USING NEURAL NETWORKS TO FORECAST RENEWABLE ENERGY RESOURCES

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Abstract: This contribution presents the application of feed-forward neural networks to the problem of time series forecasting. This forecast technique is applied to the water flow and wind speed time series. The results obtained from the forecasting of these two renewable resources can be used to determine the power generation capacity of micro or mini-hydraulic plants, and wind parks, respectively. The forecast values obtained with the neural network are compared against the original time series data in order to show the precision of this forecast technique.

1 INTRODUCTION

The study of trends and patterns of complex systems is of great interest since the results obtained from these studies support the decision-making process in many activities. In particular, applications such as electric load forecasting (Wei and Jie, 2008); (Bunnoon et al., 2009); (Hahn et al., 2010), economic forecasting (Fang-yuan and Feng-you, 2008), forecasting natural and physical phenomena (Makarov et al., 2010) have been widely studied.

In this context, due to the neural networks ability to discover patterns in nonlinear and chaotic systems, they can be used to predict the behavior of these systems more accurately than many current techniques, such as Exponential Smoothing, and Holt-Winters' methods (Gelper et al., 2009).

Neural network have shown to have great potential for renewable resources forecasting. Examples using neural networks in power generation based on renewable energy like water (Xinhua and Zhuying, 2010), wind (Chen and Lai, 2011), and solar (Ghanbarzadeh et al., 2009) can be found in the literature.

In this paper a feed-forward neural network is applied to know the future behavior of the water flow and wind speed time series. Results obtained from the water flow time series can be used to determine if a micro or mini-hydraulic plant can be installed, the theoretical power generation and the technical characteristics of each electro-mechanical component of the micro-hydraulic generation system (Peña et al., 2009). On the other hand, with the results obtained from the wind speed time series, the power generation capacity of a wind park that will have in the next days can be determined (Lange and Focken, 2005).

The rest of this paper is organized as follows: Section II explains the general structure of a neural network; Section III presents a case study of the application of the neural network to the problem of water flow time series forecasting; Section IV shows the results obtained in the forecast of a wind speed time series; finally, Section V draws the main conclusions of this research work.

2 NEURAL NETWORKS

A neural network is a computational model that is closely based on the neuron cell structure of the biological nervous system. Feed-forward neural networks are composed of layers of neurons in which the input layer of neurons is connected to the output layer of neurons through one or more layers of intermediate neurons, as shown in Figure 1.

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The training process of the neural network involves adjusting the weights until a desired input/output relationship is obtained. The majority of adaptation learning algorithms are based on the back-propagation algorithm (De Jesus and Hagan, 2007). Through back-propagation algorithm, the neural network forms a mapping between inputs and desired outputs from the training set by altering weighted connections within the network.

The training method used in this research is the Levenberg-Marquardt back-propagation algorithm (LMBP). The LMBP algorithm can train a neural network with high degree of efficiency because it uses a combination of the back-propagation algorithm, the gradient descent method, and the Gauss-Newton method (Wenshang et al, 2008).

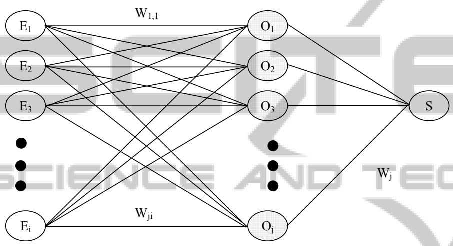

Figure 1: Neural network general scheme.

3 WATER FLOW TIME SERIES FORECASTING

In hydraulic plants the water is the raw material. Thus, it is important to know its behavior with the time. In order to determine the hydroelectric potential of the water flowing through a river or stream, it is necessary to know the average monthly water flow and the difference in heights to which water can fall.

The average monthly water flow is defined as the amount of water passing through a particular point in each instant time. The difference in heights to which the water flow can fall is measured from the level at which the water enters to the canal used to carry the water to the turbines and the level of the water at which the water is returned to the river.

The historical water flow measurements can be organized into a time series. Figure 2 shows the water flow time series used in this work. This historical data corresponds to the measurements taken from the "The Naranjillo" hydrometric station, in Actopan River, Veracruz, México (CONAE, 2005). The time series has 300 monthly observations, from the period of January 1961 to December 1985.

For this case study, a neural network containing three layers and thirty neurons in each layer was implemented in the C# language. 200 data from the time series were used to train the neural network and the last 100 data were used for the validation of the obtained forecast.

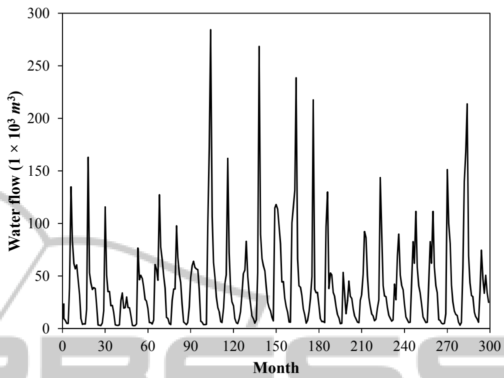

Figure 2: Water flow time series.

