

# Comparative Prediction of Groundwater Fluctuation by CWTFT-ANFIS and WT-ANFIS

N. Vetrivel\* and K. Elangovan

Department of Civil Engineering, PSG College of Technology, Coimbatore - 641004, Tamil Nadu, India; vetrivel.nagarajan@gmail.com, elangovan2k@hotmail.com

## Abstract

**Objective:** To evaluate the ability of prediction performance of ANFIS (Adaptive Neuro Fuzzy Inference System) model on groundwater level fluctuation in Lower Bhavani River Basin (LBRB). **Method:** To improve the accuracy of prediction of ANFIS model, WT (Wavelet Transform) and CWTFT (Continuous Wavelet Fast Fourier Transform) are performed as preprocessing techniques. Model development is carried out through three different input parameters (duration, groundwater recharge and groundwater discharge) and one output parameter (groundwater fluctuation) for the period of 2009-2015 on monthly stress basis. **Findings:** Based on the comparative prediction by the models CWTFT-ANFIS and WT-ANFIS over conventional ANFIS model through calibration and validation process on different reaches of the study area, optimum model is identified. Statistical indices are performed to measure the best fitting and trend identification for the each prediction.

**Keywords:** ANFIS, CWTFT, Fluctuation, Groundwater, Lower Bhavani River Basin, Wavelet

## 1. Introduction

Groundwater is the major source to interact with local aquifer system to maintain the sustainable ecosystem management<sup>1</sup>. The main objective of effective groundwater management system (GMS) is to regularize the water utility without much disturbing to the soil water condition. The major constraints like incremental trend in population, poor urbanization plans and illegal/over exploitation of groundwater source are developing the massive challenging situation to maintain such GMS. Also, a region like arid and semi-arid, groundwater is the only source for all kind of utility<sup>2</sup>, further small increase in exploitations leads in huge distress condition to the existing aquifer system. This highlights the importance of estimation of groundwater potential and

controlled utility of groundwater to meet the present demands and future as well.

An accurate prediction of groundwater level is playing a vital role for the development of effective management policies<sup>3</sup>. Practically, hydrological model is associated with many interconnected constraints which create a position to collect huge field data measurement. Physical interactions of hydrological parameters are highly stochastic, non-linear, space-independent and complex in nature for the effective groundwater model development<sup>4</sup>. Soft computing techniques are playing an effective role in taking care of such interconnected constrained analysis since late 1970s<sup>5</sup>.

Comparative prediction of artificial neural network and Adaptive Neuro-fuzzy Inference System on groundwater level prediction are carried out<sup>6,7</sup>. Conducted a

\*Author for correspondence

study on comparison of three methods; ANN, ANFIS and Time Series Models to predict and forecast the groundwater level fluctuation in North Mahyar plain<sup>8</sup>. Forecasting of weather conditions in Indian scenarios by comparative prediction by ANFIS, ARIMA and curve fitting technique is evaluated<sup>9</sup>. Correlation investigation between Auto-Regressive Integrated Moving and Average (ARIMA) and ANFIS models also carried out to predict the climate estimation<sup>10</sup>. ANFIS model is adopted in the process of prediction of surface roughness of steel materials<sup>11</sup>. Neural Network is adopted to predict the reservoir water level based on spatial variation of rainfall pattern<sup>12</sup>.

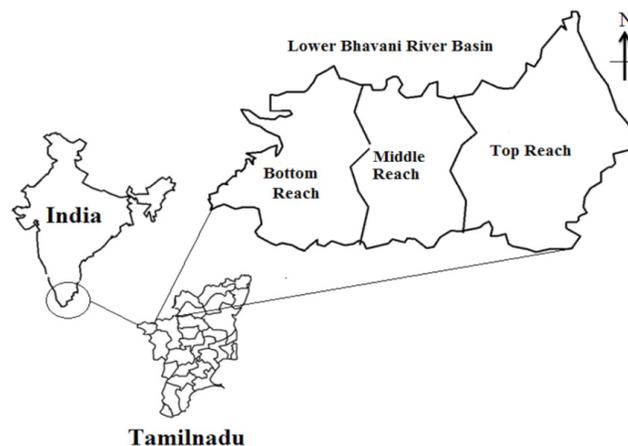
Comparing to other soft computing techniques, neural network and fuzzy system are the identical one. Based on the inference, the pre-processed input and/or output data in ANN and ANFIS models are results in high prediction level. Among the various types of pre-processing techniques, Wavelet transforms performed well in decompositions of signals and improve the ability of prediction and forecasting of soft computing models at different resolution levels<sup>13,14</sup>. Appreciable improvement was observed in continuous wavelet transforms compare to wavelet transforms to identify the temporal variability of rainfall and runoff values<sup>13</sup>.

