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HYDROLOGICAL TIME SERIES FORECASTING USING ANFIS MODELS WITH AID OF WAVELET TRANSFORM

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ABSTRACT

The precise and accurate models of hydrological time series that are embedded with high complexity, non-stationarity, and non-linearity in both spatial and temporal scales can provide important information for decision-making in water resources management and environmental related issues. Hybrid wavelet transform (WT) and adaptive neuro-fuzzy inference system (ANFIS) has been used in this study to improve the forecasting capability of ANFIS model by decomposing the time series into sub-time series (approximation and details) using wavelet transform then combining the effective and significant time lags of sub-time series to form a set of input variables. The present study attempts to add the effective and significant time lags of original time series as extra variables to the input variables set. In addition, different combinations of variables, 1-3, from the set of input variables as inputs to the ANFIS model were used to forecast the time series.

To examine the potential of the approach for practical applications, the model is applied to forecast, one step-ahead, the monthly data of hydrological time series (rainfall, evaporation, minimum and maximum temperature, average wind speed and reservoir inflow) for Kirkuk, Sulaimani, Dokan and Darbandikhan meteorological stations in Iraq. The best fit models were selected using the coefficient of determination (R^2) and root mean square error ($RMSE$). Based on the results, the proposed model has high performance in forecasting the monthly minimum and maximum temperature, evaporation and reservoir inflow with R^2 values ranged from 0.93 to 0.99 and relatively good performances in forecasting the monthly rainfall and average wind speed with R^2 values ranged from 0.77 to 0.93.

KEYWORDS: *Forecasting, Time series, Wavelet, ANFIS*

1. INTRODUCTION

Accurate and correct forecasting of hydrological time series such as rainfall, temperature, evaporation, etc. has prompted great interest in water resources engineering and can be an important aid to managers and planners in conjunction with the planning and optimal use of water resources. Hydrologic time series forecasting studies in the past several decades has produced great exhilaration and care, and a huge number of models and approaches have been proposed to improve the accuracy of forecasting. The models can be divided into statistical methods, physical methods, and intelligent approaches. However, generally, none of these forecasting methods could become a superior and capable model for any hydrologic time series because of hydrological systems are affected by many factors such as climate, land cover, soil infiltration rates, evapotranspiration, which is dependent on stochastic components, multitemporal scales and nonlinear characteristics and each category of methods have various advantages and deficiencies (Solgi, Nourani, & Pourhaghi, 2014).In order to increase models performance, researchers have been continuously developing new technologies and methods for the hydrological forecasting. In recent years, many hybrid approaches take advantage of more than one forecasting method to carry out the research work and engineering practice in different fields. Application results indicate that the hybrid methods have been higher forecasting precision than a single forecasting method (SHALAMU, 2009) and (Cheng, Feng, Niu, & Liao, 2015).

The adaptive neuro-fuzzy inference systems (ANFIS) is one of the hybrid approaches that combine fuzzy logic and neural network technology as it provides an accurate and powerful alternative in modeling numerous processes. More recently, literature has found the application of ANFIS in many fields, such as, regional electricity loads, ophthalmology, reservoir operation, wind speed, evaporation, river flow prediction, etc. (Galavi & Shui, 2012), (Altunkaynak, Ozger, & Cakmakci, 2005), (Firat, Turan, & Yurdusev, 2009), (Bushara & Abraham, 2015), (Kuamr & Kalavathi, 2016) and (Dastorani, Afkhami, Sharifidarani, & Dastorani, 2010). Many successful applications demonstrate that, with the advantages of good generality and predict accuracy; ANFIS is an efficient and promising approach in hydrological forecasting.

On the other hand, one of the methods that have been considered in recent years in the field of hydrology is the application of wavelet theory as a new and effective method in signals and time series analysis such as decomposing, denoising, deseasonalization, detecting of outliers and trends, forecasting, etc. (Bilen & Huzurbazar, 2002), (Detzel & Mine, 2014), (Szolgayova, Arlt, Blöschl, & Szolgay, 2014), (Unal, Aksoy, & Akar, 2004), (Gonzalez-Concepcion, Gil-Farina, & Pestano-Gabino, 2010) and (Kwon, Lall, & Kh, 2007). Furthermore, as a result of recently technological advances, computational intelligence approaches have become progressively common in hydrological modelling. Compared to conceptual and physical methods, computational intelligence models require minimum observation data to simulate intricate hydrological problems (Badrzadeh, 2014). Many studies have been carried out to improve the accuracy and reliability of hydrological time series forecasting by applying the wavelet multi-resolution analysis in conjunction with computational intelligence techniques such as neural networks and adaptive neuro-fuzzy inference systems (Abhishek, Singh, Ghosh, & Anand, 2012), (Solgi, Radmanesh, Zarei, & Nourani, 2014), (Alizdeh, Joneyd, Motahhari, Ejlali, & Kiani, 2015), (S. & Deka, 2016), (Nakhaei & Nasr, 2012) and (Ahmed, El-Shafie, Karim, & El-Shafie, 2012).

Due to use of wavelet transform and ANFIS in various disciplines, especially science related to water, and according to rarely use of wavelet transform in Kurdistan Region, Iraq, forecasting hydrologic time series with a hybrid model (WT-ANFIS) of wavelet transform (WT) and adaptive neuro-fuzzy inference system (ANFIS) is examined in this study. Hence, the main purpose of this study is to develop an accurate model based on combining the wavelet transform with ANFIS technique for forecasting some hydrological time series (rainfall, evaporation, minimum and maximum temperature, average wind speed and reservoir inflow).

2. STUDY AREA AND USED DATA

The hydrological time series for Kirkuk, Sulaimani, Dokan and Darbandikhan meteorological stations in Iraq are selected as the case study as shown in Figure-1. The hydrological time series that used in this study are rainfall, evaporation, minimum and maximum temperature, average wind speed and reservoir inflow. For reservoir inflow time series, the model applied to Dokan and Darbandikhan reservoirs, which are located in Sulaimani province, Kurdistan Region, Iraq. These two reservoirs are large freshwater reservoirsimpounded by the Dokan and Darbandikhan dams which are located on the lesser Zab and Diyala-Sirwan rivers respectively (Nature Iraq, Darbandikhan Basin Project, 2008). Many people benefit from Dokan and Darbandikhan reservoirsand their waters for drinking, irrigation, fisheries, recreation and electricity generating (Nature Iraq, Darbandikhan Lake Poisoning Event, 2008).

According to the availability of data, number of monthly data of hydrological time series for different meteorological stations in Iraq has been used in the current study as shown in Table-1. Data preprocessing such as normalization, standardization, rescaling, etc. is a common procedure dealing with a large number of time series data. In the current study, the first step in the proposed model is standardization of data then at the end of model running the output reversed to original scale.

3. METHODOLOGY

3.1 Wavelet Transform

Wavelets are a type of functions used to localize a given function in both position and scaling. They are used in applications such as signal processing and time series analysis (Veitch, 2005). Wavelets form the basis of the wavelet transform, which is searched for relationships between the signal or time series and the wavelet function. This calculation is done at different scales of a and locally around the time of b, which results a wavelet coefficient ($W(a, b)$) which fills up the transform plane (Nourani, Baghanam, Adamows, & Gebremichael, 2013). There are two main types of wavelet transforms: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The first is intended to work with functions defined over the whole real axis

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while the second deals with functions that are defined over a range of integers, usually $t = 0, 1, \ldots, N-1$, where N denotes the number of values in the time series (Soman, Ramachandran, & Resmi, 2011).

Wavelet function or mother function $\psi(t)$is the function that has oscillation character and satisfies the integrates to zero, it is square integrable or, equivalently, has finite energy and admissibility condition. For any square integrable function $f(t)$, the continuous wavelet transform of the function with respect to a wavelet $\psi(t)$ is defined as (Rao & Bopardikar, 1998):

$$W(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|a|}} \psi^{*}\left(\frac{t-b}{a}\right) dt \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \quad (1)$$

Where a and b are real and * denotes complex conjugation. Thus, the wavelet transform is a function of two variables and both $f(t)$ and ψ(t) belong to $L^2(R)$.

