Long term rainfall forecasting by integrated artificial neural network-fuzzy logic-wavelet model in Karoon basin

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Physical, mathematical models and statistical distribution are applied to forecasting, whereas in natural resources, it is difficult to choose models that are closed to reality. Rainfall forecasting as an important dynamic process is ever favored by the researchers. Analyzing the behavior of these phenomena by intelligent systems is completely better than classical methods, because of high non-linear dynamic atmospheric phenomena. In this paper, a long term forecasting method is presented by a combination of intelligent methods with the use of the past month rainfall in karoon basin and global meteorological signals such as southern oscillation index (SOI), north athletics oscillation (NAO), sea level pressure (SLP), sea surface temperature (SST) and 41 years historical data. This method is obtained by the combination of artificial neural network, fuzzy logic and wavelet functions. In this model, several scenarios have been examined for the karoon basin of Iran, through the signals. SST and NAO signals show the best results, and then, the long-term forecasts are done for periods of six months, one year and two years. The results of the integrated model showed superior results when compared to the two-year forecasts to predict the six-month and annual periods. As a result of the root mean squared error, predicting the two-year and annual periods is 6.22 and 7.11, respectively. However, the predicted six months shows 13.15.

Key words: Intelligent networks, long-term prediction, meteorological signals, artificial neural network, fuzzy logic, wavelet function.

INTRODUCTION

Forecasting of rainfall is one of the most difficult elements of the hydrologic cycle; however, this is related to the spacious range of variability it displays over a wide range of scales both in space and time. Rainfall forecasting could be used as a tool for policy making decisions and macro-country policies. Long term rainfall forecasting can help politicians decide in the fields of water resources, reduce damage caused by droughts and floods, on time reservation of water in low water period and finally help to manage risk in water resources, drought and flood management. Since forecasting is often done in 48 h in a 3 day scale, by using meteorological models, long-term models are still subjected to global research. The usual models that are used for prediction are as follows:

1. Classic (synoptic) meteorological dynamic model
2. Using satellite images and data,
3. Hydrological models
4. Mathematical models including numerical methods, statistical methods and regression and static series.
5. Experimental models, using empirical formula
6. Physical models and simulations in the laboratory
7. Conceptual methods, modern methods and intelligent

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networks  
(Artificial neural networks - fuzzy logic - wavelet function - genetic algorithm and ...).

In this paper, we use intelligent system to forecast the long term period of rainfall; then the results are compared with the mathematical models as ARIMA. As such, it is a current forecasting model that is used for long term forecasting. ARIMA models include 3 parameters (p, d and q). ARIMA (p, d and q): ARIMA models are, in theory, the most general class of models for forecasting a time series which can be stationarized by transformations such as differencing and logging. The acronym ARIMA stands for "Auto-regressive integrated moving average." Lags of the differenced series appearing in the forecasting equation are called "auto-regressive" terms, while lags of the forecast errors are called "moving average" terms, and a time series which needs to be differenced in order to be made stationary is said to be an "integrated" version of a stationary series.

Random-walk and random-trend, autoregressive and exponential smoothing models (that is, exponential weighted moving averages) are all special cases of ARIMA models. A nonseasonal ARIMA model is classified as an "ARIMA (p, d and q)" model, where: p is the number of autoregressive terms, d is the number of nonseasonal differences and q is the number of lagged forecast errors in the prediction equation (Box et al., 1978).

METHODOLOGY

Artificial neural network (ANN)

Artificial neural network is considered to be a viable approach to forecast the future spatial distribution of rainfall over catchments. An ANN with sufficient complexity is capable of approximating any smooth function to any desired degree of accuracy. In addition, ANNs are computationally robust, having the ability to learn and to generalize from examples to produce meaningful solutions to problems even when the input data contain errors or are incomplete.

ANN is a highly parallel distributed network of connected processing units called neurons. It is motivated by the human cognitive process, that is, the network has a series of external inputs and outputs which take or supply information to the surrounding environment. Inter-neuron connections are called synapses, which have associated synaptic weights. These weights are used to store knowledge which is acquired from the environment (Gomm and Evans, 2007).