Based on the detailed literature, no research is carried out with CWTFT and WT on ANFIS prediction. The present scope of the research work is to compare the prediction of hybrid CWTFT-ANFIS model and WT-ANFIS model over conventional ANFIS on monthly stress (groundwater level) prediction and forecasting at different reaches of Lower Bhavani River Basin, Tamilnadu, India.

## 2. Materials and Methods

### 2.1 Study Area

Fourth largest basin in Cauvery basin is “Bhavani River Basin” with coverage of 6500 km<sup>2</sup> area. The boundary condition of Bhavani River Basin is observes as, hilly terrain in western part, discontinuous hills in northern side and flat terrain in south-eastern part. It has two distinct sub-basins, Upper Bhavani River Basin (4100 km<sup>2</sup>) and Lower Bhavani River Basin (2400 km<sup>2</sup>). The annual average precipitation is observed about 750 mm. Figure1 details the study area pertaining to the present scope and it is divided in to three reaches for effective interpretation of model development.



**Figure 1.** Study Area -Lower Bhavani River Basin.

The study area is heavily disturbed with over abstraction of groundwater for the various utilities from domestic, irrigation, research and industrial usage. It is observed that, the past trend of groundwater fluctuation is clearly indicating the distress condition of existing aquifer system. So the development of groundwater management policies or correction to the existing policies are mandatory in order maintain the sustainable groundwater system.

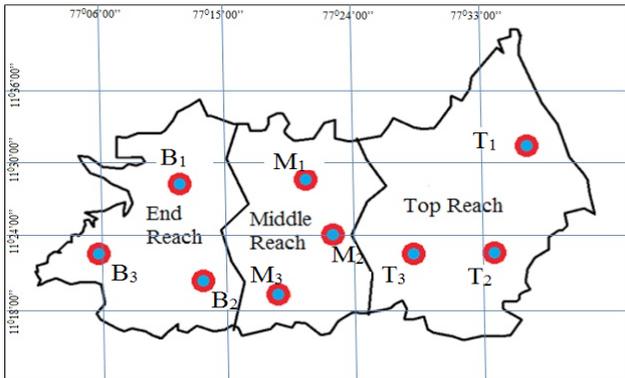
### 2.2 Methodology

This present work is carried out with detailed literatures and field observed data collected from Public Works Department (Groundwater and Surface water Data centre, Tharamani, Chennai). Monthly stress data from 2009 to 2015 are reviewed through detailed field study, and sub basin information of groundwater system in LBRB. Based on the field condition and interconnected constraints, Duration, Groundwater recharge and Groundwater discharge are identified as a input parameters and Groundwater fluctuation is considered as a predictable parameter by ANFIS, WT-ANFIS and CWTFT-ANFIS models. In order to measure the prediction performance, statistical indices are performed. On the basis of best fitting condition, comparison of CWTFT-ANFIS and WT-ANFIS over conventional ANFIS are carried out.

### 2.3 Datasets

Nine locations of observation wells are taken into consideration (three per each reach) for the model run. The distribution of groundwater in and around the study area is observed based on the input parameters during the

design period from 2009 to 2015 on monthly stress basis. Figure 2 details the location of observation wells at different reaches of the present study area.