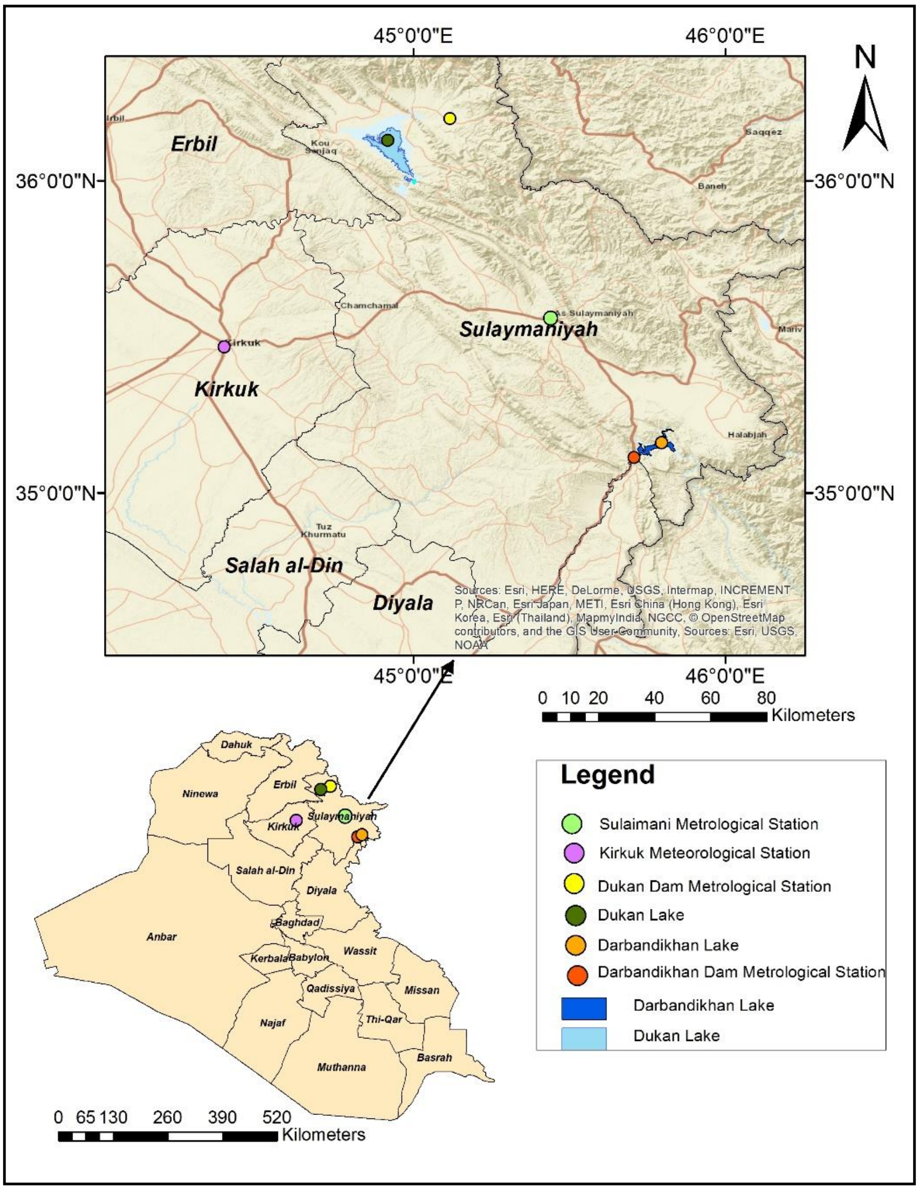

Fig.(1):- The study area showing the locations of meteorological stations and reservoirs.

Table (1):- Number of available monthly data of hydrological time series for different meteorological stations in Iraq.

Meteorological Station	Hydrological Time Series	Number of Data	From	To
Kirkuk	Rainfall	96	January-2000	December-2007
	Evaporation	96	January-2000	December-2007
	Minimum Temperature	96	January-2000	December-2007
	Maximum Temperature	96	January-2000	December-2007
Sulaimani	Rainfall	240	June-1993	May-2013
	Evaporation	240	January-1996	December-2015
	Minimum Temperature	240	January-1996	December-2015
	Maximum Temperature	240	January-1996	December-2015
	Average Wind Speed	240	January-1996	December-2015
Dokan	Rainfall	240	January-1996	December-2015
	Evaporation	240	January-1996	December-2015
	Minimum Temperature	240	January-1996	December-2015
	Maximum Temperature	240	January-1996	December-2015
	Average Wind Speed	155	February-2003	December-2015
	Reservoir Inflow	240	October-1992	September-2012
Darbandikhan	Rainfall	240	June-1993	May-2013
	Reservoir Inflow	240	August-1995	July-2015

The discrete wavelet transform (DWT), besides, provides sufficient information about analysis and synthesis of the original signal, with a significant reduction in the computation time. Discrete wavelets are usually part by part continuous functions which scaled and translated in discrete steps (Radunovic, 2009):

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}}\psi\left(\frac{t - nb_0a_0^m}{a_0^m}\right) \quad \ldots \quad (2)$$

Where m and n are integers, while $a_0 > 1$ is the fixed scaling step. It is taken to be $a_0 = 2$, so that the division on the frequency axis is dyadic. The translation factor is taken to be $b_0 = 1$, so that the division on the time axis of the selected scale is uniform:

$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n) \quad \ldots \quad (3)$$

Discrete dyadic wavelets of this form are commonly chosen to be orthonormal. For a discrete time series, S_t, the dyadic wavelet transform becomes (Nourani, Baghanam, Adamows, & Gebremichael, 2013):

$$W_{m,n} = 2^{-m/2}\sum_{t=0}^{N-1}\psi(2^{-m}t - n)S_t \quad \ldots \quad (4)$$

Where $W_{m,n}$ is the wavelet coefficient for the discrete wavelet of scale $a = 2^m$ and location $b = 2^m n$. The equation above considers a finite time series, $S_t,\ t = 0, 1, 2, \ldots, N-1$; and N is an integer power of two $N = 2^C$. This gives the ranges of m and n as, respectively, $0 < n < 2^{C-m} - 1$ and $1 < m < C$. At the largest wavelet scale ($m = C$) only one wavelet is required to cover the time interval, and only one coefficient is produced. At the next scale (2^{m-1}), two wavelets coverthe time interval, hence two coefficients are produced, and so on down to $m = 1$, the a scale is 2^1, i.e. 2^{C-1} or $N/2$ coefficients are required to describe the signal at this scale. The total number of wavelet coefficients for a discrete time series of length $N = 2C$ is then $1 + 2 + 4 + 8 + \cdots + 2^{C-1} = N - 1$. Additionally, a signal-smoothed component, A, is left, which is the signal mean. Thus, a time series of length N is broken into N components. The inverse discrete transform is given by:

$$S_t = A_C + \sum_{m=1}^{C}\sum_{n=0}^{2^{C-m}-1} W_{m,n}2^{-m/2}\,\psi(2^{-m}t - n) = A_C + \sum_{m=1}^{C} D_m \quad \ldots \quad (5)$$

Where A_C is the approximation sub-signal at the level C and D_m aredetail sub-signals at levels $m = 1, 2, \ldots, C$. The wavelet coefficients, D_m, provide the detail signals, which can capture small features of interpretational value in the data. The residual term A_C represents the background information of data. Wavelet functions have many kinds, Haar, Daubechies, Coiflet, Symlet, etc.,

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which are often applied in wavelet analysis. Figure-2 illustrates some of the commonly used wavelet functions and schematic multiresolution decomposition of discrete wavelet transform. Daubechies functions are the most popular functions that widely used to solve a broad range of problems and represent the foundations of wavelet signal processing that used in numerous applications (Soman, Ramachandran, & Resmi, 2011).

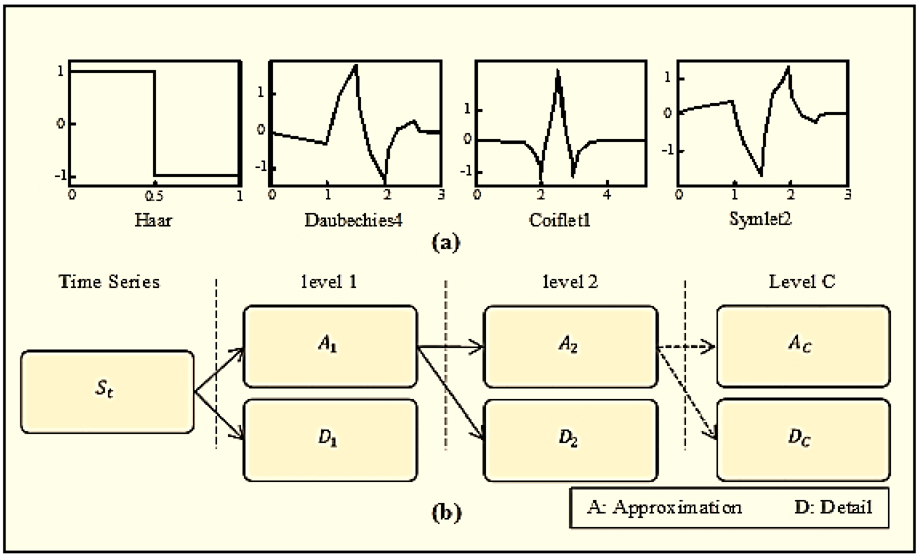

Fig.(2):- (a) Some of the wavelet functions, (b) Schematic multiresolution decomposition of DWT.

This study focuses on the practical interpretation of the multiresolution decomposition of a discrete signal for the hydrological time series data using the Daubechies function, i.e. to decompose the original time series into approximation and details. Figure-3 shows a typical discrete wavelet transform of time series using three resolution levels and Daubechies function (db_5).

