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An Integrated Intelligent Technique for Monthly Rainfall Time Series Prediction

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Abstract—**This paper proposes a methodology to create an interpretable fuzzy model for monthly rainfall time series prediction. The proposed methodology incorporates the advantages of artificial neural network, fuzzy logic and genetic algorithm. In the first step, the differences between the time series data are calculated and they are used to define the interval between the membership functions of a Mamdani-type fuzzy inference system. Next, artificial neural network is used to develop the model from input-output data and the established model is then used to extract the fuzzy rules. The parameters of the created fuzzy model are then optimized by using genetic algorithm. The proposed model was applied to eight monthly rainfall time series data in the northeast region of Thailand. The experimental results showed that the proposed model provided satisfactory prediction accuracy when compared to other commonly-used prediction models. Due to the interpretability nature of the model, human analysts can gain insight knowledge of the data to be modeled.**

Keywords—Time Series Prediction; Monthly Rainfall Data; Fuzzy Logic; Artificial Neural Network; Genetic Algorithm; Interpretability; Northeast Region of Thailand

I. INTRODUCTION

In agricultural countries such as Thailand, efficient water management is necessary to provide effective flood and drought prevention, reservoir operation, contract negotiation, and irrigation scheduling [1]. One of the key issues in water management is the accurate forecasting of rainfall. Accurate rainfall forecasting will provide accurate and timely projection of flow forecasting in the river basins. However, due to the complexity nature of the rainfall, this task is not trivial. Hydrological processes such as rainfall depend on many complex factors that are not clearly understood [2]. Therefore, to perform this task, data-driven based models seem to be a promising approach to tackle this problem.

Recently, intelligent techniques such as Artificial Neural Network (ANN) have been successfully adopted in hydrological studies [3]. These techniques have provided considerable accurate results and they could be established without the need of prior knowledge [4]. Consequently, such techniques are attractive for researchers and hydrologists. Examples are Somvanshi et al. [5] who applied ANN to rainfall time series data whereas Jain and Kumar [6] applied ANN to streamflow time series data. Their results demonstrate that ANN had provided better accurate results over the conventional Box-Jenkins (BJ) approach.

Due to the high flexibility of ANN, modular concept can be applied to enhance the prediction accuracy. Wu et al. [4] proposed ANN and modular ANN with data preprocessing techniques to predict rainfall time series. They applied three preprocessing techniques to smoothen time series data. Furthermore, they also successfully applied ANN combined with support vector regression in their subsequent works [2]. However, although ANN is able to provide good quantitative results, the qualitative drawback of ANN still exits. The model interpretability is deprived due to the black-box nature of ANN model.

Interpretability is another important issue in data-driven modeling. Interpretable models can provide insight knowledge of the data to be modeled when prior knowledge is unknown [7]. Fuzzy Logic (FL) [8] is a grey-box model which has been successful applied in many disciplines including hydrological areas [9], [10]. Compared to the black-box nature of ANN, fuzzy modeling formulates the system knowledge with rules in a transparent way for interpretation and analysis. However, establishing an efficient interpretable fuzzy system is not an easy task because interpretability and accuracy issues can be contrasting objectives [11].

Adaptive Neuro Fuzzy Inference System (ANFIS) [12] is another technique that has been successfully applied in hydrological area. ANFIS is a Sugeno-type FIS [13] which has its parameters adjusted to the training data by using backpropagation algorithm. Nayak et al. [14] and Kermani et al. [15] introduced ANFIS model to river flow time series prediction. Wang et al. [16] showed the performance of ANFIS in predicting monthly discharge time series. Although ANFIS is more transparent to human analysts than ANN, its consequent part is still not intuitive as much as Mamdani-type FIS [17]. Furthermore, applications of ANFIS in hydrology usually belong to the class of prototype-based modeling. This technique sometimes causes the model to loss its interpretability during the learning process [7].

As mentioned, this paper proposes a methodology to create an interpretable Mamdani-type FIS model to monthly rainfall time series prediction problem. The proposed methodology combined advantages of ANN, FL and Genetic Algorithm (GA) [18] and applied to eight monthly rainfall

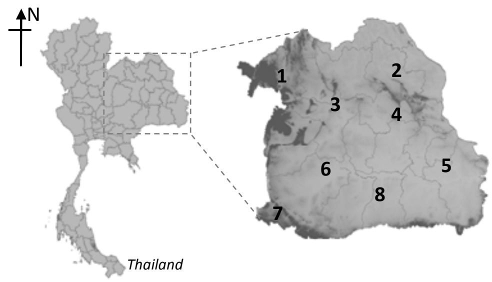


Fig. 1. The case study area is located in the northeast region of Thailand.

time series data in the northeast region of Thailand. This paper is also an improvement from previous work [19].

