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Monthly Stream Flow Prediction for Small Hydropower Plants in Pungwe River in Mozambique Using the Wavelet Method

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Abstract: The effects of a discrete wavelet-transformation data-preprocessing method on neural-network-based monthly streamflow prediction models in producing energy from small hydro power plants in the Pungwe River basin in Mozambique were investigated. Data from a Vanduzi gauging station in Pungwe River basin were collected. Eight different single-step-ahead monthly stream flow neural prediction models were developed. Coupled simulation involving use of MATLAB and of a Wavelet-Neural Network was employed. Different models were tested using the same sample in each case, an Artificial Neural Network (ANN) being found to performance best. The major objective of the research project was to analyze the monthly stream flow predictions in the Pungwe River, to be able to make as appropriate decisions as possible during dry or wet spells, and also to resolve as effectively as possible conflicts regarding water resourses.

Keywords: Renewable Energy, Hydropower, Wavelet Artificial Neural Network, Monthly Flow Prediction

1. Introduction

Due to an energy crisis that has developed energy consumption has become a serious problem in Mozambique especially in the large and thiestly populated cities such Maputo, Beira and Nampula. According efforts a being made there to replace current of energy sources mix in Mozambique by renewable energy such hydropower technology. The conversion to hydropower energy represents one of the best energy alternatives in Mozambique today since this energy source is abundant, is renewable, provides clean energy and can create very considerable job opportunities (EDM, 2015; IEA, 2009; Cuamba et al., 2010; Uamusse *et al*., 2014 and FUNAE).

Studying river flow level and their fluctuations at different times of the year can contribute very much to achieving a sustainable development of both water resources and of energy planning. The productions hydropower energy represents a highly promising clean energy technology's, despite its having certain potential disadvantage as compared with use of biomass, solar energy, and wind energy. The major probleams here its high capital investment costs.

Steam flow perdiction is highly important in activities concentrated with the operation and optimization of water resources, both at the planning and at the management level. For this reason, the development of mathematical models able to provide reliable long-term forecasting here has long attracted the attention of hydrologists (Santos and Silva, 2013; Seo *et al*., 2014).

In the present, the applicability specifically Pungwe River two hybrid models for flow predictions, the Wavelet Neural Fuzzy and Wavelet Artificial Neural Network (WANN) model is investigated. Water-flow prediction can play an important role in water resources management with a river basin. In the present study, different methods have been used to predict monthly flow. The main objective of the research project was to analyze prediction of the monthly stream flow in the Pungwe River to be able make as suitable decisions as possible regarding relevant matters during both dry and wet spells, and also to be able to resolve posssible conflicts regarding water recourses.

In recent years, many studies of river flows and application of artificial networks to various aspects of hydrological modelling have been carried out (Partal and Kisi, 2007; Muhanmadi *et al*., 2008; Sreekath et al 2009; Nourani *et al*., 2013; Santos and Silva 2013; Nayak *et al*., 2013; and Seo *et al*., 2014). The aim of the hydrological modeling is to improve performance ANN so as better be able to predict seasonal time series. Several structures of ANN that can serve to predict seasonal time series are taken up.

A number of scientific paper in hydrological area concerning streamflow prediction methods, and time series analysis have shown WANN, ARIMA and WANFIS models to perform their being rich in the information they provide and being highly systematic in their approach to the modeling of flow (Kisi, 2007; Kisi, 2008; Nejad and Nourani 2012; Santos and Silva 2014; Rezaeianzadeh et al., 2014).

Nonetheless, use of wavelet transforms for time series treatment together with ANN, despite their flexibility and their broad applicability involve difficulties (Neurani *et al 2013*, Santos and Silva, 2013). The use of vaious methods for pre-processing the imput data has been shown to be as an effective approach to improving the performance of ANN models. An example of this is to use of certain Wavelets that have received attention recently because of their providing useful decomposition of the original time series into high-to intermediate and low frequency components.

More accurate knowledge concerning the stream flow system along the Pungwe River will help in planning how many Hydro-power plants can sensible be built along the river, as well as in planning regarding other forms od water its use for consumption, such as its use for domestic purpose, for care of animals and for irrigation purpose, as well as for avoiding possible conflicts in the sharing of water along the river basin.