Adaptive neuro-fuzzy inference systems (ANFIS)

Neural network

Neural network is learnt during the training process with existing data and used in the future for forecasting. Each neural network structure, known as network architecture, is included in a number of neurons per layer. However, the number of layers and simulation functions will be determined by a trial and error method.

Fuzzy logic

The competition of a fuzzy inference system generally consists of three major steps: (1) fuzzification, (2) inference (or reasoning) and (3) defuzzification. Fuzzification is the process of obtaining the outputs of a fuzzy system and the rule of inference defines an operational form of a fuzzy model. The compositional rule of inference is among the most often used and has many variations such as the max-product rule and max-min rule.

Fuzzy inferences are expressed based on the knowledge that exists about a specific subject. In other words, fuzzy interference means production and determination (if -then) rules that express the relationship between different factors as inputs or cause and other factors as output or effect. However, neural networks and fuzzy logic are two robust tools for designing intelligent controllers.

Neuro fuzzy modeling

Several algorithms of neuro fuzzy modeling are available in the literature, such as fuzzy inference networks (Keller et al., 1992b), fuzzy aggregation networks (Keller et al., 1992a)[8], neural network-driven fuzzy reasoning (Takagi and Hayashi, 1998), fuzzy modeling networks (Horikawa et al., 1992), ANFIS (or adaptive neuro-fuzzy inference system) (Jang, 1993) and fuzzy associative memory systems (Kosko, 1992).

ANFIS, proposed by Jang (1993), is based on the first-order Sugeno fuzzy model, whereas the ANN paradigm is used in a multiplayer feed-forward back-propagation network.

1. ANFIS are a class of adaptive networks that are functionally equivalent to fuzzy inference systems, which represent Sugeno Tsukamoto fuzzy models. However, it uses a hybrid learning algorithm known as ‘Sugeno Model’ (Trabelsi and Lafont, 2004).

It is assumed that the fuzzy inference system has two inputs x and y and one output z. A first-order Sugeno fuzzy model has rules as the following: (Figure 1)

2. Rule 1: If x is A1 and y is B1, then f1 = p1x + q1y + r1
3. Rule 2: If x is A2 and y is B2, then f2 = p2x + q2y + r2

Layer 1 – I

1. Oi is the output of the ln node of layer I.
2. Every node i in this layer is an adaptive node with a node function
\[
O_{i,j} = \mu A_i(x) \text{ for } i = 1,2, \ldots, \text{or}
\[
O_{i,j} = \mu B_{i-2}(x) \text{ for } i = 3,4
\]
3. x (or y) is the input node i and Ai (or Bi) is a linguistic label associated with this node. Therefore, Oi is the membership grade of a fuzzy set (A1; A2; B1; B2).

Layer 1 – II

1. Typical membership function: \( M_{A_i}(x) = \exp \left( -\left( \frac{x - c_i}{a_i} \right)^2 \right) \)
2. ai, bi, ci are the parameter set.
3. Parameters are referred to as premise parameters.

Layer 2

1. Every node in this layer is a fixed node labeled ‘prod’.
2. The output is the product of all the incoming signals:
$W_i = M_A^i(x) \times M_B^i(y), i = 1, 2$

3. Each node represents the fire strength of the rule.
4. Any other T-norm operator that performs the AND operator can be used.

Layer 3
1. Every node in this layer is a fixed node.
2. The $i^{th}$ node calculates the ratio of the $i^{th}$ rule's firing strength to the sum of all rule's firing strengths. $W_i = \frac{W_i}{W_i + W_2}$ Or

$W_i = \frac{W_i}{\sum_{i=1}^{r} W_i}$
3. Outputs are called normalized firing strengths.

Layer 4
1. Every node $i$ in this layer is an adaptive node with a node function:
   $W_i f_i = W_i (p_i x + q_i y + r_i)$
   i) $w_i$ is the normalized firing strength from layer 3.
   ii) $f_i, p_i, q_i, r_i$ is the parameter set of this node.
   iii) These are referred to as consequent parameters.