The paper is organized as follows: Section 2 describes the case study area and datasets. The proposed methodology is presented in Sections 3. Section 4 shows the experimental results and Section 5 presents the discussions. Finally, Section 6 provides the conclusion.

II. Case Study Area and Datasets

The case study area is located in the northeast region of Thailand (Fig. 1). Eight monthly rainfall time series collected from the study area are used to evaluate the proposed models. An example of the time series is depicted in Fig. 2 and the statistics of the eight datasets are shown in Table 1. The data from 1981 to 1998 are used to calibrate the proposed models and the data from 1999 to 2001 are used to validate the models. This study used the models to predict one step-ahead, that is, one month. Accuracy of prediction is evaluated by mean absolute error (MAE) and root mean square error (RMSE) as given in equation (1) and (2).

$$MAE = \sum_{i=1}^{m} |Oi - Pi| / m \quad (1)$$

$$RMSE = \sqrt{\sum_{i=1}^{m} (Oi - Pi)^2 / m} \quad (2)$$

where O_i and P_i are the observed and the predicted values respectively, and m is the number of predicted data. The correlation coefficient (R) is also used for assessment.

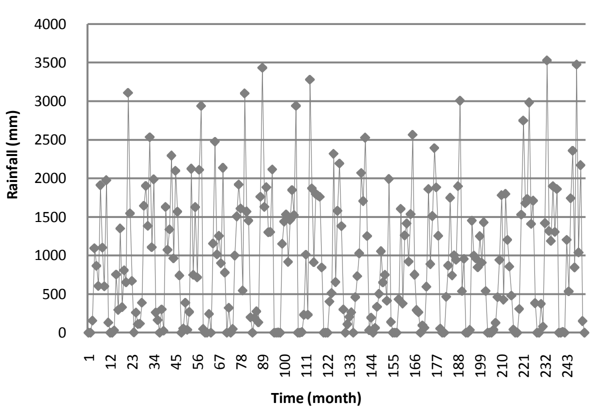


Fig. 2. An example of monthly rainfall time series data (Case 1).

TABLE I. Datasets' statistics

Statistics	Case 1	Case 2	Case 3	Case 4
Mean	929	1303	889	1286
SD	867	1382	922	1425
Kurtosis	-0.045	-0.100	0.808	0.532
Skewness	1.655	0.952	1.080	1.131
Minimum	0	0	0	0
Maximum	3527	5099	4704	6117
Latitude	17.25N	17.15N	16.66N	16.65N
Longitude	101.80E	104.13E	102.88E	104.05E
Altitude	283	176	164	155
Statistics	**Case 5**	**Case 6**	**Case 7**	**Case 8**
Mean	1319	981	1296	1124
SD	1346	976	1289	1153
Kurtosis	-0.224	1.229	1.590	1.725
Skewness	0.825	1.154	1.276	0.961
Minimum	0	0	0	0
Maximum	5519	4770	6558	6778
Latitude	15.50N	15.40N	14.63N	15.40N
Longitude	104.75E	102.35E	101.30E	103.40E
Altitude	129	152	476	152

III. The Proposed Methodology

The overview of the proposed methodology consists of five steps as depicted in Fig. 3. In the first step, appropriate input features are selected. Next, a Mamdani-type FIS and its MFs are generated. After that, fuzzy rules are generated in the third step. Fourth and final steps are the optimization process. While the optimization steps can be grouped into one process, however, in order to control the number of parameters in the optimization and as the objectives of these two steps are different, separating the optimization into two sub-processes is therefore more suitable. The details of each step are as follows:

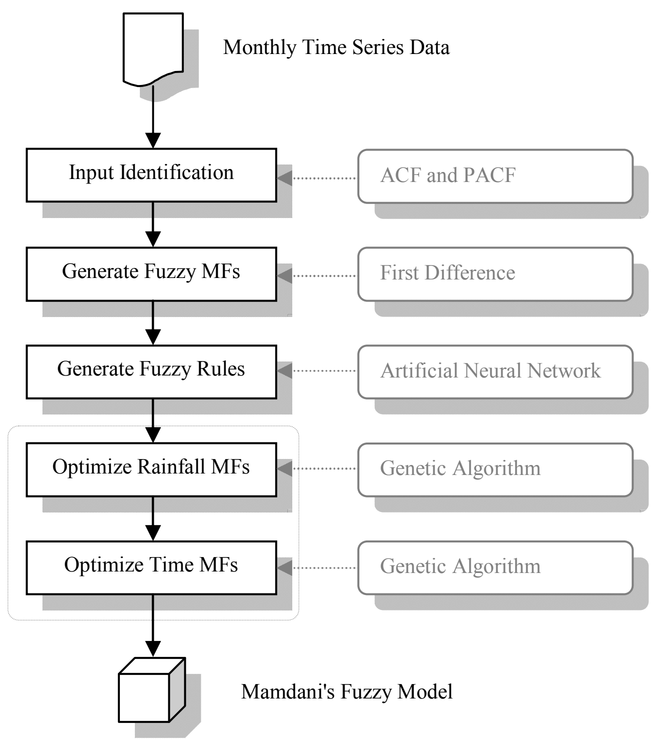


Fig. 3. Overview of the proposed methodology.