Monthly flow modeling and prediction of water flow in the Pungwe River flow was carried out by use of a wavelet-neural network (WNN) method in combination with use of neural networks (NN) and Neural Fuzzy Modeling based of use of monthly flow data from a gauging station in the Pungwe River basin in Mozambique. Renewable energy sources have also have been of considerable in this research investigation problems of climate particulary because of their relevant to changes brought on by global warming of fossil fuels contributing to an increase in greenhouse gases (Kisi, 2007, Kisi 2008, Naghizadeh *et al*,. 2012 Nourani *et al*., 2014)

2. Description of the Study Area

The Pungwe river basin is located between the latitudes 18S and 20S and the longitudes 33E and 35E. Its covers a total catchment area of some 31150 km^2 according to a recent estimate, and has a perimeter of 318.08 km. The Pungwe River has its origin in the eastern highlands of Zimbabwe and flows eastwards through the Mozambican provinces of Manica and Sofala on its way to the Indian Ocean at Beira. The Zimbabwean part of the basin has an area of 1 460.7 km^2, the Mozambican part having an area of 29 689.8 km^2.

The climate of the Pungwe River basin encompass two climate types, the one during the six month long dry season, and others during remaining six months being the annually rainy season. The precipitation for December to February is 2000 mm, the average monthly rainfall for the month of February alone being 300 mm. As can be seen in Figure, in The mountains there is normally rain every month of the year, with a concentration of it in the month of November-April, wheres the area east of mountains has a pronounced concentration of the rain during the warm season of November-April, for the most part there being no precipitation at all there from May to October. In region classified being humid tropical with variations in temperature from an average of 22°C toan average 29°C. The mean rainfall varies from 300 mm in January to 20 mm in July.

