Temporal Evaluation of Adaptive Neuro-Fuzzy Inference System for Rainfall Time Series Modeling

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Abstract—**Accurate prediction of future rainfall based on current conditions and historical events is important for both weather forecasting and water resource management domains. Adaptive Neuro-Fuzzy Inference System (ANFIS) is state-of-the-art soft computing technique extensively applied by many meteorologists and civil engineers to forecast rainfall and runoff. ANFIS has been frequently reported the superior performance over conventional statistical and mathematical modeling methods. The adaptive and learning abilities through artificial neural network architecture in addition to the uncertainty handling capability with the fuzzy inference system are the key ingredients of the ANFIS's success. In this work, we present the temporal evaluation of ANFIS on modeling rainfall time series. The main purpose of this empirical study is to observe the performance of ANFIS on predicting future rainfall based on historical data with varying time frames. For the temporal evaluation, we perform monthly rainfall data lagging from 1, 3, 6, 12 up to 18 months. Predictive performance of ANFIS with different time-frame data has been evaluated and compared against other efficient modeling techniques including linear regression, chi-squared automatic interaction detection, support vector regression, and artificial neural network. The experimental results reveal that ANFIS is the best model to predict short and medium-term rainfall in temporal dimension of 1 to 3 month lagging periods. Nonetheless, the conventional linear regression technique shows the best performance on predicting long-term rainfall with lagging periods from 6 to 18 months.**

I. Introduction

Rainfall is the major and important source of water supply in Thailand as well as other countries in the tropical region that lacks of snow and high mountains to be alternative water resource. Efficient management of water is not only necessary for agricultural production and serving human's need in daily life, but also essential for the living of livestock and wild animals. Knowing in advance the precise amount of rain is obviously beneficial to water resource planning.

However, to predict correctly the occurrence and amount of rainfall is difficult due to the nondeterministic nature of this phenomenon. As a consequence, rainfall prediction is still a challenging task for meteorologists. Techniques applied for rainfall prediction are mainly in three categories: statistical and numerical computation, satellite-based modeling, and machine learning approaches. Statistical and numerical techniques applied for predicting rainfall include linear regression [1], [2], multiple linear discriminant analysis [3], autoregressive [4], [5], and a variety of computational methods [6], [7]. For satellite-based weather forecasting, modeling methods adopt remote sensing data [8], geographic information system -- GIS [9], and global navigation satellite system -- GNSS [10]. Even though numerical computation and modeling based on information from ground stations and satellites are among operational practices used by most weather forecasting agencies, weather prediction with machine learning and artificial intelligence heuristics have gained more and more interest from researchers and scientists as the new technology can complement existing techniques with the superior ability to deal with uncertainty and non-linear events [11].

Machine learning techniques applied to forecast weather and precipitation include decision tree learning [12], Bayesian probabilistic prediction [13], support vector classification and regression [14], [15], and many variations of neural networks [16], [17], [18]. State-of-the-art deep learning based on the neural network architecture such as autoencoder [19] and convolutional neural network [20], [21] are also recently applied to forecast rainfall. To deal with dynamic and uncertain characteristics of rainfall, some researcher [22] proposes a combination of fuzzy logic and neural network.

In this research, we also apply fuzzy logic theory to handle the inherent uncertainty of the rainfall forecasting problem. The power of fuzzy logic is achieved through the adoption of an adaptive neuro-fuzzy inference system (ANFIS), which is well-known for solving many vague problems. The focus of our study is to investigate characteristics of ANFIS when dealing with long and short-tem forecasts. Performance of ANFIS is observed and compared against linear regression, decision tree learning, support vector regression, and artificial neural network. A brief introduction to ANFIS concept and its successful applications in various domains are presented in Section 2. A framework of our research is illustrated in Section 3. Experimentation and results are demonstrated in Section 4. The paper is concluded in Section 5.

II. ANFIS Preliminaries

Adaptive neuro-fuzzy inference system, or ANFIS, has been introduced by Jang since 1993 [23]. ANFIS is a hybrid system to incorporate ability to handle vagueness provided by the fuzzy inference system and the adaptability taken from the

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neural network architecture. Structure of ANFIS is generally composed of five layers, as shown in Fig. 1. For simplicity, the input presented in Fig. 1 is assumed to be two variables, x and y, and each variable is fuzzified by two membership functions (example is adapted from [24], [25]).