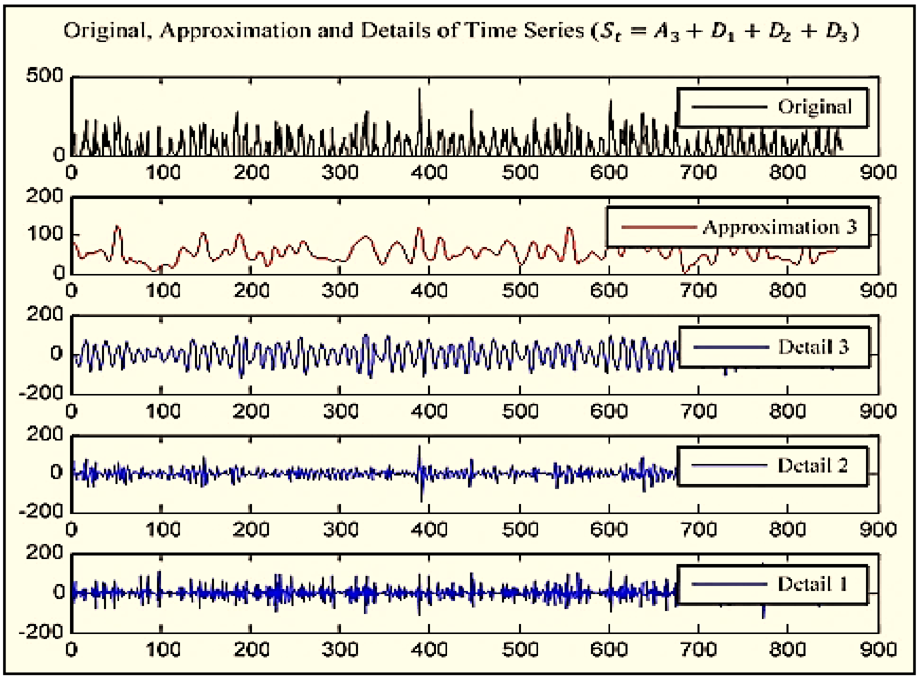

Fig.(3):- Typical discrete wavelet transform using three decomposition levels and Daubechies function (db5).

3.2 ANFIS Technique

A neuro-fuzzy system is defined as a combination of neural networks and fuzzy inference system. In adaptive neuro-fuzzy inference system (ANFIS) the membership functions (MFs) parameters are fitted to a dataset through a hybrid learning algorithm (George & Ioana, 2007). ANFIS eliminates the problem of defining the membership function (MF) parameters and design of if-then rules in fuzzy system design by using the learning capability of ANN for automatic fuzzy rule generation and parameter optimization (Firat, Turan, & Yurdusev, 2009). Besides, ANFIS has the advantage of allowing the extraction of fuzzy rules from numerical data. Therefore, in the present study, with aids of MATLAB software, the ANFIS methodology is proposed to self-organize model structure and to adapt parameters of the fuzzy system for forecasting monthly hydrological time series.

There are two types of fuzzy inference systems, Sugeno-Takagi and Mamdani. In this study, Sugeno Takagi fuzzy inference system model is used for forecasting hydrological time series. The ANFIS incorporates five-layer network to implement a Takagi-Sugeno-type fuzzy system as shown in Figure-4, which is considered for simplicity as a fuzzy system with only two inputs and one output. The output of each layer is the input of the next layer. The ANFIS uses the least mean square training algorithm in the forward computation to determine the linear consequents of the Takagi-Sugeno rules, while for the optimal tuning of an antecedent MF, backpropagation is used (Palit & Popovic, 2005). Figure-4 (a), illustrates the fuzzy reasoning mechanism for the first order Takagi-Sugeno model to derive an output function (f) from a given input (x, y):

$$\left.\begin{array}{llll} Rule\ 1: & If\ x\ is\ A_1\ and\ y\ is\ B_1 & then & f_1 = p_1x + q_1y + r_1 \\ Rule\ 2: & If\ x\ is\ A_2\ and\ y\ is\ B_2 & then & f_2 = p_2x + q_2y + r_2 \end{array}\right\} \ldots\ldots \quad (6)$$

Where f_i is the output, x and y are the crisp inputs to the node i, A_i and B_i are the linguistic labels, $(p_i,\ q_i,\ r_i)$ are the consequent parameters, μ_{A_i} and μ_{B_i} are the MFs for A_i and B_i linguistic labels, respectively. Figure-4 (b) shows a typical ANFIS architecture with two inputs, (x, y), and one output, (f). The ANFIS building with all the relationships between the input and output of each five layers are described as follows:

Layer 1 (input nodes): Each node in this layer generates membership grades of an input variable. The node output is defined by O_i^1 is calculated by:

$$O_i^1 = \mu_{A_i}(x) \quad i = 1, 2 \qquad or \qquad O_i^1 = \mu_{B_{i-2}}(y) \quad i = 3, 4 \ \ldots\ldots\ldots.\ldots\ldots\ldots \quad (7)$$

In this study, the triangular membership function is used as:

$$O_i^1 = \mu_{A_i}(x) = max\left(\min\left(\frac{x - a_i}{b_i - a_i}, \frac{c_i - x}{c_i - b_i}\right), 0\right) \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \quad (8)$$

Where $(a_i,\ b_i,\ c_i)$ are the parameter set that changes the shapes of the MFs with the maximum equal to 1 and the minimum equal to 0; and called premise parameters or antecedent parameters. For triangular function, a_i and c_i locate the feet of the triangle and the parameter b_i locates the peak.

Layer 2 (rule nodes): the outputs of this layer, called firing strengths O_i^2, are the products of the corresponding degrees obtained from the layer 1:

$$O_i^2 = w_i = \mu_{A_i}(x).\mu_{B_i}(y) \qquad i = 1, 2 \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots\ldots\ldots \quad (9)$$

Layer 3 (average nodes): main target is to compute the ratio of firing strength of each i^{th} rule to the sum firing strength of all rules. The firing strength in this layer is normalized $\overline{w_i}$ as:

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum_{i=1}^{2} w_i} \qquad i = 1, 2 \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots.\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (10)$$

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Layer 4 (adaptive nodes): the contribution of i^{th} rule towards the total output or the model output and the function defined is calculated by:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \qquad i = 1,2 \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (11)$$

Layer 5 (output nodes): this layer is called as the output nodes in which the single node computes the overall output by summing all incoming signals:

$$O_i^5 = f = f(x,y) = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = \bar{w}_1 f_1 + \bar{w}_2 f_2 \quad \ldots\ldots\ldots\ldots\ldots \quad (12)$$

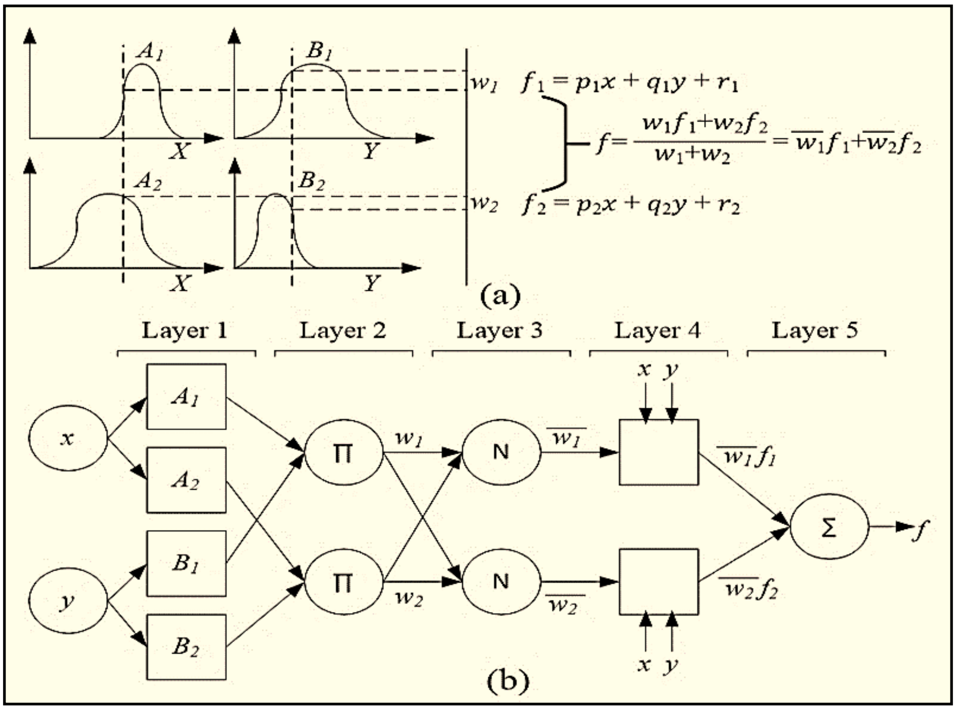

Fig.(4):- (a) First-order Takagi-Sugeno fuzzy model, (b) Equivalent ANFIS architecture.