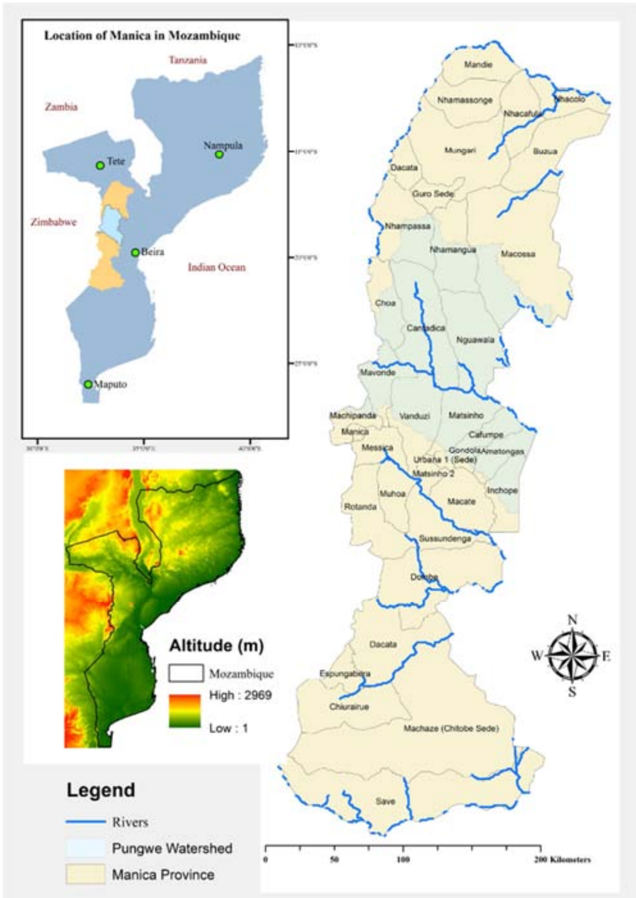


Figure 1. *Location of the Pungwe River basin in Manica, Mozambique.*

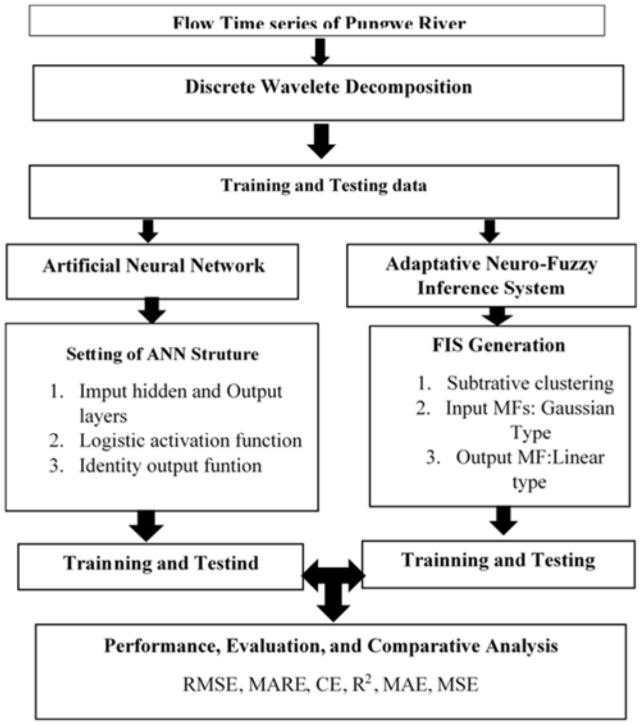


Figure 2. *Flowchart of the methodology involved.*

3. Methodology

The following activities in line with the aims and objectives of the research project, were or had been carried out: a review of the literature with particular: (Partal and Kisi 2007; Sreekath *et al.* 2009; Muhanmadi et al., 2010; Khan, 2012; Nourani *et al*., 2013; Santos and Silva 2013; Santos and Silva, 2014; Nayak et al., 2014; Seo *et al*., 2014), collections of materials, development Matlab technology and data collection that had been carried out for 588 month, or 49 year period.

Figure 2 is a flowchart concerning flow prediction, one making use of an ANN and of an adaptive neuro-fuzzy interference system.

3.1. Wavelet Analysis and Neural Network Model

Wavelet transformation is a mathematical technique in terms of which a signal is transformed from the time domain to the frequency domain trough integral calculus. This transformation being described by equation 1. In a WNN, a time series is decomposed into its higher-and its lower-frequency components, yielding multiple levels of details, as well as sub-time series, that provide an interpretation of the structure and history of the original time series with both the time and the frequency domain a variety of coefficients being employed (Chiu, 1994; Badrzadeh, 2013; Nayaka *et al*,. 2013; Solgi *et al*,. 2014 Alizdeh et al,. 2015).

$$W(a,b) = \int_{-\infty}^{+\infty} x(t)\phi_{a,b}(t)\,dt \quad (1)$$

$$\phi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\left(\frac{t-b}{a}\right) \quad (2)$$

where $x\ (t)$ represents the temporal signal, $\varphi(t)$ being a mother wavelet function with the time and the frequency domain, a being a scale parameter; b being a position parameter, and W (a, b) being the wavelet coefficients.

$$\int_{-\infty}^{\infty} \phi(t)dt = 0 \quad (3)$$

$$0 < \int_{-\infty}^{\infty} |\phi(t)|^2 dt < \infty$$

Wavelet transformation is more effective instrumental it than a Fourier transform is in studying non-stationary time series. The major advantage of wavelet transformation is the possibility it provide simultaneously obtaining information regarding the location and the frequency of a signal, whereas Fourier transformations separate a time series into sine waves of various frequencies. There are two types of wavelet transformations continuous wavelet transform (CWT) and discrete wavelet transform (DWT).

CWT calculations require a rather extended set of computations and considerable resources. One can note discrete nature of the observations data regarding the flow the time series. DWT (the original signal time series), passes through two complementary filters and emerges as an approximation of the detailed components. DWT is preferred in particular in hydrological predictions (Dibike and solomatie, 2001; Kim and Valdes, 2003; Kisi, 2006; Neurani et al., 2011; Honey et al, 2013)

In practical applications, hydrology researchers have access to discrete rather than continuous time signals (Khan 2012, Nourani et al., 2013; Santos and Silva 2014).