The first layer of ANFIS is called a fuzzy layer in which each unit in the layer computes membership grade of an input variable. The second layer is called a production layer because each node multiplies the incoming membership grades to evaluate the degree of truth. This degree of truth can also be considered as the strength to fire a fuzzy rule. The third layer is the so called normalized layer as each degree of truth is normalized with respect to the total value. The fourth layer is defuzzy layer in which each node in the layer calculates the output rules. Based on the example shown in Fig. 1, the output of the fourth layer is composed of two rules:

Rule 1: If ($\mu(x)$ is μ_A) and ($\mu(y)$ is μ_C) then $f_1 = p_1x+q_1y+r_1$

Rule 2: If ($\mu(x)$ is μ_B) and ($\mu(y)$ is μ_D) then $f_2 = p_2x+q_2y+r_2$

When μ_A and μ_B are membership functions for input x, μ_C and μ_D are membership functions for input y, and μ is fuzzification operation. The set of parameters $\{p, q, r\}$ is called the consequent parameters. The normalized weight of each rule (w_{1N} and w_{2N}) is then applied to calculate the contribution of each rule toward the final output, which is a combination of the two rules. The last layer is to produce the global model output which is the weighted average of each rule obtained from the previous layer. On evaluation phase, the global output, $f_{predict}$, is to be compared against the actual value of a training data record, f_{actual}. If the prediction error is higher than predefined threshold, the ANFIS network can propagate back to adjust parameters in the previous layers.

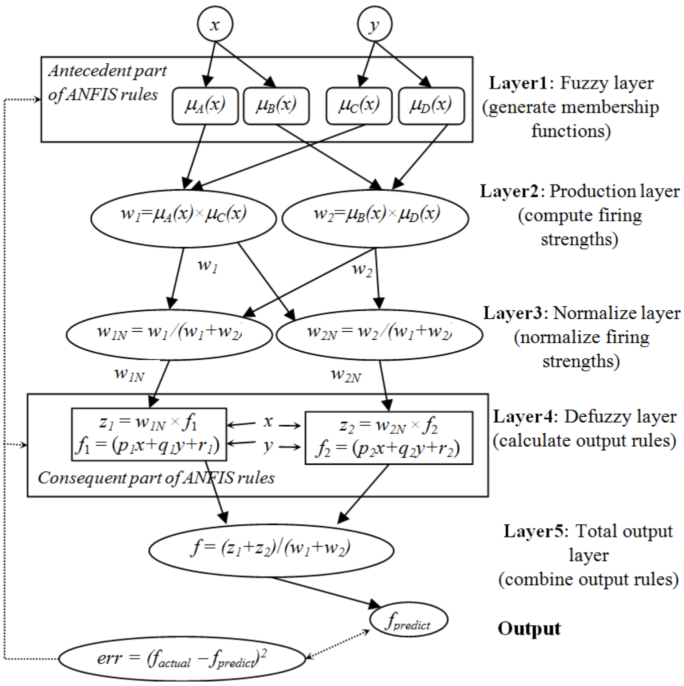

Fig. 1. Schematic concept of ANFIS composing of five layers in which layers 2, 3, and 5 are to perform fixed operations, while layers 1 and 4 are adjustable to generate the most accurate set of antecedent-consequent rules

It can be seen from the structure in Fig. 1 that ANFIS generates a rule-based prediction model. The antecedent part of the rules is in layer 1 which is a fuzzy layer, and the consequent part is in the fourth layer which is the defuzzy layer. ANFIS performs a machine learning task by propagating backward to adjust parameters in layers 1 and 4 to minimize squared error between the model output and the actual output of the training data.

Since its introduction, ANFIS has been applied extensively to solve different kinds of problems ranging from stock market prediction [26], [27], [28], financial and business analyses [29], [30], [31], mechanical engineering, geo-science, and medical engineering [32-39], environmental science [40-45], climate and hydrology analyses [46-49].

For a specific application domain of rainfall prediction, ANFIS has been applied in numerous research works covering many local areas [50-60]. These works apply ANFIS for both short and long-term periods with positive results regarding accuracy of the forecasting. These reported results, however, incur doubt whether the ANFIS performs the best in any granularity of time frame. We thus focus in this work the empirical study towards ANFIS performance that has been trained and tested on datasets with different time-frames. The observed performance is compared against statistical-based technique and other machine learning algorithms.