The calculated forecast data obtained with the neural network and the historic data are compared in Figure 3. From this Figure it can be observed, that the forecasted data matches satisfactorily the original time series.

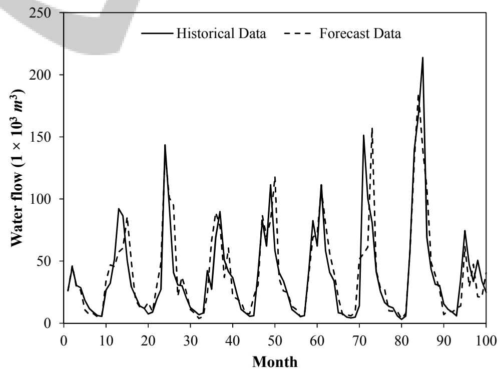

Figure 3: Neural network forecast data.

In order to evaluate the accuracy of the obtained forecasts, the absolute error was calculated. The absolute error (AE) is defined as the magnitude of the difference between the exact value and the approximation; it is the difference between the historical data contained in the time series and the forecasted data. The AE is determined by (Koller and Friedman, 2009),

$$AE = ABS(y_h - y_f) \tag{1}$$

where AE is the absolute error; y_h is the historical data; and y_f is the forecasted data.

The Figure 4 shows the AE obtained for each one of the 100 forecasted data using the neural network. The maximum AE obtained is 95.16, the minimum AE is 0.04, while the average AE is 12.9. From this graph, it can be also observed that AE is bigger when the time series presents high values, especially around the 75 and 85 data from the time series.

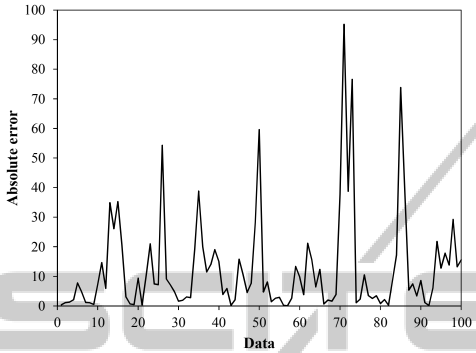

Figure 4: AE obtained with the water flow time series.

4 WIND SPEED TIME SERIES FORECASTING

Forecasting techniques are frequently used in wind generation systems to understand the behavior of the wind in the days ahead. Based on these results, the power generation capacity of wind turbines installed in a certain area can be calculated.

This power generation capacity is used to make technical and economic decisions, e.g., transmission system operators are interested in know the production capacity of a wind farm in order to maintain the balance of power transmitted through the network, while in a deregulated system, the wind farm owner is interested in know the production capacity at least 48 hours in advance to raise the necessary strategies to compete in the energy market (Bathurst et al., 2002).

In this case study, the time series used correspond to wind speed measurements made by the Comisión Federal de Electricidad (CFE) in the hybrid wind-photovoltaic generation system, "San Juanico", located in Baja California Sur, México.

Figure 5 illustrates the "San Juanico" wind speed time series; this time series contains 744 measurements recorded on an hourly basis at a height of 33 m, in the month of March, 2000.

The neural network used in this case study contains three layers and forty-eight neurons in each layer. The first 624 data from the time series were used to train the neural network and the last 120 data were used for the validation of the obtained forecast.

The forecasts data obtained by applying the neural network are shown in Figure 6. The forecasted data satisfactorily matches the original time series; however, it cannot adequately reproduce some of the peaks taking place in the original time series.

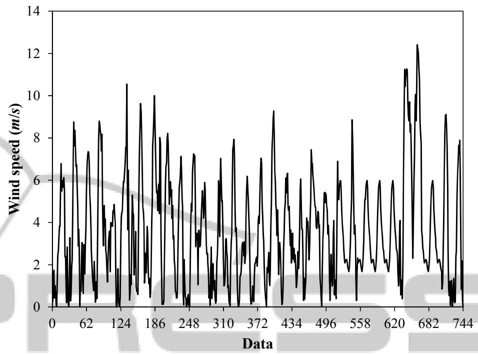

Figure 5: Wind speed time series.

The AE obtained from the forecasted data using the neural network is shown in the Figure 7. The maximum AE obtained is 6.97, the minimum AE is 4×10^{-3}, while the average AE is 1.28.

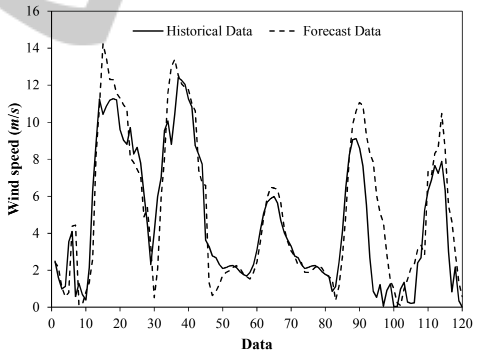

Figure 6: Neural network model response.