**Figure 2.** Location of observation wells in the study area.

### 2.4 Statistical Indices

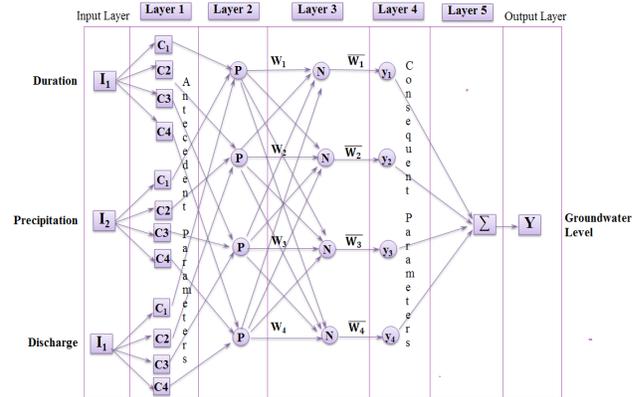
To evaluate the best fitting between observed and predicted parameters of all identified soft computing models, R-Squared ( $R^2$ ), Mean Square Error (MSE), Root Mean Square Error (RMSE), Coefficient of Convergence (COC) and Mean Absolute Error (MAR) are performed. These statistical indices are valuable to measure the goodness fit between the observed and predicted values of output parameter at different reaches of the study area.

### 2.5 Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS is the combination of Neural Networks (NN: capable of training property) and Fuzzy Inference Systems (FIS: capable of inference ability during uncertain situations)<sup>15</sup>. ANFIS was originally formed by Jang (1993) and it has a similarity of human-like proficiency with in a specific constraints. The training process in ANFIS is resulting from the Neural Network concept<sup>16</sup>. Advantage of fuzzy logic is it has simple explicit knowledge representation with if-then relationships between the identified parameters<sup>17</sup>.

ANFIS contain two Inference System, i.e., Mamdani and Sugeno Fuzzy Inference System (FIS). Based on the literatures, comparatively Sugeno type of FIS combined with neural networks is perform well in optimization process especially for dynamic and non-linear system of interconnected constrains<sup>18</sup>. ANFIS is a “data driven

approach” through NN technique is performed as the best solution to hydrological problems. The structure of ANFIS is consisting of variety of layers, i.e., fuzzification, inferences process, defuzzification and cumulative prediction as detailed in Figure 3.



**Figure 3.** ANFIS architecture for model development.

Where,  $I_1, I_2$  and  $I_3$  are the input parameters and  $Y$  is the predicted output,  $C_1, C_2, C_3$  and  $C_4$  are the linguistic label (Low, Medium, High and Very High) related with the node functions. The performance is carried out with supervised learning system in which each input vector has a corresponding desired output vector. During training process, the input vectors are correlated with results in output vector. The actual output vector is compared with the target output in order to minimize the existence of error signals through adjusting the weights between the parameters until the original output matches with the target output.

The process of ANFIS is starting from layer 1 to layer 5 patterns. The input data pertaining to model development is in qualitative form, so these data must be fuzzified by best membership functions in order to get optimum performance of the model. The progress of each Layer movement in ANFIS is detailed as follows,

Layer 1: Input values are fuzzified according to the membership functions (Mfs: Triangular, Trapezoidal, Gaussian, Gbell and splin-based etc.). Here the data are fuzzified in to fuzzy subset based on the seasonal variation and hydrological cycle of the LBRB.

Layer 2 and 3: Inference processes in which the rules and membership function are applied. On the basis of inter relation between fuzzy inputs and outputs, fuzzy rules are generated.

Layer 4 and 5: Cumulative output is defuzzified in to known output form which is further fed for prediction and correlation process.

## 2.6 Wavelet Transform (WT)

Wavelet transform is a mathematical function which is capable of decomposes the continuous time signal in to a time scale illustration process without disturbing their relationships<sup>19</sup>. Here the data series is broken down in to 'wavelets' based on transformation functions<sup>20</sup>. Wavelet Transformation is best suitable to model data normalization in order to improve the frequency of prediction level by the models<sup>21</sup>. From the literatures, WT is well suitable for long time intervals with low-frequency information and shorter intervals with high-frequency information. It is well suitable to cover a data like trends, breakdown point, and discontinuities signal analysis techniques. Groundwater level fluctuation is one of such time series data which is need to be decomposed in to a time frequency wavelet and obtain the best performance of the identified model.