The same authors advise, for purpose of prognosis, use of a hybrid model ANN and ANFIS model in line with the scheme presented in the Figure 3 below. That Figure is a schematic diagram of a hybrid WNN model having one one input, the time series signals being decomposed by use of a wavelet transformations subsignal produced serving as an input a neural network.

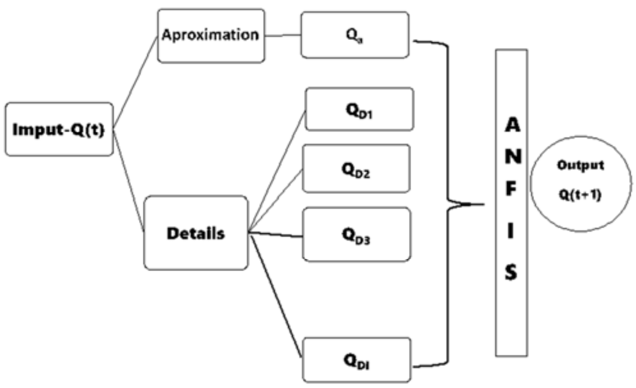


Figure 3. *Schematic diagram of a hybrid WANN model.*

In terms of developing strategies in line with the objectives of this work, one question concerns the kind of wavelet transformations used to be (CWT, DWT) and to be combined with ANN and with ANFIS. Table 1. summarizes the possibilities there are of building models.

Table 1. *Wavelet transformations strategy employed.*

Model Struture	Wavelet transform	Model ANFIS
Model 1- NN	Without Pré-Treatment	Neural Network
Model 2-ANFIS	Without Pré-Treatment	Neural-Fuzzy
Model 3-CWTNN	CWT	Neural- Network
Model 4-DWTNN	DWT	Neural Network
Model 5-CWTANFIS	CWT	Neural-Fuzzy
Model 6-DWTANFIS	DWT	Neural-Fuzzy

3.2. Artificial Neural Network (ANN)

Artificial neural network are computational and mathematical models having a wide range of applications and having a market ability to forecast correctly the type of modeling needed for a nonlinear hydrological time series (for flow, and for precipitation).

The ANN Procedure involve e combining neural networks to predict components of up to 5 layers, and subsequently combining the simulated network values to reconstruct the original signal by near of a wavelet reconstruction technique. This model basically functions in terms of an inverse decomposition process, as shown in Figure 5. For ANN, the backpropagation algorithm involve automatically acquires the knowledge, needed but the learning process is relatively slow and analysis of a trained network is difficult (Jain *et. al*., 1999; Badrzadeh et al., 2013).

3.3. Wavelet Artificial Neuro Fuzzy Inference System (WANFIS)

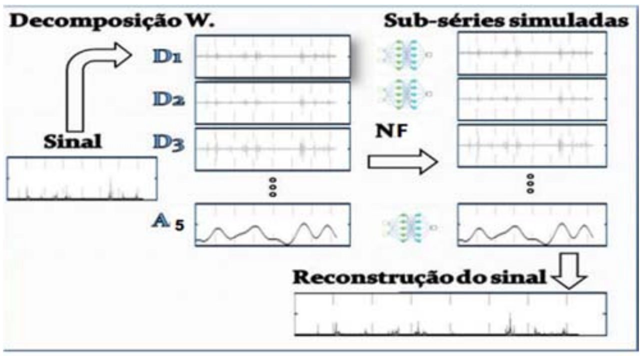
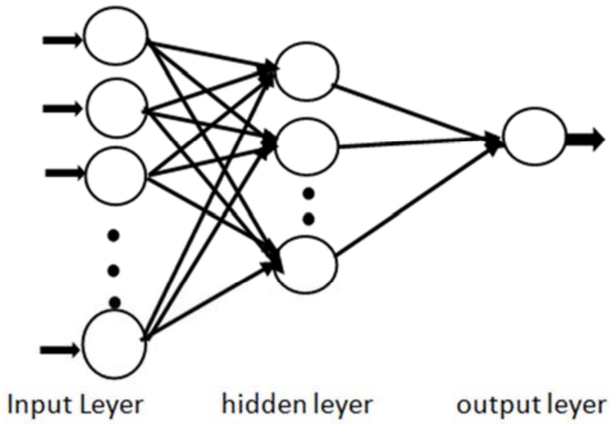