A. Input identification

The objective of predicting rainfall using antecedent values is to generalize a relationship in the following form:

$$y = f(x^m) \tag{3}$$

where x^m is a m-dimensional input vector representing rainfall value with different time lags and y is a one-dimensional output representing predicted rainfall value. In general, x^m is not known prior and there is no consistent theory to define x^m for non-linear techniques [16].

In general, two statistical methods, the autocorrelation function (ACF) and the partial autocorrelation function (PACF), are employed to determine the dimension *m* of input vectors [2], [16]. The ACF and PACF are generally used in diagnosing the order of the autoregressive process. Fig. 4 shows an example of ACF and PACF of the dataset. ACF exhibits the peak value at lag 12 and PACF showed a significant correlation at 95% confidence level interval up to lag 12. Therefore, these suggested that twelve antecedent rainfall values contain sufficient information to predict future rainfall.

However, for a FIS model, selecting 12 lags can result in the increase of complexity in fuzzy rules and will cause the *readability* problem, especially, in the antecedent part [7]. Furthermore, due to the issue of curse of dimensionality, the number of fuzzy parameters could increase tremendously. Even using the phase space reconstruction to identify input may not be a good solution to this problem. However, as the monthly time series is periodic in nature, adding time coefficient as a supplementary feature is a promising approach [20], [21], [22].

Time coefficient (C_t) is used to assist the model to scope prediction into specific period. It may be $C_t = 2$ (wet and dry period) or $C_t = 12$ (calendar months). This study adopted $C_t = 12$ as a supplementary feature. Once C_t is added into the system, 12-lag information may be redundant. This study proposed the use of first lag that crosses the confidence interval line as the minimum information for the model. Therefore, two first lags of rainfalls and C_t are considered as the model inputs. This selection conforms to the suggestion in [21] and [22] in that 2-lag antecedence is sufficient information for monthly time series prediction.

B. Generate Fuzzy MFs

In order to create MFs for an interpretable fuzzy system, two aspects must be considered simultaneously. The created MFs should be *distinguish* [7], [23] and should reflect the nature of the time series at the same time. Huarng [24] suggested that the appropriate interval length between two consecutive MFs for time series data should be at least a half of the fluctuations in the time series. The fluctuation in time series data is the absolute value of the first difference of any two consecutive data. This concept is adopted in this study and it is adapted to fit to the nature of the monthly rainfall data.

In this paper, the absolute values of the first difference of time series is calculated and percentile at 25, 50 and 75 of these values are adopted to explain the fluctuation of the rainfall at low, medium and high periods. The low period of the rainfall is defined as zero to percentile 50 of the rainfall values, the medium period is defined as percentile 50 to percentile 75. Above percentile 75 are defined as high period. This procedure is applied to first lag, second lag inputs and output of the fuzzy model. In this study, triangle MF is preferred to Gaussian MF because the asymmetric characteristic of the MF is more flexible.

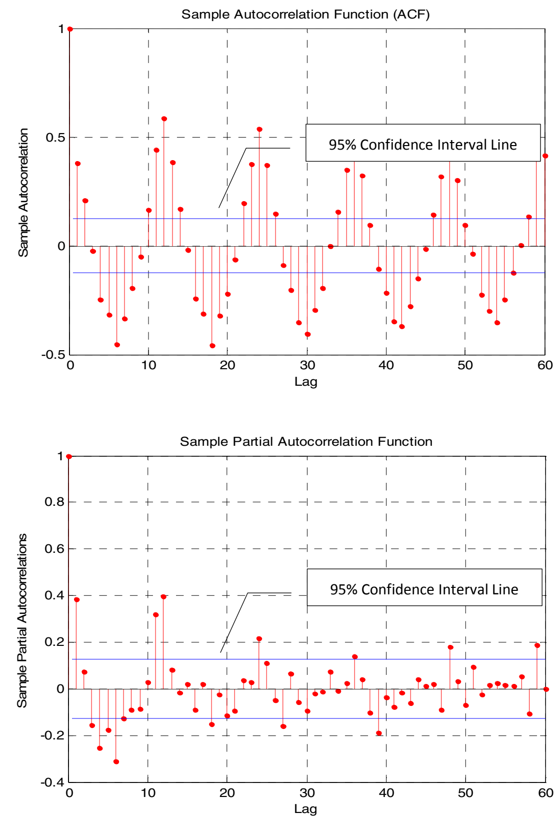


Fig. 4. ACF and PACF of rainfall time series data (Case 1).

