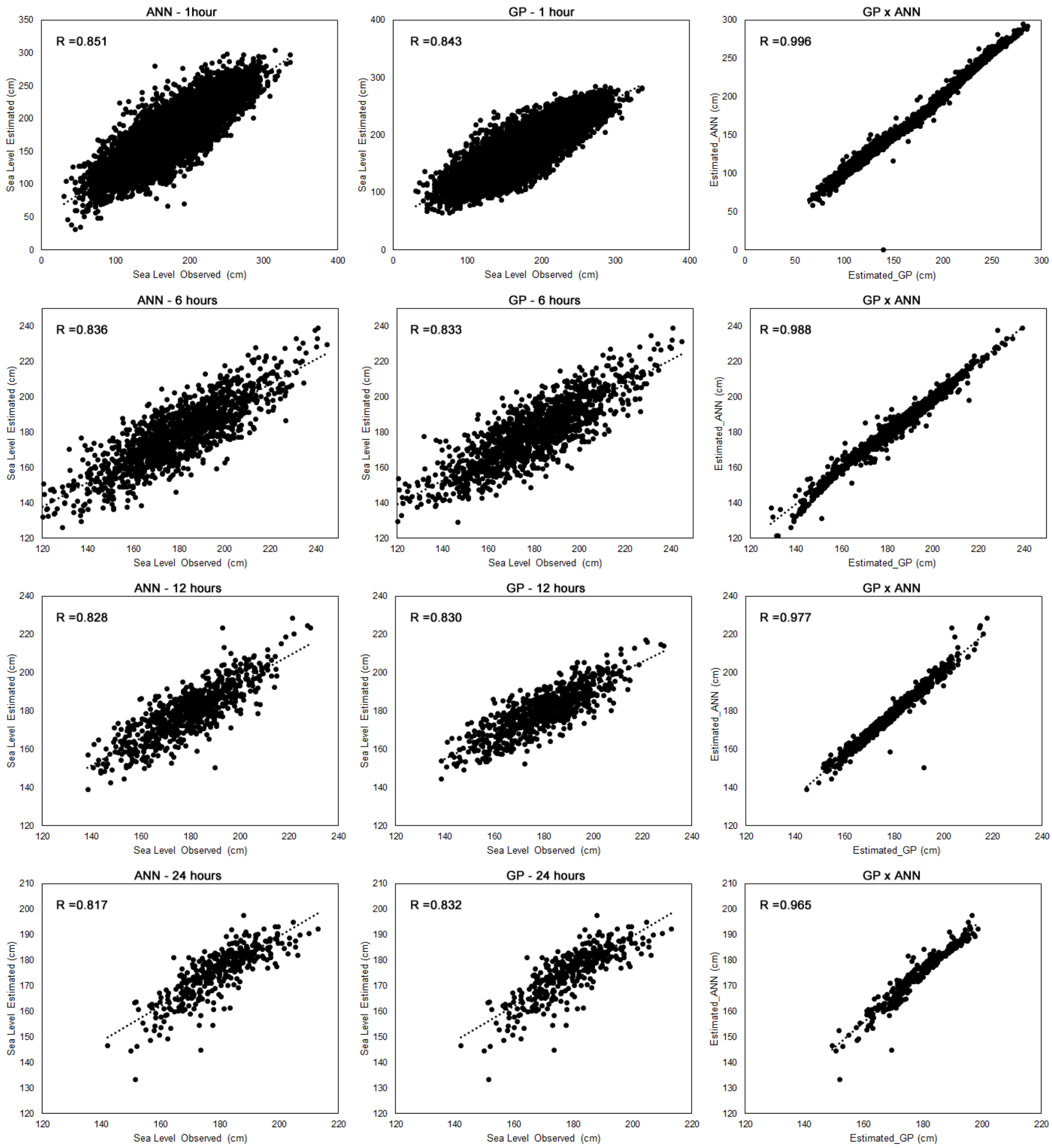

Figure 3 - The correlation between the observed and predicted data, considering all the analysed times (1h, 6h, 12h and 24h) for ANN (first column) and GP (second column). The third column corresponds to the correlation between the estimated data for ANN and GP.

When the time series were analysed, the findings fit the results of basic statistics. **Figure 4** shows the time series for January and July with an interval of 1h in sea level values. The results for both models are similar and not accurately explain the extreme values in the variations of the sea level. **Figure 5** shows the time series for all the analysed period and with an interval of 24h in sea level values. Clearly after September 1997, both models have difficulty representing sea levels daily, while the predicted values for the previous months are more reliable.