3.3 Hybrid Wavelet ANFIS

In the present study, a hybrid wavelet transforms adaptive neuro-fuzzy inference system (WT-ANFIS) model was developed to forecast monthly hydrological time series for different meteorological stations in Iraq. Figure-5 illustrates, schematically, the layout and stages of the developed model. In order to apply the model using the available hydrological time series data, an MATLAB code was written to perform all processes in the stages of the developed model (WT-ANFIS). Different number of input variables (time lags), decomposition levels of wavelet, Daubechies functions (db) and triangular membership functions (MFs) have been applied.

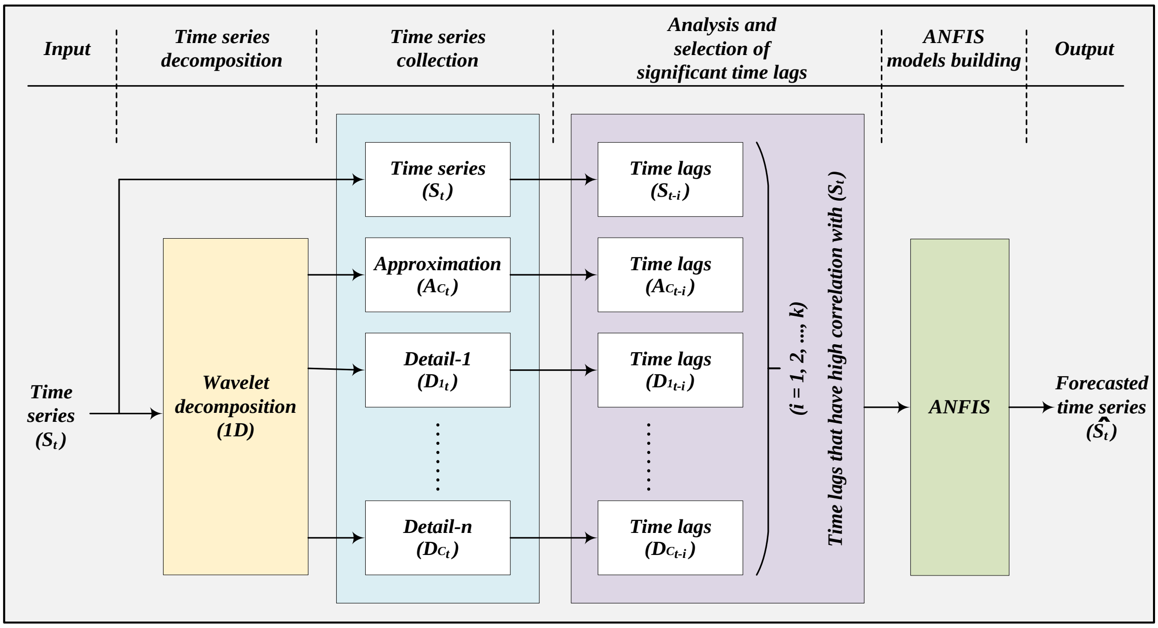

Fig.(5):- Structure of the developed model (WT-ANFIS) by combining of wavelet transform and ANFIS technique.

4. TIME SERIES FORECASTING

4.1 Input Variables Selection

Determination of effective and significant input variables is the most important steps in model construction. However, the number of potentially important inputs can be large by inclusion of unnecessary inputs, as such inputs do not provide any useful information about the underlying relationship, but increase the size and complexity of the model, making the task of extracting important information from the data difficult. Besides, neglecting effective inputs result in a loss of important information, which can be detrimental to the predictive performance of a model. Consider modeling a time series S_t, where itis required to forecast the value of S_{t+1} at time $t+i$, where i is the lead time. The inputs to the model are typically chosen as the values of the time series up to time $t$and the output will be the forecasted value. In addition, to previous values of the time series, one can utilize the values or forecasts of other time series or external variables as inputs that have a correlated or causal relationship with the time series to be forecasted. For forecasting a hydrological time series in this study, exogenous time series that used is the extracted sub-time series (approximation A and details D) from original time series by wavelet transform. The functional form of this type of model is:

$$S_{t+i} = f\left(S_{lags}, A_{C_{lags}}, D_{1_{lags}}, D_{2_{lags}}, \dots, D_{C_{lags}}\right) \quad \dots\dots\dots\dots\dots\dots\dots\dots \quad (13)$$

Where f is the unknown function mapped by the model, i is an index representing lead time, and $lags$ are the effective and significant time lags of original time series and sub-time series (approximation and details) considered important in modeling S_{t+i} and C is the decomposition level considered in the wavelet transform of time series. In this study, the appropriate time lags are determined by using a statistical approach which is based on the heuristic that the potential influencing variables corresponding to different time lags can be identified through statistical analysis of the time series data that uses autocorrelation and cross-correlation between the variables. Analyzing and selection of the significant time lags of the original time series and sub-time series (approximation and details) to form the input variables to ANFIS model for the original time series is based on the autocorrelation coefficients, and for the sub-time series (approximation and details) is based on the cross-

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correlation coefficients between the original and sub-time series (approximation and details).

4.2 Model Structure Development

The most critical steps in preparing a satisfactory forecasting model is choosing appropriate input variables, as these variables determine the structure of the model and affect the results of the model. As mentioned earlier, the effective and significant time lags of original time series, and sub-time series (approximation and details) were selected, depending on the autocorrelation and cross-correlation statistics, to form the set of input variables to ANFIS model. The number of variables in the set of input variables depends on the decomposition level (C) and the number of selected time lags (G) that have higher correlation coefficients from each series. For example, if the decomposition level is 3 and the number of selected time lags from each series is 4, then the number of variables in the set of input variables will be $[(C+2)\times G=(3+2)\times 4=20]$. As a basic recommendation, depending on the number of time series data (N), the degree of decomposition was found (Solgi, Radmanesh, Zarei, & Nourani, 2014):

$$C = Int[log(N)] \dots\dots\dots\dots\dots\dots \quad (14)$$

In this study, according to the number of time series data, $C = 2$ were determined and to be more precise, 1 to 4 decomposition level were examined using Daubechies wavelet functions ($db2-db10$). Using all variables in the set of input variables as inputs to ANFIS model will increase the model complexity and hence affects the model parsimony. To determine which variables should be the input arguments to produce a best ANFIS model, there is a set of input candidates ($S_{lags}, A_{C\,lags}, D_{1\,lags}, D_{2\,lags}, \dots, D_{C\,lags}$) and the output to be forecasted is (S_t). For best model selection, more computationally intensive approach is to do an exhaustive search on all possible combinations of the input candidates. Therefore, different combinations up to 3 variables of the set of input candidates were used as input variables to ANFIS model. However, the approach usually involves a significant amount of computation if all combinations are tried. For instance, if 3inputs are selected out of 20, the total number of ANFIS models is $Comb(20,3) = 20!/((20-3)!\times 3!) = 1140$. To achieve the computation for combinations of input variables, the MATLAB code has been included with a search function for best ANFIS model based on the minimum $RMSE$ for checking dataset.

There are different types of MFs in ANFIS and different number of MFs can be introduced for each input. In the grid partitioning method, ideally for n MFs and p input variables there could be n^p different if-then rules. Consequently, increasing the number of membership functions on the input variables will increase the number of fuzzy if-then rules; simultaneously, it increases the model complexity and hence affects the model parsimony. Moreover, a fuzzy model with a large number of rules often encounters the risk of over fitting the data (Nayak, Sudheer, Rangan, & Ramasastri, 2005). In the present study, to obtain the best ANFIS structure, MFs of 2 to 4 of triangular MFs for inputs were tested and trained. No significant improvement in model performance is observed with respect to the change in the number of triangular MF above 4. However, as the number of MFs increases, the time taken for model training increases as well. Therefore, the model with 2 and 3 triangular MFs was selected as best numbers of MFs for further analysis.

As mentioned earlier, the monthly data records for each hydrological time series were collected from different meteorological stations. The dataset was divided into two subsets, training and checking dataset. In order to get more reliable evaluation and comparison, models are tested with checking dataset that was not used during the training process. The checking dataset consists of a total of 24 data records, which is the last 24 months of the hydrological time series. Different, decomposition levels of wavelet ($C\!:1-4$), Daubechies wavelet functions ($db2-db10$), number of time lags for each series ($G\!:1-4$), triangular MFs ($2-4$) and input variables (1-3) to ANFIS model have been applied, and results have been compared with each other to get the best model performances for each hydrological time series.