An example of the generated MFs is shown in Fig. 5. It is clear that these generated MFs show the *completeness of partition of input variable* [7], [23] and the *normalization* [7], [23] criteria for the interpretable fuzzy system.

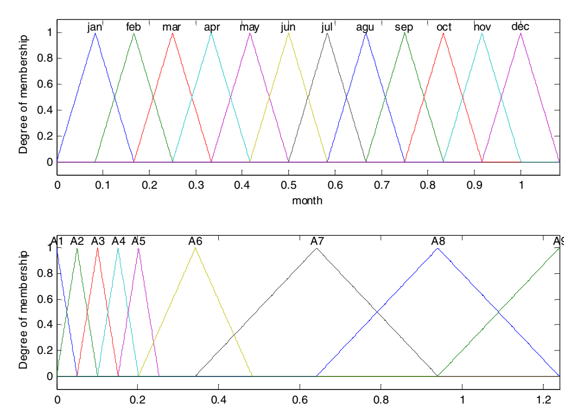


Fig. 5. An example of C_t's MFs and Rainfall's MFs (Case 1).

C. Generate Fuzzy Rules

One drawback of FL is its lack of self-learning ability to generalize the input-output relationships from training data. This study uses the learning ability from ANN to create fuzzy rules. The procedure to create fuzzy rules is as follows:

Step 1. Use one hidden layer back-propagation neural network (BPNN) to learn from the training data. The number of input nodes is 3 and output node is 1. The number of hidden node is selected by trial and error.

Step 2. Prepare the set of input data. The set of input data is all the points in the input space where the degree of membership values is 1 in all dimensions. (This input data are the antecedent part of the fuzzy rules).

Step 3. Feed the input data into the BPNN, the output of BPNN are then mapped to the nearest MF in the output dimension of fuzzy model. (This output data are the consequence part of the fuzzy rules).

Using this procedure, the readability fuzzy rules are generated in the form: "IF *month = M* AND *first lag = A* AND *second lag = B* THEN *rainfall = C*".

D. Optimize Fuzzy MFs

In Fig. 3, the process consists of rainfall's MFs and time's MFs optimization. The first one is to optimize MFs of input 2, input 3 and output, while the second one is to optimize input 1's MFs. Actually, such processes could be done in a single process. However, the objectives of these two processes are different and to control the number of parameters in each optimization process, this study separates the optimization process into two sub-processes.

The objective of the first one is to fit the fuzzy rules and fuzzy MFs of rainfall variable. As these two parameters come from two approaches, they may not fit well. The objective of the second optimization is to capture uncertainty in time dimension. This study hypothesizes that the substantial uncertainty in time dimension will be well extracted when rainfall parameters are already fitted.

In the first part of optimization process, the GA chromosome consists of the sequence of input 2, input 3 and output respectively. In turn, the inputs and output are the sequence of MFs which consists of three parameters of triangle MF (a, b, c). The parameters are allowed to be searched in a small space [25], [26].

Let a, b and c be the initial value of MF's parameters and let x be a parameter to be optimized, the search space of x is $[x - \alpha, x + \alpha]$ and α is defined as

$$\alpha = \sigma * \frac{1}{2}(c - a) \tag{4}$$

where σ is user's parameter ranged in [0,1]. In other word, searching space α is depended on the size of the initial MF.

In the second part of the optimization process, the GA chromosome is the sequence of MFs of input 1. The search space is set in a different way.

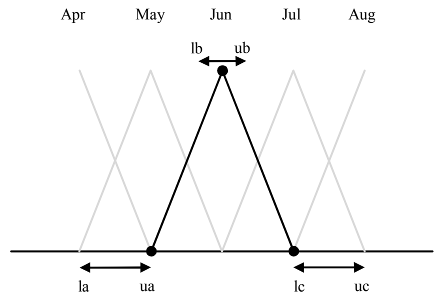


Fig. 6. Search space of MFs in time input dimension.

Fig. 6 demonstrates a conceptual example of how to set the search space of parameter a, b and c. Search space of a and c are set in this manner in order to allow the FIS to capture the uncertainty in time between months and search space of b is set in this manner in order to allow FIS to reduce some firing strength of that month. Furthermore, this setting is to prevent the FIS model from *indistinguishability* [7]. The search space for parameters a and c are equal to the intersection range of the two MFs and half of the intersection for parameter b as demonstrated by the arrows in Fig. 6.