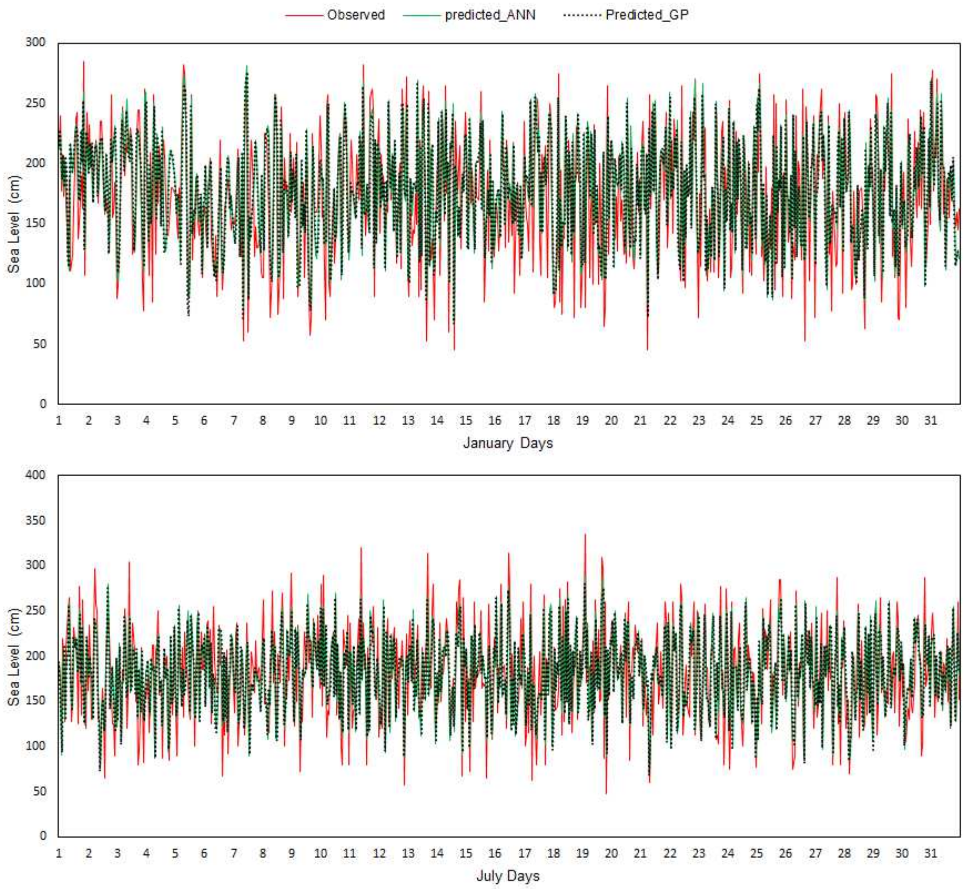

Figure 4 – Temporal series considering the values observed and predicted (ANN and GP) of level with 1h range for January and July 1997.

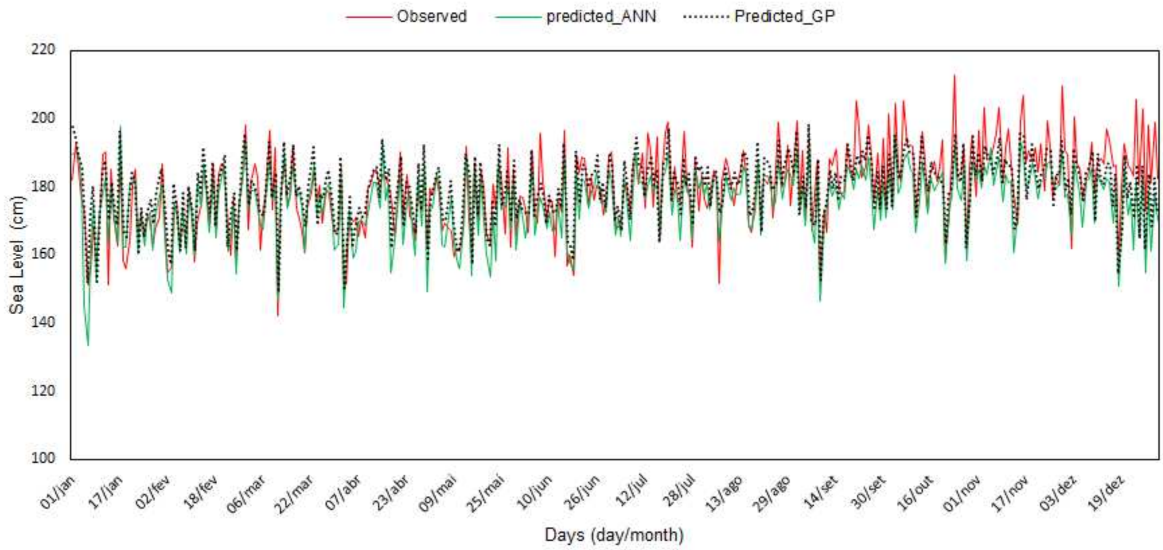

Figure 5 – Temporal series considering the values observed and predicted (ANN and GP) of level with 24h range for all period analysed (1997).