4.3 Model Performance Evaluation Criteria

Accuracy is the most important criterion for evaluating forecasting models or choosing between competing models. In general, the more accurate forecasting model is the closer the forecasted values to the observed values of the time series. The performances of the models developed in this study are evaluated according to the coefficient of determination (R^2) and root mean squared error ($RMSE$) statistical evaluating criteria which are given as follows:

$$R^2 = \left(\left(\sum_{i=1}^{N} (y_i - \bar{y})(\hat{y}_i - \tilde{y}) \right) \Bigg/ \left(\sqrt{\sum_{i=1}^{N} (y_i - \bar{y})^2 (\hat{y}_i - \tilde{y})^2} \right) \right)^2 \quad \ldots\ldots \quad (15)$$

$$RMSE = \left(\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \right)^{0.5} \quad \ldots \quad (16)$$

Where N is the number of data points, y_i, $\bar{y}$ are the observed data and the mean respectively and $\hat{y}$, $\tilde{y}$ are the corresponding forecasted data and the mean respectively. The coefficient of determination (R^2) is commonly used statistical criteria and provides information on the strength of linear relationship between the observed and calculated values. The root mean squared error ($RMSE$) is statistical criteria that indicate a quantitative measure of the model error in units of the variable. Model performance is indicated well when RMSE value is close to zero.

Checking dataset is a more realistic way for evaluating a model's accuracy; in which, some of the data at the end of the series are neglected before the models are built. Then the models are compared based on how well they forecast the data, which have been prevented in state of how well they forecast the same data which has been used for modeling (Makridakis, Wheelwright, & Hyndman, 1998). Therefore, in the current study for selecting and comparison of predicting models, the time series data were split into two datasets. The model will construct using first set of the data (training dataset). Then the model is used to forecast the remaining data points (checking dataset). To obtain information about the model's ahead forecasting performance; the resulting out of the model forecasts is compared to the observed values. The above measures are used for checking dataset and models that yield best values for these statistics on checking dataset, would be chosen as a best model. For all monthly time series data used in this study, the last two years (24 months) of the data were used as checking dataset, then the models were fitted on the remaining data and used to forecast 24 months ahead (checking dataset).

5. RESULTS AND DISCUSSION

A hybrid wavelet transform (WT) adaptive neuro-fuzzy inference system (ANFIS)model (WT-ANFIS) is presented for forecasting hydrological time series from time lags values of original time series and sub-time series (approximation and details) that produced from transforming the original time series using wavelet technique.

For rainfall time series of the meteorological stations, as seen in Tables-2, the WT-ANFIS models are evaluated based on their performance in training and checking datasets. The results show, generally, that the best models are obtained when the input variables include a combination of time lags of original time series and sub-time series (approximation and details) as for Sulaimani and Dokan stations or only the time lags of transformed time series as for Kirkuk and Darbandikhan stations. In addition, it is observed that, among the examined models, the structure of all best WT-ANFIS models consists of three input variables. The comparisons demonstrated, almost, that the wavelet decomposition level of 3 using Daubechies function above $db3$ and triangular MFs of 3 lead to accurate WT-ANFIS models. As it is clear, the most effective models input variables among the different variables are the time lags of details of sub-time series. The rainfall models have shown significant variations in the performance evaluation. According to the values of the determination coefficients R^2 (0.94, 0.93) and root mean square error $RMSE$ (9.3, 14.38) for training and checking datasets respectively, the performance of the proposed model for rainfall time series of Kirkuk station is better than the other models, due to using less numbers of data points in the model (96 months). Although the performance of the model that uses a less number of data points is better, however; statistically, it represents the hydrological characteristics of the time series for a long period. The results reveal that WT-ANFIS model is efficient and can provide an acceptable forecasting for monthly rainfall among the four meteorological stations used. Furthermore, for testing and checking datasets, the observed and calculated values of rainfall for the proposed model for all stations are

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shown in Figure-6. According to calculated values as it is clear from the figure, it is concluded that the proposed model WT-ANFIS has good performance in the estimation of the minimum and maximum values of rainfall time series. With regard to the forecast periods, it is evident that the performances of the models were found to relatively deteriorate at higher lead times.

Table (2):- Performance of developed model WT-ANFIS for monthly rainfall time series of different stations.

Meteorological Station	Best Input Variables	Best Decomposition Level	Daubechies Function	MFs	*RMSE*		R^2	
					Training	Checking	Training	Checking
Kirkuk	D1(t-1), D2(t-3), D3(t-6)	3	db8	2trimf	9.30	14.38	0.94	0.93
Sulaimani	D1(t-1), D3(t-5), S(t-1)	3	db5	3trimf	19.23	21.12	0.91	0.87
Dokan	A(t-24), D1(t-1), S(t-12)	1	db4	3trimf	22.16	26.30	0.87	0.82
Darbandikhan	D1(t-1), D2(t-3), D3(t-12)	3	db8	3trimf	22.49	19.14	0.87	0.87

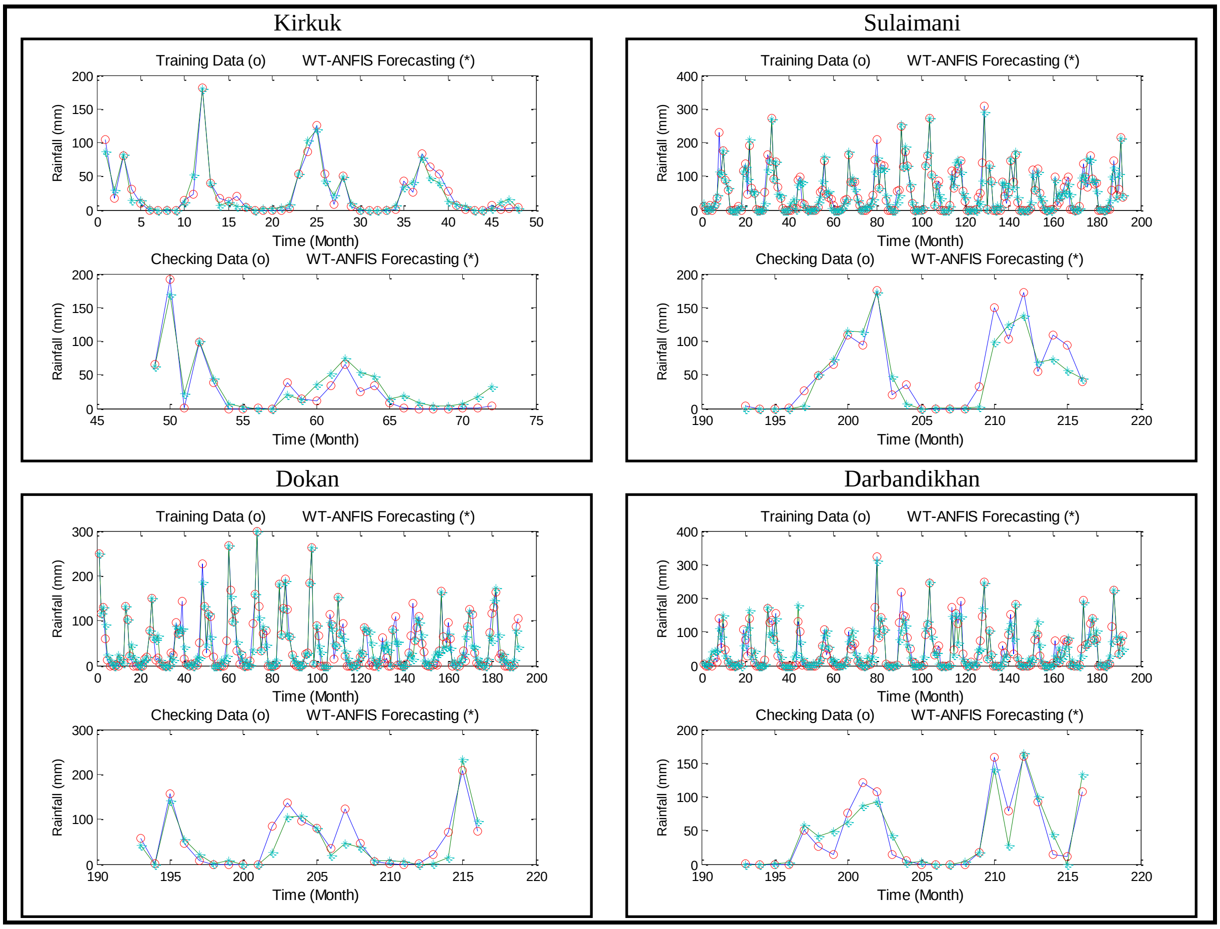

Fig.(6):- Observed and calculated values of rainfall time series by developed model WT-ANFIS.

According to the available data, the developed model WT-ANFIS is applied to forecast the monthly evaporation time series of three meteorological stations (Kirkuk, Sulaimani and Dokan) in Iraq. From the results shown in Table-3, it is clear that the developed model has high performances in forecasting the monthly evaporation in all meteorological stations. Besides, the models with high performances are obtained by combining the time lags of original time series and sub-time series transformed by wavelet with 2 levels of decomposition.