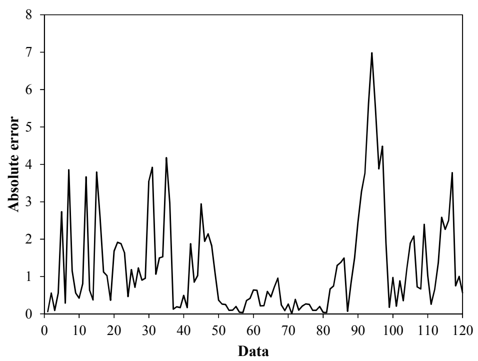

Figure 7: AE obtained with the wind speed time series.

Visually, the forecast accuracy obtained in this case study with respect to the previous one seems to be lower, but the average AE is bigger for the first case study, this is due to the magnitude of measured quantities. Also, please consider that the water flow through rivers tends to be periodic over time, while wind speed is not and it depends on other physical factors.

5 CONCLUSIONS

A feed-forward neural network has been applied to forecast the future behavior of two different sets of time series based on the measurements of renewable energy resources, such as water flow and wind speed.

In the first case study, the neural network was used to estimate the future behavior of a water flow time series. In the second case study presented, the application of this forecast technique to the problem of determining the future behavior of the wind speed at a given site has been illustrated. The obtained results in both cases show that the neural network adequately represents the historical data contained in the time series.

The obtained results are of great value as they provide insight into the generation capacity that will have a micro or mini-hydraulic plant and wind system in the days forecasted, respectively.

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REFERENCES

Bathurst, G. N., Weatherill, J., Strbac, G., 2002. Trading wind generation in short term energy markets. *IEEE Transactions on Power Systems*, vol. 17, no. 3, pp. 782-789.

Bunnoon, P., Chalermyanont, K., Limsakul C., 2010. A Computing Model of Artificial Intelligent Approaches to Mid-term Load Forecasting: a state-of-the-art-survey for the researcher. *International Journal of Engineering and Technology*, vol. 2, no. 1, pp. 94-100.

Chen, L., Lai, X., 2011. Comparison between ARIMA and ANN Models Used in Short-Term Wind Speed Forecasting. *Asia-Pacific Power and Energy Engineering Conference 2011*, vol. 1, pp. 1-4.

CONAE (Comisión Nacional de Ahorro de Energía)., 2005. *Current situation of the national mini-hydro and the potential available for the states of Veracruz and Puebla, Mexico*. CONAE, México.

De Jesus, O., Hagan, M. T., 2007. Backpropagation Algorithms for a Broad Class of Dynamic Networks. *IEEE Transactions on Neural Networks*, vol. 18, no. 1, pp. 14-27.

Fang-yuan, L., Feng-you, G., 2008. Economic forecasting research based on artificial neural network technology. *Control and Decision Conference*, vol. 1, no. 1, pp. 1151-1155.

Ghanbarzadeh, A., Noghrehabadi, A. R., Assareh, E., Behrang, M. A., 2009. Solar radiation forecasting based on meteorological data using artificial neural networks. *7th IEEE International Conference on Industrial Informatics*, vol. 1, pp. 227-231.

Gelper, S., Fried, R., Croux, C., 2009. Robust forecasting with exponential and Holt–Winters smoothing. *Journal of Forecasting*, vol. 29, no. 3, pp. 285-300.

Hahn, H., Meyer-Nieberg, S., Pickl, S., 2009. Electric load forecasting methods: Tools for decision making. *European Journal of Operational Research,* vol. 199, no. 3, pp. 902-907.

Koller, D., Friedman, N., 2009. *Probabilistic Graphical Models, Principles and Techniques*. The MIT Press, USA.

Lange, M., Focken, U., 2005. *Physical Approach to Short-Term Wind Power Prediction*. Springer, USA.

Makarov, Y. V., Etingov, P. V., Huang, Z., Ma, J., Chakrabarti, B. B., Subbarao, K., Loutan, C., Guttromson, R. T., 2010. Integration of wind generation and load forecast uncertainties into power grid operations. *IEEE Transmission and Distribution Conference and Exposition*, vol. 1, pp. 1-8.

Peña, R., Medina, A., Anaya-Lara, O., McDonald, J. R., 2009. Capacity Estimation of a Minihydro Plant Based on Time Series Forecasting. *ELSEVIER - Renewable Energy*, vol. 34, no. 5, pp. 1204-1209.

Wei, S., Jie, Z., 2008. Short time load forecasting based on simulated annealing and genetic algorithm improved SVM. *CCC 2008, 27th Chinese Control Conference*, vol. 1, pp. 81-85.

Wenshang, X., Zhenbo, Y., Qingming, Y., Yanliang, S., Tianwen, D., 2008. Research on the methods of improving the training speed of LMBP algorithm. *World Congress on Intelligent Control and Automation 2008*, vol. 1, pp. 5281-5286.

Xinhua, C., Zhuying, L., 2010. The application of neural network technology in floodwater forecast. *2nd International Conference on Networking and Digital Society*, vol. 2, pp. 419-421.