For both processes, the fitness function is the minimize sum square error between observed values (O) and predicted values (P) of the training data and it is given as

$$SSE = \sum_{i=1}^{S}(P_i - O_i)^2 \tag{5}$$

where S is the number of training data.

IV. Experimental Results

In order to assess the prediction accuracy, the proposed model is compared to some hydrological commonly-used models, namely, Autoregressive Moving Average (ARMA) [4], [16], BPNN [2], [4], [5], [6] and ANFIS [14], [15], [16]. Furthermore, the proposed model is also compared to BPNN that used to create fuzzy rules and the model before optimized.

A. Models preparation

In order to select the optimal ARMA models, Akaike Information Criterion (AIC) is adopted [4], [16]. This study generated ARMA models from calibration data by replacing parameters p and q of ARMA model from 0 to 12. The parameters that gave lowest AIC value were used for ARMA model. Table 2 shows the ARMA models for eight datasets.

TABLE II. The selected parameters and AIC values

Case	(p,q)	AIC	Case	(p,q)	AIC
1	(4,4)	13.417	5	(5,3)	13.751
2	(10,9)	13.982	6	(12,1)	13.536
3	(6,3)	13.379	7	(12,0)	14.334
4	(8,11)	14.182	8	(11,2)	13.850

For BPNN and ANFIS, there is no consistent theory to select the number of input. However, the work of [2], [4], [16] recommended the use of ACF and PACF to investigate the appropriate inputs. Considering ACF and PACF in Fig. 4, it pointed out that time series show autoregressive process up to lag 12. Therefore, 12-lag inputs should provide sufficient information for the models.

TABLE III. THE ARCHITECTURE AND EPOCH OF BPNNS AND ANFIS

Case	hn / cls	Case	hn / cls
1	3 / 2	5	2 / 2
2	2 / 2	6	3 / 3
3	3 / 3	7	2 / 2
4	3 / 2	8	3 / 2

The architecture of BPNN and ANFIS are twelve input nodes and one output node. The optimal number of parameters was selected by trial and error. To investigate the optimal number of parameters, calibration data were separated into two parts. The first part was used to train models and the second part was used to test the models.

In the case of BPNN, the experiments varied the number of hidden nodes from 2 to 6. An example of the results is shown in Fig. 7 (top). From the experiment, the number of two or three hidden nodes can provide minimum error. Table 3 summarizes the number of hidden node (*hn*) of BPNN of eight datasets. Furthermore, when the number of training epochs is larger than 15, the error of testing data started to increase. Therefore, the number of epoch was limited to 15.

In the case of ANFIS, the prototype-based model is used. Sugeno-type FIS was generated from fuzzy c-mean clustering technique and was then optimized by ANFIS procedure. An example of the results is shown in Fig 7 (bottom). The experiment pointed out that small number of cluster provided better prediction. The effect of error to number of epochs is more sensitive than BPNN. Only 2 or 3 epochs are enough to generalize data. The number of selected cluster (*cls*) of ANFIS is presented in Table 3.

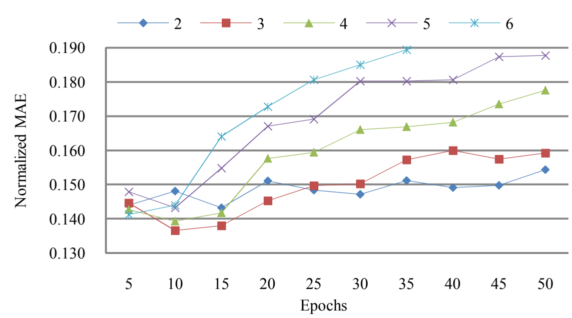
In the case of the proposed model, BPNN used to create fuzzy rules were selected in the same manner. The value of σ in the first optimization was set to 0.25 so as to preserve the shape of MFs after optimized. The number of population was 100 for both optimizations and the number of generation was 30 and 15 for first and second optimization respectively, where the best and average fitness values were met. Reproduction scheme elite count was set to 2 and crossover fraction was set to 0.8.

B. Quantitative results

From now on, $BPNN_{12}$ refers to BPNN with twelve antecedence lags input, $BPNN_3$ refers to BPNN with C_t and two antecedence lags input, MFIS-ORG is the proposed model before optimization, MFIS-OPT_1 and MFIS-OPT_2 are the proposed models after the first and the second optimization respectively. Table 4, 5 and 6 show the experimental results. MAE and RMSE of each case are normalized by its mean of the dataset. The *Average* column in the Tables 4 and 5 show the average values of these normalized errors.