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Moreover, the most effective models input variables among the different variables are the time lags of approximation of sub-time series. Also, like rainfall models, the selected best models have 3 input variables, 2 to 3 triangular MFs and Daubechies functions above $db4$.The highest and the lowest values of coefficient of determination R^2 and root mean square error $RMSE$ respectively are recorded for monthly evaporation time series of Dokan meteorological station with R^2 of (0.99, 0.98) and $RMSE$ of (16.16, 17.84) for training and checking datasets respectively. By applying the developed model WT-ANFIS to evaporation time series, the observed and calculated values of training and checking datasets for all stations are very close to each other as shown in Figure-7.

Table (3):- Performance of developed model WT-ANFIS for monthly evaporation time series of different stations.

Meteorological Station	Best Input Variables	Best Decomposition Level	Daubechies Function	MFs	$RMSE$		R^2	
					Training	Checking	Training	Checking
Kirkuk	A(t-12), A(t-1), D2(t-1)	2	db5	2trimf	21.94	30.28	0.98	0.97
Sulaimani	A(t-11), D1(t-1), S(t-1)	2	db8	3trimf	17.15	19.42	0.98	0.97
Dokan	A(t-1), A(t-11), S(t-6)	2	db9	3trimf	16.16	17.84	0.99	0.98

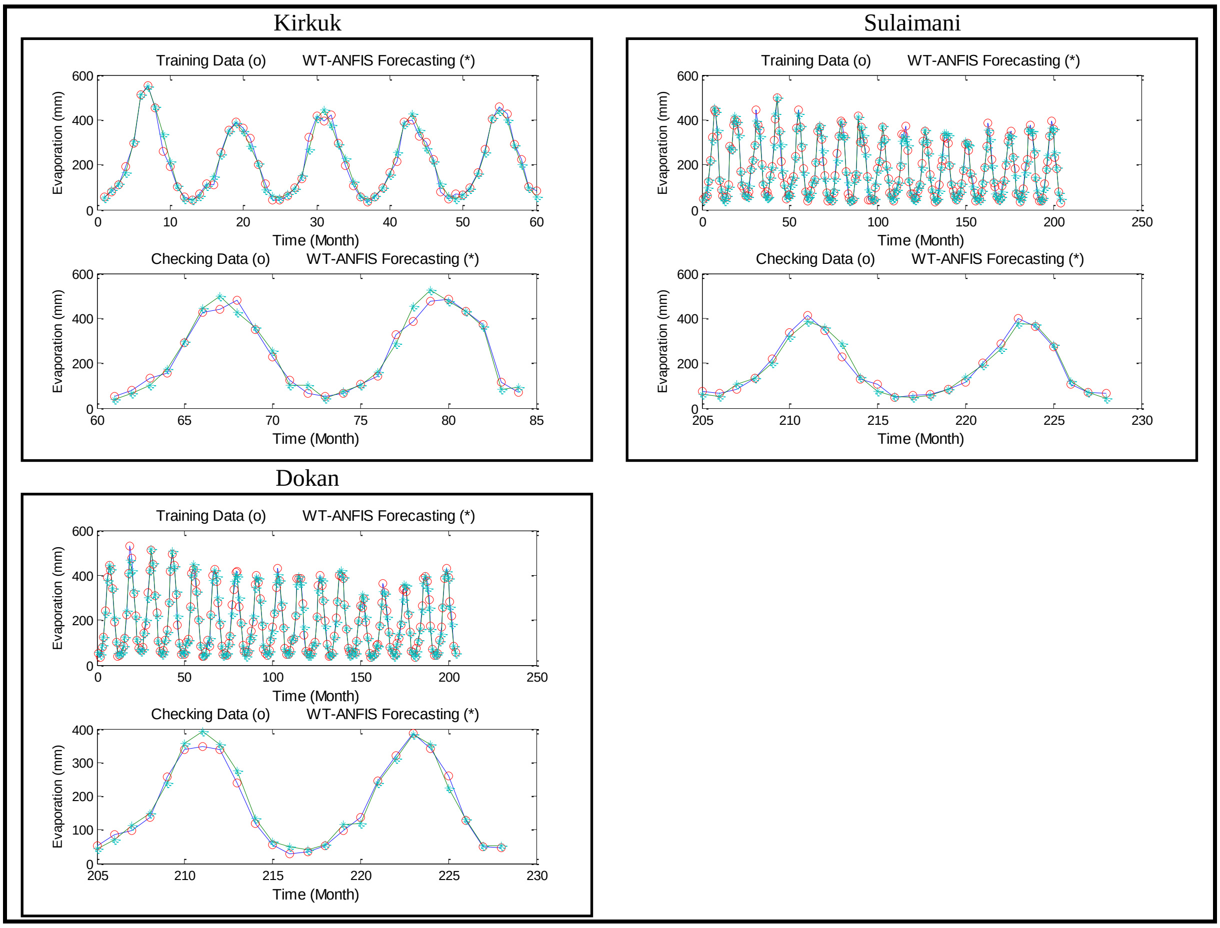

Fig.(7):- Observed and calculated values of evaporation time series by developed model WT-ANFIS.

The hybrid WT-ANFIS model was also tested with the monthly time series of minimum and maximum temperature for Kirkuk, Sulaimani and Dokan stations. The developed hybrid model shows high performances, in terms of performance evaluation criteria, in one step-ahead forecasting of both monthly minimum and maximum temperature as shown in Table-4 and Table-5 respectively. The results, generally, show that the best temperature models are obtained by

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combining the time lags of original time series and sub-time series (approximation and details) and using decomposition levels of 1 to 2, input variables of 2 to 3 and triangular MFs of 2 to 3. Comparing the overall results of stations, the minimum values of the determination coefficients R^2 of (0.97, 0.96) were observed for monthly minimum temperature series of Sulaimani meteorological station for training and checking datasets respectively. In which this model uses, only, the time lags of transformed time series (approximation and details). On the other hand, the maximum value of the determination coefficient R^2 of (0.99) was observed for monthly minimum and maximum temperature series for training dataset of Kirkuk meteorological station. The checking dataset results of hybrid WT-ANFIS model for Dokan station having better accuracy compare to the other stations. The values of R^2 of (0.99) and minimum root mean square error $RMSE$ of (1.23) which is the better result was observed for monthly maximum temperature series of Dokan station.

Table (4):- Performance of developed model WT-ANFIS for monthly minimum temperature time series of different stations.

Meteorological Station	Best Input Variables	Best Decomposition Level	Daubechies Function	MFs	$RMSE$		R^2	
					Training	Checking	Training	Checking
Kirkuk	A(t-6), S(t-6)	2	db9	3trimf	1.05	1.96	0.99	0.97
Sulaimani	A(t-12), A(t-1), D2(t-12)	2	db2	3trimf	1.73	1.86	0.97	0.96
Dokan	A(t-1), A(t-11), S(t-1)	1	db4	3trimf	1.53	1.60	0.97	0.97

Figure-8 shows the observed and modeled values of minimum and maximum temperature time series by developed model WT-ANFIS for Kirkuk, Sulaimani and Darbandikhan meteorological stations. From the figure, it can be observed a high coinciding between the observed and calculated values, and the minimum and maximum values in the measured data is modeled very well by the hybrid WT-ANFIS model.

Table (5):- Performance of developed model WT-ANFIS for monthly maximum temperature time series of different stations.

Meteorological Station	Best Input Variables	Best Decomposition Level	Daubechies Wavelet	MFs	$RMSE$		R^2	
					Training	Checking	Training	Checking
Kirkuk	A(t-12), A(t-1), S(t-1)	1	db2	2trimf	1.29	2.09	0.99	0.97
Sulaimani	A(t-1), D2(t-2), S(t-12)	2	db7	3trimf	1.47	1.54	0.98	0.98
Dokan	A(t-1), A(t-11), S(t-1)	2	db9	3trimf	1.54	1.23	0.98	0.99

Furthermore, forecasting of monthly average wind speed time series of Sulaimani and Dokan meteorological stations were examined using the developed hybrid WT-ANFIS model. The best model for Dokan station was obtained by combining the time lags of original time series and details of transformed time series using wavelet transform with decomposition levels of 2, Daubechies function ($db6$) and 2 triangular MFs as presented in Table-6. On the other hand, for Sulaimani station, the best model was obtained by combining the time lags of approximation and details of transformed time series with a decomposition level of 1, Daubechies function ($db9$) and 2 triangular MFs.Comparing the WT-WANFIS model performance for Sulaimani and Dokan stations in terms of R^2 and $RMSE$ reveals that there is relatively a big difference between the values of R^2 and also $RMSE$ of training and checking datasets. From Table-6 it can be concluded that the developed forecasting model provides a more accurate forecasting of monthly average wind speed for Dokan meteorological station than Sulaimani meteorological station. In the terms of evaluation criteria of checking dataset, the developed model results demonstrate good performance in forecasting the average wind speed for Dokan station with R^2 value of (0.91) and $RMSE$ value of (0.18). In addition, the model has moderate performance for Sulaimani station with R^2 value of (0.77) and $RMSE$ value of (0.24) for checking dataset. Figure-9 shows the observed and calculated average wind speed by developed WT-ANFIS model for Sulaimani and Dokan stations. The figure clearly depicts small differences between the observed and the modeled time series data.