III. Research Framework

There are six main steps in our comparative study, as shown in Fig. 2.

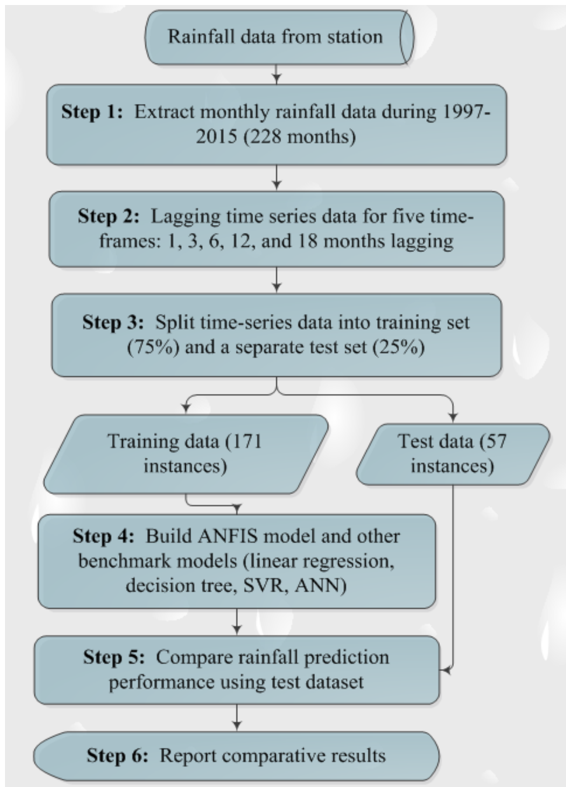

Fig. 2. Steps in performing a comparative study of long and short-term rainfall forecasting

The first step is data extraction from database of the ground station. Extracted data contains 228 data instances. The monthly rainfall data are then set to be of different five time-frames: 1-month, 3-month, 6-month, 12-month, and 18-month lagging periods. The 1-month lagging means that rainfall prediction in current time is based on the historical rainfall data in the previous month; the other lagging time-frames can be interpreted in the same manner.

Once completing data preparation, all lagged data are split into two separate data sets. The majority data set comprising of 171 data instances is used for training learning algorithms to build a rainfall forecast model. The remaining of 57 data instances are for evaluating model performance based on the two metrics: prediction error (root mean square error -- RMSE) and correlation coefficient (R). The best model is expected to have the lowest RMSE, but highest R value to confirm strong association between target variable and predicting variable.

To build rainfall prediction model with ANFIS, we set one Gaussian membership function at the antecedent part (or the fuzzy layer) and one linear function at the consequent part (or the defuzzy layer). To speed up ANFIS execution, we apply subtractive clustering with influence radius equals 0.55 and choose a hybrid method as optimization scheme. Maximum number of epoch to train ANFIS is 100 with initial step parameter being set to be 0.01, step size decrease rate is 0.9, and 1.1 step size decrease rate.

As a benchmark for performance comparison, we adopt linear regression as a representative of statistical technique. Algorithms based on machine learning methods are chi-squared automatic interaction detection (CHAID) from a decision tree learning group, support vector regression (SVR) and artificial neural network (ANN) from a non-linear learning group. For SVR, we set three different kinds of kernel functions: linear, polynomial, and radial basis function. For ANN, we use one hidden layer but vary number of nodes in the hidden layer as 3, 6, and 9 nodes.

IV. Experimentation and Results

A. Data and area of study

The rainfall data used in this work are obtained from the P1 gauging station located along the Ping river flowing through Chiang Mai province in the north of Thailand (as shown in Fig. 3). The geographic location of P1 station is at the latitude 18^{o} 47' 09" and longitude 99^{o} 00' 29" [61]. Sufficient rain amount in the north is important for agricultural sector in both the northern and central areas as the Ping river flows from the north through the central to accompany other rivers to become the Chao Phraya river which is the main reservoir for clean water feeding the Bangkok metropolitan and surrounding living and industrial areas.

We use monthly rainfall data during the past 19 years (1997-2015) as our case study. During the studied period, minimum rainfall amount is 0 millimeter (mm.), maximum is 388.30 mm., standard deviation is 94.03, and skewness is 1.05. Rainfall distribution is shown as a histogram in Fig. 4.