According to these average values, the accuracy of all models are ranked as MFIS-OPT_2 > MFIS-OPT_1 > $BPNN_3$ > MFIS-ORG > ANFIS > ARMA > $BPNN_{12}$. In comparison with the commonly-used models in hydrology, the proposed models can meet the accuracy requirement. These results also point out that:

- $BPNN_{12}$ did not show superior results than ARMA in this study. However, it does not mean that $BPNN_{12}$ is not an efficient method. The dataset in this study are relatively small in comparison with the datasets used in other studies mentioned before. The number of training data may not be enough when BPNN's input is large (12 dimensions). In general, efficient ANN models prefer large training data. The accuracy of $BPNN_{12}$ may be better if more training data are available.
- ANFIS is capable to capture the uncertainty in the data because it provided better results than $BPNN_{12}$ and ARMA. However, the use of ANFIS should be handled with care because such model showed higher sensitivity than $BPNN_{12}$. As can be seen in Fig. 7, ANFIS tended to loss generalization in only few epochs. This is one reason that BPNN was used instead of ANFIS to generate fuzzy rules in the proposed method.
- Using C_t as the supplementary feature for periodic time series data is an efficient way to improve the prediction accuracy. According to the experimental results, $BPNN_3$ provided considerable improvement from $BPNN_{12}$ and ANFIS.
- Conversion from $BPNN_3$ to MFIS-ORG inevitably decreases some prediction accuracy. However, this issue can be address by the optimization process. One can see that the prediction accuracy of MFIS-ORG was improved when fuzzy rules and MFs were fitted well (MFIS-OPT_1).
- The uncertainty in the time dimension has significant effect to the prediction accuracy of the proposed models. Once the MFs in time dimension were optimized (MFIS-OPT_2), the accuracy of the proposed models were improved.



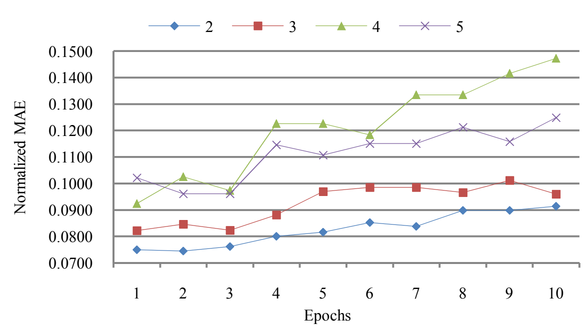


Fig 7. Trial & error process of (top) BPNN and (bottom) ANFIS.

TABLE IV. MEAN ABSOLUTE ERROR (MAE) OF VALIDATION PERIOD

Model	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Average
ARMA	688	626	529	707	823	560	671	471	**0.562**
$BPNN_{12}$	526	631	551	793	806	648	736	592	**0.581**
ANFIS	516	505	515	671	683	585	661	473	**0.511**
$BPNN_3$	476	512	443	631	722	518	639	486	**0.487**
MFIF-ORG	493	508	472	681	679	530	581	547	**0.496**
MFIS-OPT_1	452	503	444	614	662	515	574	491	**0.469**
MFIS-OPT_2	449	497	373	608	613	506	571	461	**0.448**

TABLE V. ROOT MEAN SQUARE ERROR (RMSE) OF VALIDATION PERIOD

Model	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Average
ARMA	888	883	771	1028	1162	836	844	645	**0.782**
$BPNN_{12}$	719	926	866	1243	1153	994	963	852	**0.851**
ANFIS	715	773	752	982	1017	829	864	679	**0.732**
$BPNN_3$	710	827	701	979	1085	752	818	701	**0.724**
MFIS-ORG	725	848	714	1018	1020	781	760	791	**0.735**
MFIS-OPT_1	679	814	690	952	992	750	757	711	**0.700**
MFIS-OPT_2	678	802	597	911	934	741	746	672	**0.670**

TABLE VI. CORRELATION COEFFICIENT (R) OF VALIDATION PERIOD

Model	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Average
ARMA	0.539	0.787	0.543	0.797	0.666	0.587	0.466	0.776	**0.645**
$BPNN_{12}$	0.731	0.761	0.572	0.740	0.656	0.465	0.371	0.664	**0.620**
ANFIS	0.764	0.844	0.583	0.835	0.738	0.613	0.468	0.772	**0.702**
$BPNN_3$	0.749	0.822	0.632	0.846	0.703	0.695	0.570	0.757	**0.722**
MFIS-ORG	0.748	0.824	0.623	0.809	0.741	0.663	0.612	0.691	**0.714**
MFIS-OPT_1	0.794	0.838	0.645	0.837	0.755	0.704	0.630	0.750	**0.744**
MFIS-OPT_2	0.800	0.844	0.732	0.855	0.781	0.718	0.634	0.767	**0.766**

In summary, the details of conversion from $BPNN_3$ to MFIS-OPT_2, the results showed that not all cases provided significant improvement. Case 3, 5 and 7 provided large improvement up to 10 percent. Case 1, 4 and 8 provided moderate improvement about 5 percent. Case 2 and 6 showed small improvement approximate 2 percent. This difference is subject to

- If the uncertainty in time series data is not strong, the prediction accuracy between those two models may not be different because BPNN is capable of handling weak uncertainty.
- In order to preserve the interpretability of the proposed model, search space is limit into a small region. GA may not be able to find better optimal solution in the constraint search space.