Figure 4. *Neuro Fuzzy Model Architecture.*

The WANFIS model was developed using wavelet sub-series as to input ANFIS, input and output data for converting into being linguistically interpretable. In this model, the procedure is the same as in ANN prediction, the model having components of up to five frequency layers, the simulated network values being combined for reconstruction of the original signal, using the wavelet technique shown in Figure 4. Fuzzy logic systems, which can reason with imprecise information, are good at explaining the decisions they arrive at but they cannot automatically acquire the rules they need to make the decisions for example, whiere as neural networks are good at recognizing patterns, they are not good at explaining how they reach their decisions involve (Jang, 1993; Chiu, 1994; Neurani et al., 2011).



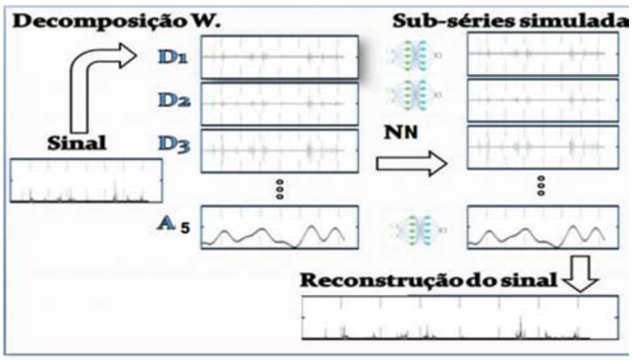


Figure 5. An *Artificial Neural network Model Architecture.*

3.4. Model Performance

The performance of different forecasting models was assessed in terms of goodness of fit once each of the model structures had been calibrated using the training data validation data set and testing data. The degree of correlation was measure R^2 in equation 6. The equation 4 concern coefficient of correlation (CE), that was used in assessing the goodness to fit between the measured flow and the simulated flow, the mean-squared error (MSE) in Equation 5 being used to evaluate the error variance (Kisi 2007; Sreekath et al 2009; Muhanmadi *et al*., 2010; Partal and; Nourani *et al*., 2013; Santos and Silva 2013; Nayak *et al*., 2014). To calculate the root-mean-square error (RMSE), the mean absolute error (MAE) and mean absolute relative error (MARE) use is make of the remaining equations presented in the same literature,

$$CE = \frac{\sum_{1}^{n}\left(Q_{obs}-\overline{Q_{obs}}\right)\left(Q_{pre}-\overline{Q_{pred}}\right)}{\sqrt{\sum_{1}^{n}\left(Q_{obs}-\overline{Q_{obs}}\right)^{2}}\sqrt{\sum_{1}^{n}\left(Q_{pred}-\overline{Q_{pred}}\right)^{2}}} \quad (4)$$

$$MSE = \sqrt{\frac{\Sigma\left(Q_{obs} - Q_{pre}\right)^2}{n}} \quad (5)$$

$$\text{EFF or } R^2 = 1 - \frac{\underset{i=1}{\overset{N}{\Sigma}}\left(Q_{obs} - Q_{Pre}\right)^2}{\sum_{I=1}^{N}\left(Q_{obs} - \overline{Q_{obs}}\right)^2} \quad (6)$$

$$MAE = \frac{\sum_{1}^{n}\left|\left(Q_{obs} - Q_{pred}\right)\right|}{n} \quad (7)$$

$$MARE = \frac{1}{n}\sum_{1}^{n}\frac{\left|Q_{obs} - \overline{Q_{obs}}\right|}{Q_{obs}} \quad (8)$$

$$RMSE = \sqrt{\frac{\sum_{1}^{n}\left(Q_{obs} - Q\,Pred\right)^2}{n}} \quad (10)$$

where Q_{obs} corresponds to observed value steam flow, Q_{pre} is correspond to the predicted value of the flow rate, and $\overline{Q}$ is the average value of the flow rate. MSE the mean square error, CE is the coefficient of efficiency and n is the number of data points used.