Fig. 3. Rainfall and stream-flow gauge station P1 located along the Ping River in Chiang Mai province of northern Thailand (image source [62])

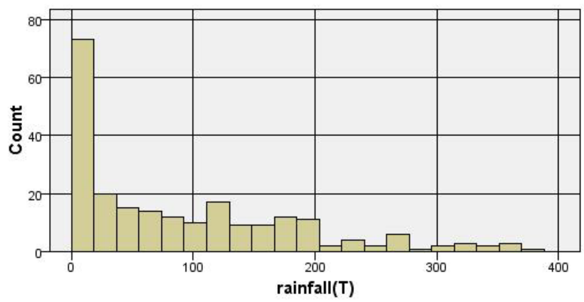

Fig. 4. Histogram of rainfall distribution in Chiang Mai province measured at P1 station during the years 19978-2015 with horizontal axis representing intervals of rain amount in millimeter unit

B. Forecasting results

As our main focus is to observe performance of ANFIS on short-term versus long-term prediction, we thus divide the experimental results into two parts; the 1-month and 3-month lagging are defined as short-term prediction, whereas 6-month, 12-month, and 18-month lagging are long-term prediction. The comparative results of ANFIS prediction performance against other learning methods in case of short-term prediction is presented in Table I. The ANFIS performance on long-term rainfall prediction as compared with other methods are shown in Table II.

The main metric that we use for selecting an appropriate forecasting method is the root mean square error (RMSE). Based on such error metric, the best method for a short-term prediction is ANFIS. For a time-frame longer than 3 months, linear regression can predict with less error than ANFIS and the best lagging period is 12 months. The R values are also considered to study association between predictors and target variable. The 18-month lagging period of training data yields the best associated model, while the 12-month lagging is the second best one. These characteristics are shown in Fig.5.

TABLE I. PERFORMANCE OF LEARNING ALGORITHMS ON SHORT-TERM RAINFALL PREDICTION

Lagging data	Algorithm	RMSE	R
1-month	ANFIS	**67.20**	**0.62**
	Linear Regression	70.43	0.57
	CHAID	75.05	0.49
	SVR (linear)	79.72	0.55
	SVR (polynomial)	83.88	0.48
	SVR (radial basis function)	80.34	0.43
	ANN (1 hidden layer, 3 nodes)	71.30	0.56
	ANN (1 hidden layer, 6 nodes)	78.07	0.53
	ANN (1 hidden layer, 9 nodes)	72.49	0.56
3-month	ANFIS	**64.45**	**0.67**
	Linear Regression	70.81	0.57
	CHAID	75.28	0.50
	SVR (linear)	78.26	0.56
	SVR (polynomial)	80.12	0.45
	SVR (radial basis function)	81.53	0.51
	ANN (1 hidden layer, 3 nodes)	70.11	0.54
	ANN (1 hidden layer, 6 nodes)	76.89	0.49
	ANN (1 hidden layer, 9 nodes)	70.58	0.56

TABLE II. PERFORMANCE OF LEARNING ALGORITHMS ON LONG-TERM RAINFALL PREDICTION

Lagging data	Algorithm	RMSE	R
6-month	ANFIS	75.90	0.52
	Linear Regression	**63.78**	**0.61**
	CHAID	70.53	0.51
	SVR (linear)	76.12	0.59
	SVR (polynomial)	79.54	0.55
	SVR (radial basis function)	80.13	0.46
	ANN (1 hidden layer, 3 nodes)	71.28	0.53
	ANN (1 hidden layer, 6 nodes)	77.03	0.48
	ANN (1 hidden layer, 9 nodes)	70.71	0.57
12-month	ANFIS	66.56	0.69
	Linear Regression	**53.54**	**0.76**
	CHAID	64.66	0.66
	SVR (linear)	74.45	0.61
	SVR (polynomial)	77.12	0.58
	SVR (radial basis function)	83.64	0.50
	ANN (1 hidden layer, 3 nodes)	72.01	0.53
	ANN (1 hidden layer, 6 nodes)	78.11	0.44
	ANN (1 hidden layer, 9 nodes)	71.10	0.59
18-month	ANFIS	64.20	0.71
	Linear Regression	**58.37**	**0.78**
	CHAID	79.59	0.52
	SVR (linear)	76.04	0.56
	SVR (polynomial)	79.29	0.52
	SVR (radial basis function)	82.29	0.51
	ANN (1 hidden layer, 3 nodes)	73.36	0.53
	ANN (1 hidden layer, 6 nodes)	77.74	0.52
	ANN (1 hidden layer, 9 nodes)	70.89	0.60