C. Qualitative results

Fig. 8 shows an example of fuzzy parameters of MFIS-OPT_2. As the model's parameters are transparently presented in term of fuzzy rules and fuzzy MFs, human analysts can make use of his/her knowledge to enhance the model capability [9]. Furthermore, when the prior knowledge of the data to be modeled is unclear or unknown, these fuzzy parameters can provide information to better understand the data.

In the work of [7], interpretability of fuzzy systems is divided into fuzzy set level and fuzzy rule level. Fuzzy set levels is low-level interpretability and fuzzy rule level is high-level interpretability. It will be used herein.

In the fuzzy set level, one can see that the *distinguishability*, *normality* and *completeness of partition in input space* of MFs were preserved after optimization. Optimized MFs are rather well structured and clear. These are important criteria in the fuzzy interpretability issues because these criteria are generally lost during the optimization process.

The number of fuzzy sets in each input dimension ranges from 9 - 13 depending on the fluctuation in time series. Although these numbers are higher than those proposed by [7] (*an appropriate number of MFs in each input should not exceed 7 ± 2)*, these numbers are necessary because they are good explanation to the fluctuation in the time series data.

In the fuzzy rule level, the proposed model provides good *readability of single rules* with only three conditions in antecedent part while ANFIS has twelve conditions. Since the fuzzy rules are extracted from generalized $BPNN_3$ by using mapping procedure, the *consistence* and *completeness* of fuzzy rules is met. In case of *the transparency of the rules structure,* as the proposed model presents the month feature

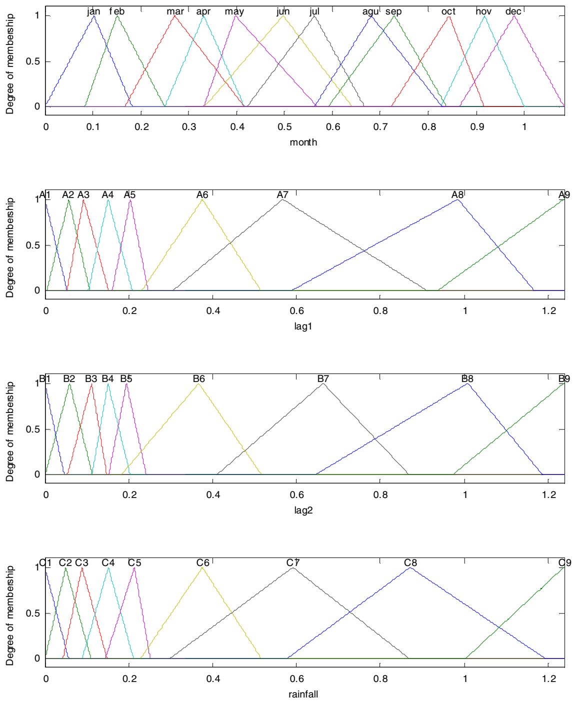


Fig. 8. An example of fuzzy parameters in MFIS-OPT$_2$ (Case 1)

as an input to the system, the fuzzy rule, *IF month=M AND* 1^{st}*lag=A AND* 2^{nd}*lag=B THEN rainfall= C*, can characterize or explain the monthly rainfall time series data in a human understanding manner.

However, although many interpretable fuzzy criteria have been met, *a modulate number of fuzzy rules* is still the problem because the proposed model has a large numbers of fuzzy rules. For example, if the number of MFs in the model is 9, the number of fuzzy rules generated is 972. This problem may need to be addressed.

For the monthly rainfall time series data in this study, a number of redundant rules (i.e., high rainfall in dry period and vice versa) can be removed later by human analysts. This can be done by using expert knowledge or by observing from historical records. Thank to the good readability structure of the fuzzy rules, this removal is not a complicated task.

V. DISCUSSIONS

Up to this point, the experimental results have been presented in term of quantitative and qualitative aspects. The results showed that the proposed model provided satisfactory prediction accuracy and acceptable model interpretability. However, the main objective of the proposed model is to create an efficient method to gain insight into the monthly rainfall time series data.

Fig. 9 presents the uncertainty in time dimension of monthly rainfall time series data via fuzzy parameters. These fuzzy MFs allow human analysts to investigate the uncertainty of the rainfall data between months. Consequently, further analysis in the data could be enhanced.