Layer 5
1. The single node in this layer is a fixed node labeled sum, which computes the overall output as the summation of all incoming signals: $f = \sum W_i f_i = \frac{\sum W_i f_i}{\sum W_i}$

The structure of ANFIS model is shown in Figure 2.
Wavelet transform

In the last two decades, wavelet transforms have been extensively tested in many fields such as signal processing, image processing, communications, computer science and mathematics (Rao and Bopardika, 1998). Grossman et al., (1984) studied wavelet transforms, motivated by the fact that certain seismic signals can be modeled suitably by combining translations and dilations of a simple oscillatory function called a wavelet (Chui, 1992).

Continuous wavelet transform

Continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by the scaled and shifted versions of the wavelet function (Wang and Ding, 2003). The result of the CWT is the continuous set of wavelet coefficients. When the wavelet coefficients are multiplied with the scaled and shifted wavelet, the constituent wavelets of the original signal are produced. The expression for a CWT signal can be shown in the following:

\[ \psi(t, a, b) = \int f(\tau) \phi_{a,b}(\tau) d\tau \]

The function \( \psi(t, a, b) \) is called the mother wavelet; moreover, it serves as a prototype for generating other window functions. The term scaling parameter refers to the location of the window. As the window shifts through the signal, the time information in the transform domain is obtained. The term scaling, s, refers to the dilation or compression of the wavelet (Veitch, 2005).

Discrete wavelet transform

The discrete wavelet transform (DWT) involves choosing scales and positions, based on powers of the two so-called dyadic scales and translation. The mother wavelet is rescaled or dilated, by powers of the two, and translated by integers. The DWT algorithm is capable of producing coefficients of fine scales for capturing high frequency information, and coefficients of coarse scales for capturing low frequency information. The DWT with respect to a mother wavelet is defined as:

\[ f(t) = \sum_{k} c_{j0,k} \phi_{j0,k}(t) + \sum_{j \geq 1} \sum_{k} w_{j,k} 2^{j/2} \psi(2^j t - k) \]

Where j is the dilation or level index, k is the translation or scaling index, \( c_{j0,k} \) is a scaling function of coarse scale coefficients, \( \phi_{j0,k} \) is a scaling function of coarse scale coefficients, and all functions of \( \psi(2^j t - k) \) are orthonormal (Sureshbabu and Farrell, 1999).

However, the DWT has many advantages in compressing a wide range of signals. With the DWT technique, a very large proportion of the coefficients of the transform can be set to zero without appreciable loss of information. Besides that, if more properties other than the stationary properties of a signal are desired, DWT would certainly be a better choice when compared to the traditional technique of Fourier transform (Daubechies, 1992).

A brief introduction of the wavelet transform (wt) is given to avoid mathematical complexity. The continuous WT of a signal \( f(x) \) depends on two variables: scale (or frequency) parameter \( a \), and time (or position) parameter \( b \). It is given as:

\[ \psi_{a,b}(x) = \int_{R} f(x) \psi_{a,b}(x) dx\]

Where the real function

\[ \psi_{a,b}(x) = |a|^{-1/2} \psi \left( \frac{x-b}{a} \right) \]

The parameters \( a \) and \( b \) vary continuously over \( R \), the real set (with the constraint \( a \neq 0 \)). The function \( w \) is called the mother wavelet which satisfies

\[ \int_{R} \psi_{a,b}(x) dx = 0 \]

The parameter \( b \) gives the position of the wavelet, while the parameter \( a \) controls its frequency. For \( |a| << 1 \), the wavelet \( \psi \) is a very highly contracted version, with the frequency content in the high frequency range. Conversely, for \( |a| >> 1 \), the wavelet \( \psi \) is very much spread out, that is, functions in low frequencies (Mallat, 1989; Yeung and Li, 2005).

THE STUDY AREA AND DATA USED

The study area selected for this research is the Karoon basin located in the west-south part of Iran. It is located between latitude 30°'00" and 54°'05" north and between 48°'00" and 52°'30" east (Figure 3).

In fact, the selection of this area is because of its importance and scope and also, its appropriate exciting historical data. Karoon River is one of the largest and longest rivers in Iran and also in the Persian Gulf and Oman Sea basin. It collects a huge volume of wide zone water and spill to the Persian Gulf.