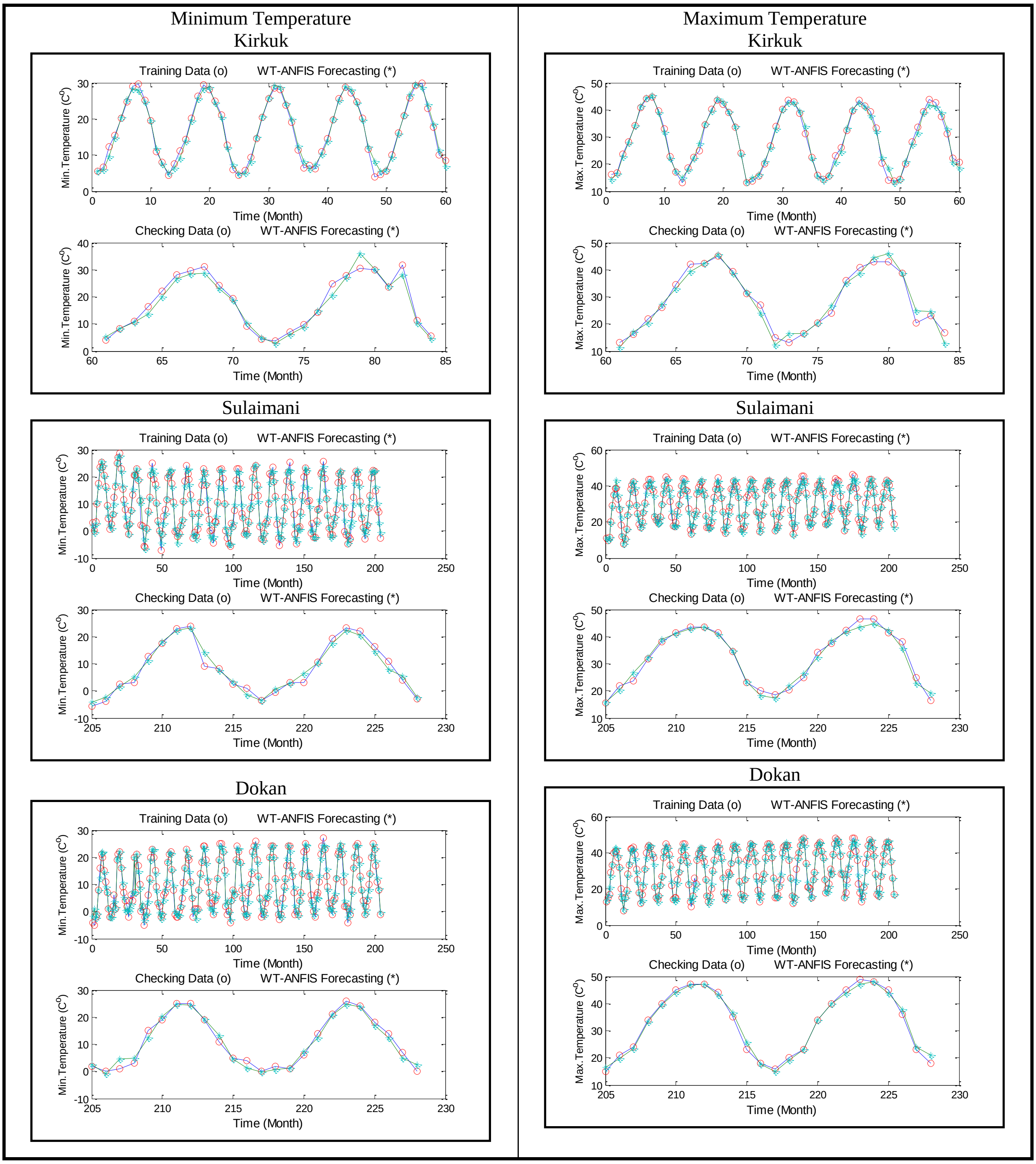

Fig.(8):- Observed and calculated values of minimum and maximum temperature time series by developed model WT-ANFIS.

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Table (6):- Performance of developed model WT-ANFIS for monthly average wind speed time series of different stations.

Meteorological Station	Best Input Variables	Best Decomposition Level	Daubechies Function	MFs	$RMSE$		R^2	
					Training	Checking	Training	Checking
Sulaimani	A(t-1), A(t-2), D1(t-1)	1	db9	2trimf	0.26	0.24	0.80	0.77
Dokan	D1(t-1), D2(t-2), S(t-1)	2	db6	2trimf	0.20	0.18	0.90	0.91

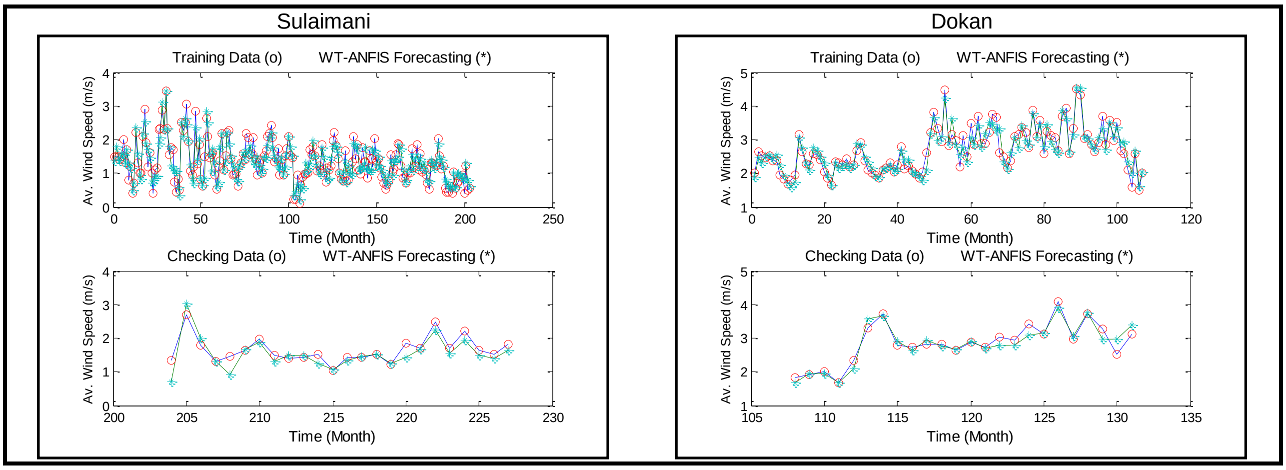

Fig.(9):- Observed and calculated values of average wind speed time series by developed model WT-ANFIS.

WT-ANFIS model has been developed to forecast the monthly reservoir inflow time series for Dokan and Darbandikhan reservoirs. The developed models have good results and high performances in terms of statistical evaluation criteria as shown in Table-7. It can be found from this table that WT-ANFIS model in both Dokan and Darbandikhan stations has the same input variables, decomposition levels and number of triangular MFs with different Daubechies function type ($db8$ and $db10$) respectively. In addition, the model in both stations has the same value of the determination coefficients R^2 of (0.95) for training dataset and for checking dataset to have higher values of R^2 (0.96) and root mean square error $RMSE$ (26.93) for Dokan reservoir and smaller values of R^2 (0.93) and $RMSE$ (9.53) for Darbandikhan reservoir.

Table (7):- Performance of developed model WT-ANFIS for monthly reservoir inflow time series of different stations.

Meteorological Station	**Best Input Variables**	**Best Decomposition Level**	**Daubechies Function**	**MFs**	$RMSE$		R^2	
					Training	Checking	Training	Checking
Dokan	D1(t-1), D3(t-5), S(t-1)	3	db8	3trimf	37.2	26.93	0.95	0.96
Darbandikhan	D1(t-1), D3(t-5), S(t-1)	3	db10	3trimf	23.94	9.53	0.95	0.93

More comparisons between the performances of WT-ANFIS models of both Dokan and Darbandikhan reservoirs for training and checking datasets are given by Figure-10. The figure presents the forecasted versus observed values of reservoir inflow for all datasets in both stations. From this figure, it can be observed a good coincidence between the forecasted and real values of reservoir inflow, and the peaks in the measured inflow data are modeled well by using the developed WT-ANFIS model. All in all, for this study, the WT-ANFIS model can be applied to provide a successful forecasting of the inflow into reservoirs.