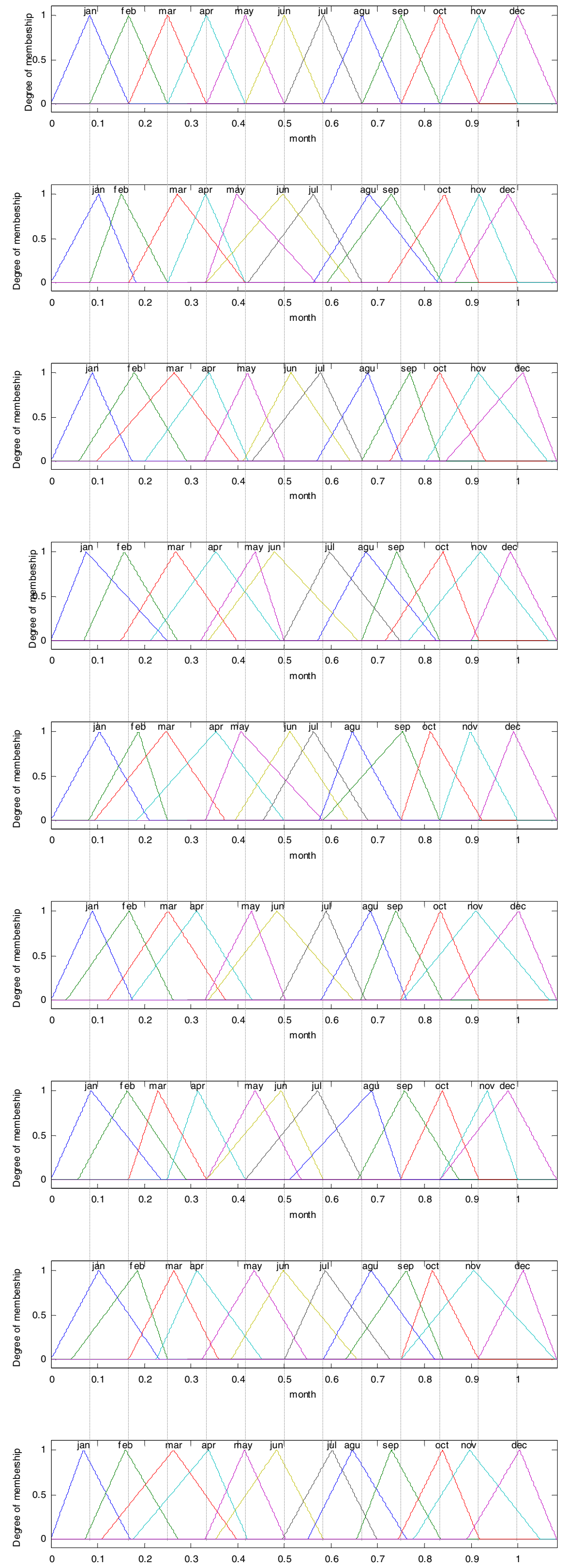


Fig. 9. A presentation of uncertainty in time dimension through fuzzy MFs (Case 1 to Case 8 are presented from top to bottom)

To analyze this uncertainty, the method such as prototype-based fuzzy modeling may not be appropriate for this task. The original shape of month's MFs can be loss when the prototypes are created or during the optimization process. Consequently, the interpretability will be inevitably decreased.

In this methodology, the fuzzy MFs have firstly been created based on the characteristics of time series data. Thus, the requirement is how to create the fuzzy rules for the model. Among several neuro-fuzzy methods [9], cooperative neuro fuzzy technique [19] seems to be the most appropriate.

This cooperative neuro-fuzzy technique uses BPNN to generalize the input-output relationships from training data and the BPNN is then used to extract fuzzy rules. This technique is matched to the requirement of methodology, in which the original shape of MFs can be preserved when the fuzzy rules are created.

VI. Conclusion

Accurate rainfall forecasting is crucial for reservoir operation, flood and drought prevention and contract negotiation because it can provide accurate and timely future projection of the flow forecasting. This study proposed an integration of intelligent techniques, namely, fuzzy logic, artificial neural network and genetic algorithm to create an interpretable fuzzy model for monthly rainfall time series prediction. Eight monthly rainfall time series data in the northeast region of Thailand were used to evaluate the proposed model. The experimental results showed that the proposed model provided satisfactory prediction accuracy when it was compared to conventional methods. Furthermore, the proposed model is transparent to human analysts through fuzzy parameters. The advantage of the proposed model is that it provides the overview of uncertainty in time dimension between months in form of fuzzy MFs. This is an important issue for human analysts to gain insight in the data to be modeled when a prior knowledge is unclear or unknown.

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