Effective meteorological phenomena in Iran

In recent years, extensive studies have been performed on international and regional level by researchers from different countries about the long and short-term changes in rainfall and their influences on different climate and meteorological parameters. With new methods in the field of signal processing and the use of them in hydrological forecasts, the accuracy of these predictions has been promoted (Trenberth and Caron, 2000). In this paper, four main affective climate signals have been applied. Meteorological parameters on a global scale are southern oscillation index (SOI), north atlantic oscillation index (NAO), sea level pressure (SLP) and sea surface temperature (SST).

A study on NAO (north atlantic oscillation) in the Middle East represents a significant correlation with seasonal variation of temperature at different stations. Precipitation in autumn at different stations in Iran has shown a significant correlation with SOI changes. Studies on the correlation between changes in sea surface temperature and rainfall in the Persian Gulf at different stations are shown to have significant changes in the Persian Gulf sea surface temperatures in such years that winter precipitation in some southern regions of Iran has been less than normal (Trenberth and Caron, 2000). Nazemosadat (1998) has shown that changes in sea surface temperature in the Persian Gulf, has significant effect on changes in mean precipitation of west and southwest areas of Iran. His studies show that winter precipitation...
(January to March) in the mentioned areas has an inverse relationship with SST Persian Gulf. However, when SST Persian Gulf has more than its expected normal value, the aforementioned areas are met with drought (Nazemosadat and Cordery, 2000).

APPLICATION OF THE METHOD

The architecture of the model is shown in Figure 4, and the applied method is defined.

There are two methods learnt by the ANFIS for updating membership function parameters: Back propagation for all parameters (a steepest descent method), which is a hybrid method consisting of back propagation for the parameters associated with the input membership functions, and least squares estimation for the parameters associated with the output membership functions. As a result, the training error decreases, at least locally, throughout the learning process.

Calibration analysis

In this model, the type of function is Sugeno fuzzy and so, the training method is back propagation. Training option for the command line, ANFIS, is a vector that specifies the stopping criteria and the step-size adaptation number of training epochs, in which 10-error tolerance = 0 initial step-size and 0.01-step-size, decrease rate = 0.9-step-size and increase rate = 1.1 as defaults. The training process stops if the designated epoch number is reached or the error goal is achieved, whichever comes first. Usually, the step-size profile is a curve that increases initially, reaches some maximum and then decreases for the remainder of the training. The ideal step-size profile is achieved by adjusting the initial step-size.

For other inputs, different scenarios are used. Errors are based on the least square error method (RMSE) and output is based on the minimum training error, that is, the difference between the observed data and the output fuzzy inference system related to those training data. Finally, results are determined based on the lowest error values, while the minimum error estimated to the 10 training epochs and SST, NAO index, monthly rainfall data and 2 Gaussian membership functions as:

\[
\text{GAUSSMF}(X, [\text{SIGMA, C}]) = \exp(-(X - \text{C})^2 / (2*\text{SIGMA}^2))
\]

For each case, data sets during 1963 - 2005 were used to calibrate the model; whereas, in this phase, forecast of two years data were compared with the actual applied amounts.
Sensitivity analysis

Sensitivity analysis should be considered an essential step to all mathematical based model application. The purpose of conducting a sensitivity analysis is two-fold, that is, first to evaluate the model’s response to changes in input parameters, and secondly, to quantify the likely uncertainty of the calibrated model resulting from uncertainties associated with the input parameters. The main advantage of performing sensitivity analysis is to identify the sensitive parameters or processes associated with the model output.

In this research, the prepared program is written in MATLAB software, and then, it is run with different scenarios. Consequently, the best performance of this model is chosen.

First (NOA, SST, SOI, SLP), it converts their historical times from the Christian era to solar calendar; then, the 41 historical average rainfall of Karoon basin is used as monthly input to the model.

However, southern oscillation index (SOI) has little difference with sea surface temperature (SST), but SST graph shows a better case. In continuity, the model is run with other scenarios for sensitive test, to choose the best input parameters. The results are shown in Figure 5.

As shown in the aforementioned diagram, between the two inputs (SST and SLP) scenario, there is not much difference; but the SST graph has a better fitness.

In Figure 6 composition of actual and forecasted data are shown without the use of 2 recent water years. Then, the obtained data from the neo fuzzy model were added with the values of noise.
isolated from the wavelet, and so they were converted to the real data.