## 2.7 Continuous Wavelet Transform (CWT)

Continuous Wavelet Transform is the sum of all time of signal multiplied by scaled, shifted form of wavelet function 'γ'. Mathematical representation of CWT is given by,

$$A(u, v) = \int_{-\infty}^{\infty} f(t) \gamma_{u,v}(t) dt \quad (1)$$

where  $f(t)$  is the signal pertaining to model analysis.  $\gamma(t)$  is the mother wavelet. In which,

$$\gamma_{u,v}(t) = \frac{1}{\sqrt{u}} \gamma^* \left( \frac{t-v}{u} \right) \quad (2)$$

where \* represents complex conjugation. This equation give a details on how a function is decomposed into a set of basic functions  $\gamma_{u,v}(t)$  called as wavelets.  $\gamma_{u,v}(t)$  is a window function called the mother wavelet, 'u' is a scale and 'v' is a translation. If  $\gamma$  is given by,

$$A_{\gamma} = \int_{-\infty}^{\infty} \frac{|\gamma(\mu)|^2}{\mu} d(\mu) < +\infty \quad (3)$$

then 'f' is reconstructed by inverse wavelet transform which is given by,

$$f(t) = A \int_{-1}^1 \int_0^{\infty} A(u, v) \gamma_{u,v}(t) dy \frac{du}{u^2} \quad (4)$$

The results of the CWT consist of many wavelet coefficients which is the function of scale and position.

## 2.8 Fast Fourier Transform (FFT)

The Fourier Transform for the discrete signal is known as Discrete Fourier Transform (DFT) which is represented by the following mathematical relationships.

$$T(k) = \frac{1}{\sqrt{n}} \sum_{i=0}^{n-1} x(i) e^{-j2\pi \frac{k}{n} i} \quad (5)$$

Where,  $k = 0, 1, 2, \dots, n-1$

This allows the computation of the spectra from discrete-time data of N samples by satisfying the Nyquist criterion. Fast Fourier Transforms (FFT) are Fast Discrete Fourier Transform algorithms, which is useful if 'n' is a regular power of 2 ( $n=2^p$ ). Combined effect of Continuous Wavelet Transformation with Fast Fourier Transform (CWTFT) is result in high performance during data pre-processing.

## 3. Results and Discussion

This section analyzes the results obtained from data pre-processing, comparative prediction between ANFIS, WT-ANFIS and CWTFT-ANFIS models. 70% of collected data are used for calibration / Training process through which weighted sum and threshold values are optimized and remaining 30% dataset is used for testing process.

### 3.1 Wavelet Decomposition of Observed Data

The original data (Groundwater Fluctuation) is decomposed into a series of detailed signals through discrete wavelet transformation which turns the original time series data in to a many lower resolution components<sup>22</sup>. All the identified parameters are decomposed with different levels of wavelets i.e., Haar, Daubechies (db2, db4) and imported to ANFIS model prediction. After many trials and error minimization process, it was found that, for groundwater fluctuation time series data, the optimum de-noised signals is arrived through Wavelet db4 at 5th level under Rigorous SURE thresholding method is detailed in Figure 4.

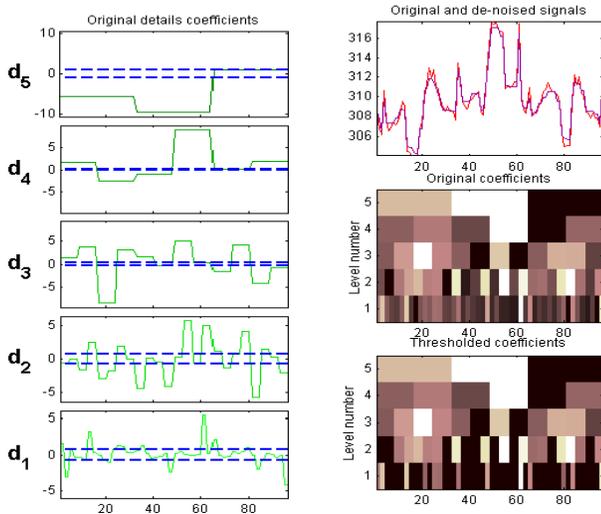


Figure 4. Wavelet decomposed time series using db4 wavelet at level 5.

### 3.2 CWTFT Decomposition of Observed Data

All parameters are decomposed with Continuous Wavelet Fast Fourier Transform in order to obtain the best performance of ANFIS models to predict the groundwater fluctuation. Many CWTFT wavelets are performed to identify the best decomposition level (morl, morlex, mexh and paul at different levels from 1 to 6) of observed data. After many trials, it was found that, the CWTFT using morl6 performs better under dyadic synthesis method which results in least relative error as possible. The decomposition level is detailed in Figure 5.