The parameters used to evaluate the validation model and the best conjunction wavelet transformations with neural networks or neuro fuzzy predictors are the following: the mean square error (MSE), defined by Equation 5, and by the linear regression coefficient (equation 6) involving the real data and the data simulated by the network.

4. Results and Discussions

The realiability of the experimental setup can be estabilished by comparing the performance of ANN with that of wavelet hybrid models for 588 month or 49 years involved. Due to the temporal series of hydrological processes here it recomended that one use 45 years for first part for training, equivalent of 80 percent than, the rest 4 yers for verificatior or testing see Figure 6.

Table 2 and Figure 7 below shows training results and test results in forecasting water flow in the Pungwe River basin by comparing the WANFIS end WANN model with results for the corresponding Root-Mean-Squere (RMSE), models making use of the degree of correlation (R^2) and the Nash-Sutcliffe of efficiency (NSE) measures and the coeficient of correlation (R).

Table 2. *Performance results for the WANN and for the WANFIS model in different situations.*

	Decomposition		Training		Testing	
	WANN	WANFIS	WANN	WANFIS	WANN	WANFIS
R^2	Sym3,3	Db3,4	0.8282	0.9061	0.6894	0.8706
RMSE	Sym3,2	Db3,4	190.1096	139.57	179,60	123.68
NSE	Sym3,2	Db3,4	0,843	0.861	0.4682	0.5261
R^2	Coif1,3	Db5,3	0.6150	0.729	0.5382	0.5454
RMSE	Coif1,3	Db5,3	199.42	178.83	172.57	164.212
NSE	Coif1,3	Db5,3	0.8047	0.79	0.7813	-0.421

The value of the correlation measure R^2 in WANFIS in Db3, 4 is higher than that for WANN where general if speaking the model should be greater than 0.5, which is considered to be an acceptable measure for a real system. Other situations using the Nash-Sutcliff of coefficient of efficiency vary between 0.46 and 0.843, which means that the model efficiency corresponds a perfect prediction being made.

Table 3 shows training results and test results for forecasting flow in the Pungwe River basin by using the ANFIS and ANN model, together with the corresponding the Root-Mean-Square (RMSE) correlation measure (R^2), the Nash-Sutcliffe efficiency measure (NSE) and the coefficient of correlation (R), the Coefficient of Correlation (CE) and the Mean Absolute Error(MAE).

Table 3. *Performance results for the ANN and the ANFIS model in situations of two different types.*

	Time		Training		Testing	
	ANN	ANFIS	ANN	ANFIS	ANN	ANFIS
R^2	2,5	2,5	0.8710	0.978	0.7621	0.982
RMSE	2,5	2,5	128.61	185.43	105.06	146.06
NSE	2,5	2,5	0.9293	0.7813	0.8667	0.5831
MAE	2,5	2,5	134.3	107.07	122.05	97.45
CE	2,5	2,5	0.6770	0.872	0.567	0.856
R^2	2,9	2,9	0.9326	0.971	0.9254	0.976
RMSE	2,9	2,9	115.64	132.76	85.4510	115.67
NSE	2,9	2,9	0.9109	0.8021	0.6420	0.7081
MAE	2,9	2,9	118.85	197.14	97.020	154.3
CE	2,9	2,9	0.9016	0.8902	0.8632	0.8871

Table 3 shows the performance results and summarizes the values for different layers in the ANFIS and ANN models It can be verified here that the results for for the two are somewhere similar. The Root-Mean-Square (RMSE) values for both models were satisfactory for velocities of betwen 85.45 and 128.61 m^3/s. On the basis of the results shown in Table 2 and Table 3, it could be noted that the number of decomposition levels had a considerable impact on the results. Since the random parts of the original time series were mainly at the first resolution level, the prediction errors were obviously also mainly at the first resolution level.