The results described above suggest that the models (GP and ANN) have similar performance when trying to predict the sea level considering different ranges of analysis (1, 6, 12 and 24 hours). However, the predicted values, when compared with actual observed values, feature a large discrepancy. This difference may be occurring due to some weather variable that is not being considered in modelling or even by the small set of data used to train, validate and test the models (only one year was modelled). Also, the highly non-linear environment could not being properly modelled. Another probably cause is linked with a very long data series used to train the models. The phenomena which determine the sea level for the next day, for instance, are those happening the previous days or so.

3 CONCLUSION

Our results with the current modelling procedure, suggest that the performance of the models (GP and ANN) have similar performance when trying to predict the sea level and that both models were able to identify the 81 86% of the variation in the sea level. It is believed that the inclusion of other variables that best define the study environment, one more concise data series and the development of other architectures might improve the sea levels forecasts. Therefore, further work is necessary using various data combinations and hybrid techniques, and more inputs such as bathymetry (or morphology) and other meteorological parameters. This time scale issue is the next step to be investigated, training the models with different data lengths, trying to establish the best length for a given forecast window.

4 REFERENCES

Cox D.T., Tissot P., Michaud P 2002. Water level observations and short-term predictions including meteorological events for entrance of Galveston Bay, Texas. *J Waterways Port Coast Ocean Eng*, 128(1):21–9.

Dedecker, A.P., Goethals, P.L.M., Gabriels, W., De Pauw, N., 2002. Comparison of artificial neural network (ANN) model development methods for prediction of macroinvertebrates communities in the Zwalm river basin in Flanders, Belgium. *Scientific World J*. 2, 96-104.

Dedecker A.P., Goethals P.L.M., Gabriels W., De Pauw N., 2004. Optimization of Artificial Neural Network (ANN) model design for prediction of macroinvertebrates in the Zwalm river basin (Flanders, Belgium). *Ecological Modelling* 174, 161-173.

Dedecker A.P, Goethals P.L.M. and De Pauw N., 2005. Sensitivity and robustness of stream model based on artificial neural networks for the simulation of different management scenarios. *In:* Lek S., Scardi M., Verdonschot P.F.M., Descy J.P. and Park Y.S. (eds.), *Modelling Community Structure in Freshwater Ecosystems*, Springer-Verlag, Berlin, 133–146.

Deo M.C., Chaudhari G., 1998. Tide prediction using neural networks. *J Comp-Aided Civil Infrastruct Eng*, 13:113–20.

Douglas, B.C., Kearney, M.S., Leatherman, S.P., 2000. Sea Level Rise History and Consequences. International Geophysics Series, Vol. 75. Academic Press, London 272 pp.

Foreman M. G. G., Cherniawsky J. Y., Ballantyne V. A., 2009 Versatile Harmonic Tidal Analysis: Improvements and Applications, *Journal of Atmospheric and Oceanic Technology*, 26, 4, 806.

Foreman M.G.G., 1977. *Manual for tidal heights analysis and predictions*. Pacific Marine Science Report, 77-10, 97pp.

Franco A.S., Rock N., 1972. The Fast Fourier Transform and its application to tidal oscillations. *Bol. Do Instituto Oceanogr. de S.Paulo*.

Franco A.S., 2009. *Marés: Fundamentos, Análise e Previsão*. Niterói, RJ: D.H.N. 344pp.

Ghorbani M.A., Khatibi R., Aytek A., Makarynskyy O., Shiri J., 2010. Sea water level forecasting using genetic programming and comparing the performance with artificial neural networks. *J Comp Geosci*, 36:620–7.

Godin, G., 1972. *The Analysis of Tides*, University of Toronto Press, Toronto, 264pp.

Marone E., Mesquita A.R., 1997. On tidal analysis with measurement errors. *Bolletino de Geofisica Teorica ed Applicata*. Vol 38, p. 3-4

Goldberg, D.E., 1989. *Genetic algorithms in search, optimization, and machine learning.* Addison-Wesley, Reading, MA, 432 pp.

Hagan, M.T., Demuth, H.B., Beale, M., 1996. *Neural Network Design.* PWS Publishing Company, Boston, Massachusetts, USA. 651 p.

Holland, J.H., 1975. *Adaptation in Natural and Artificial Systems*. University of Michigan Press, Ann Arbor, MI.