**Verification test**

Evaluation of network performance was achieved via computation of three goodness of fit criteria, coefficient of determination and ‘root mean square error’ (RMSE). The RMSE was used to measure the forecast accuracy, which produces a positive value by squaring the errors.

Sum square errors (SSE) and the relative mean square error (RMSE) are shown as (Whitmore, 1997):

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}
\]

\[
R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}
\]

\[
SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2
\]

**Validation model test**

The validation test of model, forecast annual for the year 2009 that is done monthly and a forecasted data placing as input for next month. For forecasting next year meteorological signals, ARIMA (3, 1 and 5) time series model was used. The parameters of model are determined by a trial and error test to obtain optimal result. These signals de-noised wavelet again and forecasted rainfall in 2009. The 2006 - 2008 validation data sets were used to test the performance of the model.

**FORECASTING RESULTS**

The RMSE increases from zero for perfect forecasts through large positive values as the discrepancies between forecasts and observations become increasingly large (Wilks 1995).

Table 1 shows the comparison of forecast errors by wavelet and ANFIS model with SST of Persian Gulf in 41 years rainfall historical time series. The wavelet neuro fuzzy model was evaluated for 3 forecast lead times (6, 12 and 24 months).

Figure 7 shows six months, an annual and two-year forecasting in 41 years historical rainfall in Karoon basin (northern oscillation index and sea surface temperature index input).

Sum square errors (SSE) and the relative mean square error (RMSE) are calculated for the integrated model forecasts with the Persian Gulf sea surface temperature (SST Persian Gulf).

Another point is that a comparison between the annual and two-year forecast results depicts that the two years forecast shows better results than the others.

As it is shown, the six-month SSE forecasts combination is 6222.63, while the root mean square error in the six months forecasted model is 13.15. Also, for annual forecast, SSE is 7284.25 for Persian Gulf SST, while RMSE is 7.11. Table 1 clearly demonstrates the fact that almost all error measures of the two years forecasting are less than the annual and six month forecasts. As shown in Figure 5, the best scenario for long-term rainfall forecast is the results of using a combination wavelet and ANFIS model with SST and north atlanic oscillation index input in karoon basin.

**DISCUSSION**

The focus of this paper was to use the integrated wavelet and neuro-fuzzy long term rainfall forecasting model. The study reported in this paper has led to the following conclusions:

1. By comparing the errors mentioned in the wavelet...
Table 1. Comparison of the 6-12-24 months forecasted data with the Persian Gulf SST input.

<table>
<thead>
<tr>
<th>Period</th>
<th>Six months</th>
<th>Annual</th>
<th>Two years</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSE</td>
<td>6222.63</td>
<td>7284.25</td>
<td>22286.25</td>
</tr>
<tr>
<td>RMSE</td>
<td>13.15</td>
<td>7.11</td>
<td>6.22</td>
</tr>
<tr>
<td>R</td>
<td>0.24</td>
<td>0.5</td>
<td>0.41</td>
</tr>
</tbody>
</table>

Figure 7. Comparison of the actual and forecasted 6-12-24 months’ data with the Persian Gulf sea surface temperature (SST) input.

Neuro Fuzzy model with the Persian Gulf sea surface temperatures input. As it is expected, in the long term forecast in karoon basin, the Persian Gulf global signals have better results.

2. Since many factors affecting rainfall are effective among all temperature conditions, such as cloud cover, wind speed and past rainfall years (months), only the last datum is available. So, to determine the inputs of wavelet Neuro Fuzzy model, rainfall data are used. Therefore, with elimination of other effective factors, it should not be expected that the estimated errors would be very low. However, values of error between actual and forecasted data are found in an acceptable level.

3. The time of forecasting in the combined model is sufficiently long and can be forecasted for more months in the future; however, forecasting algorithm remains convergent. For example, long term rainfall is obtained from the existed data that are forecasted monthly for a short period of time and this process is repeated for months until the forecasted data are divergent. If the estimated data are acceptable, then the total data are used and forecasted in future years. This subject is advantageous to the integrated wavelet neuro fuzzy model, which has higher accuracy than other methods used to estimate time series.

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