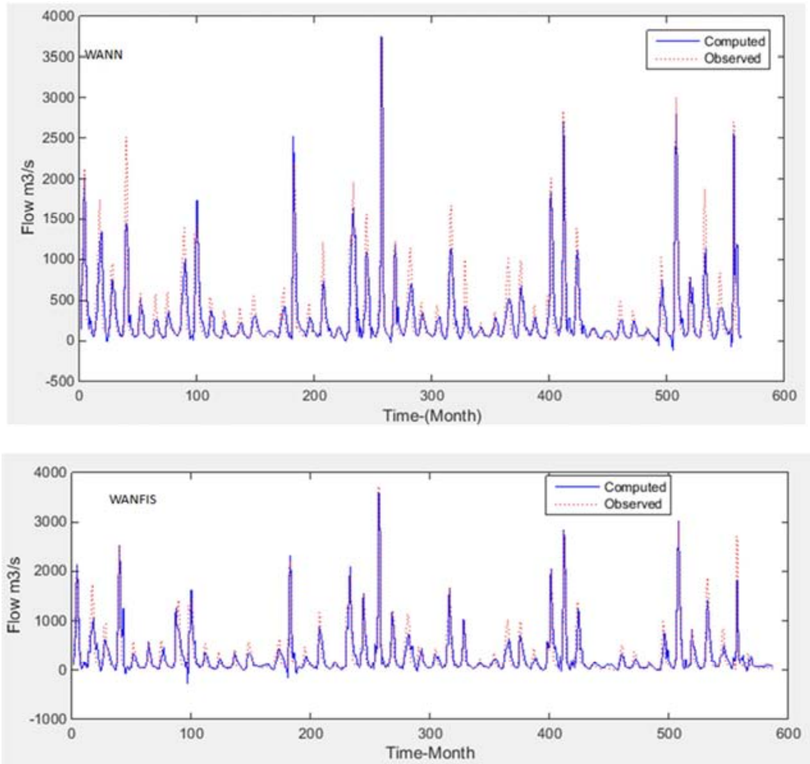


Figure 6. *Time series for observed and computed WANN above and WANFIS (below) value.*

Figure 7 shows scatter plots of the observed flow data and of the simulation data during the period of validation. The difference between the regression line and 45° is only slight, are the regressions value for all situations being approximately 1.0, This makes it clear that the data here is closely are correlated over time so that conditions do not vary appreciably year to year and that it would be sensible to build hydropower plant.

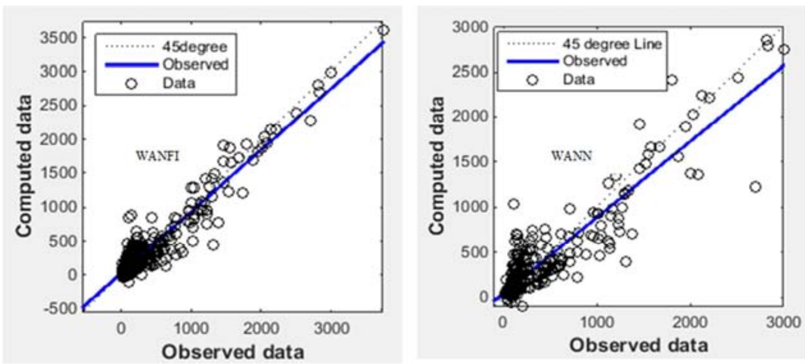


Figure 7. *Regression of WAFIS and WANN model.*

5. Conclusions

The data set used in the modelling experiment here was a time series of the average monthly river discharge during the period of 1960–1994, as collected at the ARA-Centro hydrological gauging station at Manica the Pungwe River basin in Mozambique. In the study carried out here time series models for different MATLAB programs, specifically for ANN, WANN, ANFIS, WANFIS were compared, using the statistical tools RMSE, MAE and R^2 to evaluate performance of the different models. It was found that for nearly all the lead times the WANN and the WAFIS model provided better and more consistent results than conventional ANN and ANFIS models did. In additions, the effects that the decomposition level had on the efficiency WANN models was studied.

The hybrid model was found to have a high level of efficiency trough is showing a high linear regression value one of 0.9548 combined with values on the Nash-Sutcliffe scale of efficiency (NSE) of between 0.46 to 0.86.

Regarding the flow prediction I would conclude that the flow present in the river remains rather constant from years to years and that Manica is a good site from build a small hydro power plant (SHP), the climate changes there not creating appreciable problem regarding the water needed to generate the power that is called for.

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