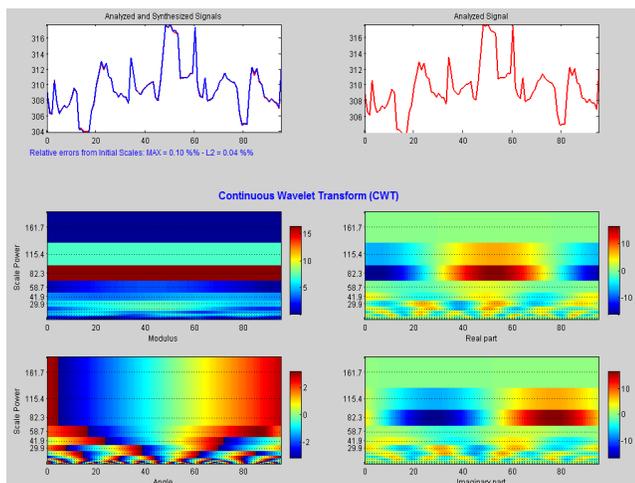


Figure 5. CWTFT decomposed time series using morl6 level.

### 3.3 Comparative Groundwater Level Prediction by the Models

The comparative prediction of CWTFT-ANFIS and WT-ANFIS over conventional ANFIS are derived based on the average error produced during prediction process by each identified model. The correlation statistics are performed between the observed and the predicted groundwater level. Table 1 details the statistical measure on each prediction by the models at different reaches of the study area during training and testing process.

Table 1. Statistical Indices on Performance of Soft Computing Models

Models	Well No	RMSE	R <sup>2</sup>	COC	MSE	MAR
ANFIS1	T1	0.504	0.927	0.910	0.008	0.334
CWTFT1		0.460	0.940	0.979	0.028	0.274
WT1		0.487	0.933	0.893	0.027	0.334
ANFIS2	T2	0.824	0.953	1.290	0.001	0.551
CWTFT2		0.688	0.970	1.022	0.003	0.516
WT2		0.637	0.972	0.950	0.001	0.477
ANFIS3	T3	0.728	0.873	0.345	0.020	0.482
CWTFT3		0.451	0.955	0.367	0.011	0.272
WT3		0.400	0.963	0.932	0.010	0.267
ANFIS4	M1	0.748	0.895	0.937	0.017	0.506
CWTFT4		0.536	0.946	0.926	0.014	0.346
WT4		0.569	0.939	0.918	0.012	0.373
ANFIS5	M2	0.501	0.807	0.793	0.006	0.357
CWTFT5		0.762	0.914	0.948	0.025	0.690
WT5		0.658	0.905	0.887	0.019	0.686
ANFIS6	M3	0.893	0.917	0.582	0.004	0.615
CWTFT6		0.653	0.957	0.989	0.078	0.470
WT6		0.741	0.943	0.928	0.001	0.533
ANFIS7	B1	0.371	0.765	0.316	0.003	0.855
CWTFT7		0.398	0.792	0.814	0.006	0.702
WT7		0.549	0.791	0.952	0.001	0.731
ANFIS8	B2	0.488	0.774	0.675	0.087	0.844
CWTFT8		0.483	0.804	0.820	0.030	0.653
WT8		0.457	0.782	0.752	0.008	0.685
ANFIS9	B3	0.328	0.844	0.416	0.032	0.835
CWTFT9		0.310	0.882	0.945	0.099	0.587
WT9		0.312	0.874	0.862	0.117	0.645

Based on the results, CWTFT-ANFIS performance is good in prediction compared with WT-ANFIS at different reaches of the study area. The best performance of CWTFT-ANFIS model is constantly led throughout the study area in all the observation locations.

## 4. Conclusion

The potential of coupled WT-ANFIS, CWTFT-ANFIS models are compared with the conventional ANFIS model in the process of prediction of groundwater fluctuation at Top, Middle and Bottom reaches of LBRB. CWTFT-ANFIS method shows a good performance throughout the study area during training and testing process is about 90.78%. Only small difference were observed in the process of prediction by CWTFT-ANFIS and WT-ANFIS model, but based on the overall performance, CWTFT-ANFIS prediction is 5.43 % better than the WT-ANFIS model compared with conventional ANFIS prediction. Apparently the developed CWTFT-ANFIS model is exactly following the groundwater fluctuations pattern and it is useful to derive the corrections to existing groundwater management policies in order maintain the sustainable groundwater management system.

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