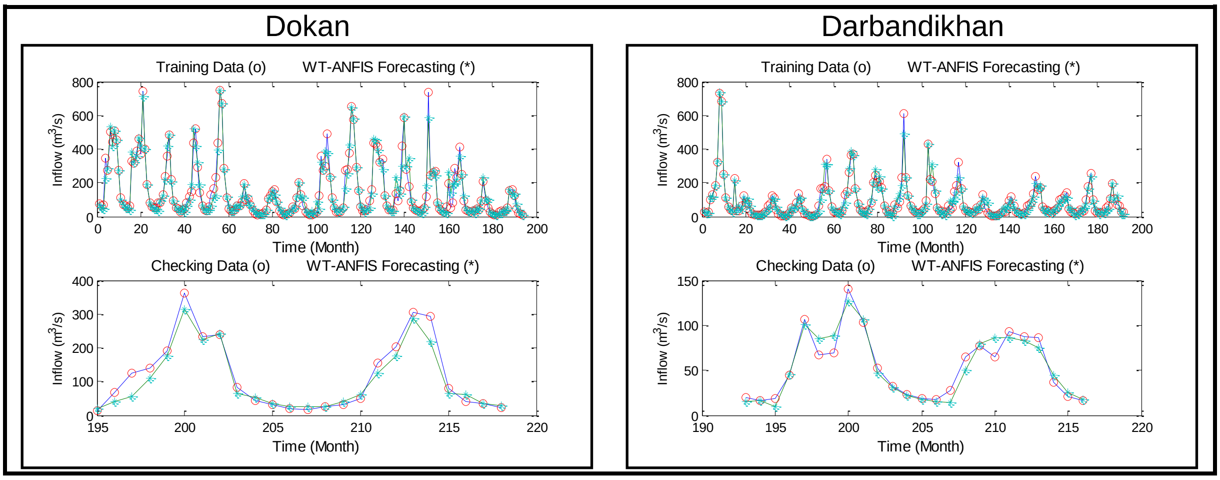

Fig.(10): Observed and calculated values of reservoir inflow time series by developed model WT-ANFIS.

Table-8 shows some descriptive statistics of the observed and forecasted hydrological time series of all stations that used in this study. An analysis to assess the potential of the developed model to preserve the statistical properties of the historical hydrological time series reveals that the time series computed by the WT-ANFIS model using a combination time lags of original time series and sub-time series transformed by wavelet reproduces the statistical properties (mean, standard deviation, skewness, kurtosis).

Table (8):- Descriptive statistics of observed and forecasted values of hydrological time series for different stations.

Hydrological Time Series	Meteorological Station	Data	Mean	Standard Deviation	Skewness	Kurtosis	Minimum	Maximum
Rainfall (mm)	Kirkuk	Observed	26.23	40.26	2.23	8.35	0.00	191.90
		Forecasted	28.83	37.81	2.07	7.62	0.00	180.36
	Sulaimani	Observed	53.24	64.16	1.35	4.54	0.00	309.60
		Forecasted	53.01	60.63	1.36	4.77	0.00	290.24
	Dokan	Observed	46.46	61.16	1.55	5.25	0.00	299.40
		Forecasted	46.16	56.61	1.88	6.85	0.00	299.43
	Darbandikhan	Observed	45.39	61.02	1.55	5.22	0.00	322.20
		Forecasted	45.68	56.67	1.62	5.83	0.00	311.94
Evaporation (mm)	Kirkuk	Observed	221.72	150.01	0.44	1.80	35.00	553.90
		Forecasted	222.86	151.34	0.46	1.85	39.55	549.37
	Sulaimani	Observed	182.11	122.16	0.54	1.99	29.20	498.20
		Forecasted	181.89	120.92	0.51	1.92	39.83	497.34
	Dokan	Observed	192.42	135.18	0.55	1.97	27.20	529.30
		Forecasted	192.91	134.48	0.53	1.91	37.00	517.37
Minimum Temperature (C^o)	Kirkuk	Observed	17.16	8.98	0.03	1.55	3.70	31.60
		Forecasted	16.97	8.88	0.09	1.62	2.71	35.93
	Sulaimani	Observed	9.52	9.35	0.16	1.72	-7.20	28.60
		Forecasted	9.53	9.13	0.17	1.71	-6.59	27.80
	Dokan	Observed	9.52	9.35	0.16	1.72	-7.20	28.60
		Forecasted	9.53	9.13	0.17	1.71	-6.59	27.80
Maximum Temperature (C^o)	Kirkuk	Observed	28.98	10.65	-0.01	1.52	13.20	45.00
		Forecasted	28.96	10.66	-0.01	1.58	11.29	46.04
	Sulaimani	Observed	30.37	10.11	-0.21	1.74	7.80	46.60
		Forecasted	30.35	9.96	-0.23	1.72	7.98	44.79
	Dokan	Observed	31.22	11.36	-0.20	1.63	8.00	49.00
		Forecasted	31.22	11.22	-0.20	1.60	8.76	47.97
Average Wind Speed (m/s)	Sulaimani	Observed	1.37	0.58	0.54	3.38	0.11	3.44
		Forecasted	1.36	0.52	0.78	4.19	0.22	3.43
	Dokan	Observed	2.72	0.64	0.46	2.81	1.49	4.50
		Forecasted	2.71	0.61	0.43	3.02	1.59	4.54
Reservoir Inflow (m^3/s)	Dokan	Observed	151.93	161.80	1.59	5.11	9.00	750.00
		Forecasted	150.54	157.16	1.56	4.94	9.11	748.50
	Darbandikhan	Observed	84.50	104.68	3.19	16.63	2.16	732.05
		Forecasted	84.43	102.12	3.17	16.58	3.42	734.75

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Finally, the results of the best hybrid WT-ANFIS models for one step-ahead forecasting in terms of the R^2 and $RMSE$ criteria are not as strong for monthly rainfall and average wind speed time series compared to the results of the model for monthly evaporation, minimum and maximum temperature and reservoir inflow time series. The results demonstrate that the hybrid WT-ANFIS can be successfully applied to establish accurate and reliable hydrological time series forecasting models using the combination values of antecedent original time series and sub-time series (approximation and details) that produced by wavelet transform as input variables. Also, it can be observed that, the WT-ANFIS model can achieve satisfactory performances for simulating the monthly hydrological time series and the model has high consistency, good stability and a great capability in forecasting of extreme values. The advantage of WT-ANFIS model is that no future values of input variables should be forecasted. However, it should be kept in mind that such forecasting models are data dependent. More reliable data will be required to achieve more reliable future forecasts.

6. CONCLUSIONS

Forecasting of hydrological time series such as rainfall, wind speed, evaporation, etc. is challenging because of the hydrologic system complexity. Enhancing the accuracy of hydrological time series forecasting has always been an important task for researchers and hydrologic forecasters. In this study, an effort is made to develop a more accurate hydrological time series forecasting model using innovative computational intelligence based methods such as the adaptive neuro-fuzzy inference system (ANFIS).

The results, generally, showed that the ANFIS model with input variables consists of time lags of original time series, and sub-time series (approximation and details) is effective and reliable in one step-ahead forecasting of hydrological time series such as rainfall, evaporation, temperature, reservoir inflow, etc. Adopting a suitable mother wavelet function in hybrid models improves the forecasting performance. In this study, Daubechies mother wavelet functions $db2$-$db10$ are applied for decomposition of input time series and resulted the most efficient modeling. The best levels of wavelet decomposition and optimal number of membership functions (MFs) in ANFIS need to be determined by trial and error. Using the optimal number of decomposition level and membership function (MF) will improve forecasting accuracy. The results show that the decomposition levels of 1 to 3 and triangular MFs of 2 to 3 lead to best fit models in terms of statistical evaluation criteria for the hydrological time series used in this study. In addition, the results confirm the strength of the proposed structure of hybrid WT-ANFIS model, in particular, for monthly evaporation, minimum and maximum temperature and reservoir inflow time series forecasting in the study area. According to the results, high values of R^2 and low values of $RMSE$ during checking period for monthly hydrological time series demonstrates the reliability and accuracy of the developed WT-ANFIS model. Moreover, the results reveal that WT-ANFIS model can give an accurate forecasting for extreme values of time series. This finding is interesting to apply such an accurate model for forecasting of peak values of time series such as reservoir peak inflow. The developed hybrid WT-ANFIS model has shown better generalization capability and ability to improve the hydrological time series forecasting accuracy. Furthermore, the results indicate that WT-ANFIS model is suitable due to cope with the non-linear characteristics of the hydrological process and provides promising evidence for combining original time series and pre-processed time series using, more specifically, the wavelet transform method to forecast hydrological time series using the ANFIS technique.

Finally, the model will be useful for Dokan and Darbandikhan reservoirs managers to obtain more accurate and stable forecasting for the inflows to these reservoirs. The results of this study may provide a motivation for monthly hydrological time series forecasting by using a combination of various available climatic variables as input variables to WT-ANFIS model to forecast a specified hydrological time series. This study may be extended to other types of mother wavelet functions, and it would also be useful to apply the proposed model on other hydrological time series for more meteorological stations in order to investigate the overall performance of the model.

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