Jain, S.K., Das, D., Srivastava, D.K., 1999. Application of ANN for reservoir inflow prediction and operation. *Journal of Water Resources Planning and Management* 125 (5), 263–271.

Khu S.T., Liong S.Y., Babovic V., Madsen H., Muttil N., 2001. Genetic programming and its application in real-time runoff forecast. *J Am Water Resour As* 37(2):439–451

Kisi, O., Shiri, J., Nikoofar, B., 2012. Forecasting daily lake levels using artificial intelligence approaches. *Computers & Geosciences* 41, 169-180.

Koza J.R., 1992. *Genetic programming: On the programming of computers by means of natural selection.* Cambridge, MA, USA: The MIT Press. p. 1–835. ISBN 9780262111706.

Kung S., 1993. *Digital neural networks*. Englewood Cliffs, NJ: Prentice Hall.

Lee T.L., Tsai C.P., Jeng D.S., Shieh R.J., 2002. Neural network for the prediction and supplement of tidal record in Taichung Harbor, Taiwan. *Adv Eng Software,* 33:329–38.

Lek, S., Guegan, J.F., 1999. Artificial neural networks as a tool in ecological modelling, an introduction. *Ecological Modelling* 120, 65-73.

Liang S.X., Li M.C., Sun Z.C., 2008. Prediction models for tidal level including strong meteorologic effects using a neural network. *Ocean Eng*, 35:666–75.

Lippmann R., 1967. *An introduction to computing with neural nets.* Volume April: IEEE ASSP Magazine; 4-22.

Makarynska D., Makarynskyy O., 2008 Predicting sea-level variations at the Cocos (Keeling) Islands with artificial neural networks. *Comp Geo-Sci*, 34:1910–7.

Marone, E., 1996. “Radiational" tides as non linear effects: bispectral interpretation. *Continental Shelf Research*. Vol. 16, No. 8, p.1117-1126, 1996.

Marone E., Mesquita A.R., 1997. On tidal analysis with measurement *errors. Bolletino de Geofisica Teorica ed Applicata*. Vol 38, p. 3-4.

Marone E., Mantovanelli A., Klingenfuss M.S., Lautert L.F.C., Prata Jr. V.P., 1997. Transporte de material particulado em suspensão, água, sal e calor na Gamboa do Perequê num evento de maré de sizígia. Expanded abstract. *VII Congreso Latinoamericano de Ciencias del Mar*, Santos, Brazil, p. 134-136.

Nitsure S.P., Londhe S.N., Khare K.C., 2014. Prediction of sea water levels using wind information and soft computing techniques. *Ap Ocean Res*, 344:351–47.

Noernberg, M., Angelotti, R., Caldeira, G. & Ribeiro De Sousa, A., 2008. Determinação da Sensibilidade do Litoral Paranaense à Contaminação por Óleo. Braz. *J. Aquat. Sci. Technol.*, 12(2), pp. 49-59.

Olden, J.D., Poff, N.L., Bledsoe, B.P., 2006. Incorporating ecological knowledge into ecoinformatics: An example of modeling hierarchically structured aquatic communities with neural networks. *Ecological Informatics* 1, 33-42.

Oliveira, M.M.F., Ebecken, N.F.F., de Oliveira, J.L.F., Nunes, L.M.P., 2009. Predição da Variação Extrema do Nível do Mar relacionada a tempestades severas utilizando Redes Neurais Artificiais. *Revista da Sociedade Brasileira de Redes Neurais* (SBRN) 7 (1), 19e29.

Pashova L., Popova S., 2011. Daily sea level forecast at tide gauge Burgas, Bulgaria using artificial neural networks. *Original Research Article Journal of Sea Research* 66(2):154–161

Pugh, D. T., 1987 *Tides, Surges and Mean Sea Level*. Great Britain: John Wiley & Sons, 472 p.

Recknagel, F., 2006. *Ecological Informatics: Scope, Techniques and Applications,* Springer, Berlin.

Rosa, L. C. d. & Borzone, C. A., 2008. Uma abordagem morfodinâmica na caracterização fisica das praias estuarinas da Baia de Paranaguá, sul do Brasil. *Rev. bras. geociênc.* , 38(2).

Rumelhart, D., Hinton G. E., Williams R. J., 1986. *Learning inteANNl representations by error propagation, in parallel Distributed Processing*, vol. 1, chap. 8, edited by D. E. Rumelhart and J. L. McCelland, MIT Press, Cambridge, Mass.

Tsai, C.P., Lee, T.L., Chu, L.H., 1999. Forecasting of wave time series using back-propagation neural network. *Journal of the Chinese Institute of Civil and Hydraulic Engineering* 11, 589e596.