It can be noticed from the trend in RMSE metric that linear regression needs more data to yield an accurate prediction. But ANFIS shows quite stable characteristics when dealing with different data time-frames, except at the 6-month lagging period that ANFIS generate forecasting results with high error. Nonetheless with less historical data, ANFIS is a reasonable method to apply for making a short-term prediction. The performance of ANFIS at 3-month lagging period is shown in Fig. 6.

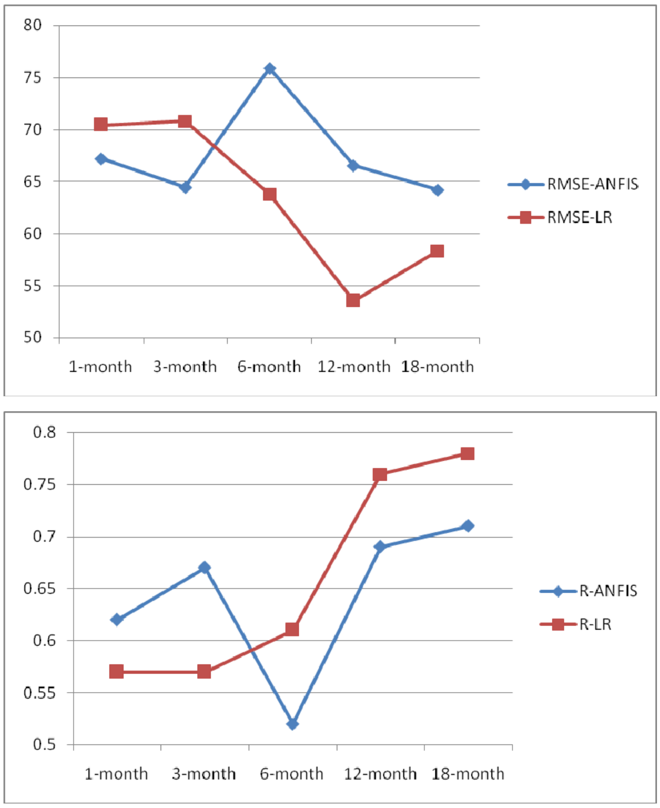

Fig. 5. RMSE (top) and R-value (bottom) comparisons of ANFIS and linear regression characteristics with data lagging for rainfall prediction is increasing from 1 month up to 18 months

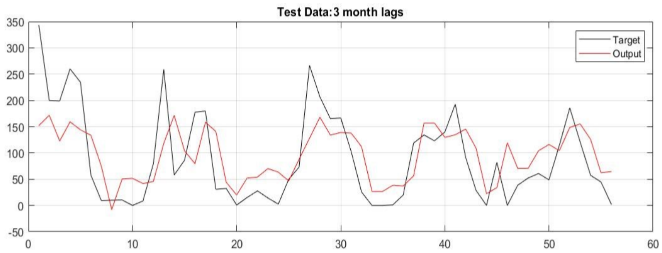

Fig. 6. Characteristics of ANFIS for a short-term prediction

V. CONCLUSION

We are interested in investigating prediction characteristics of ANFIS when applied to rainfall forecasting. ANFIS is an adaptive system having learning ability resembling the neural network and being able to deal with uncertainty from the advantage of fuzzy inference mechanism. The focus of this work is to empirically study performance of ANFIS with it has to make a short-term versus long-term rainfall forecasting. For the short-term forecasting observation, historical data are set to lag for 1 and 3 months and the ANFIS models are built from these 1-month and 3-month lagging data. With long-period forecasting, data are set to lag for 6-month, 12-month, and 18-month. The forecasting results are compared against the other methods including linear regression, chi-squared automatic interaction detection, support vector regression, and artificial neural network.

The observed results are that ANFIS is the best model for a short-term prediction on a 3-month lagging data set. For a long-term forecasting, linear regression performs better than ANFIS. This study use only historical rainfall data to train the models. We thus plan to investigate ANFIS characteristics on multiple data features as our future work.

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