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DYNAMIC EVOLVING NEURAL FUZZY INFERENCE SYSTEMS FOR EVENT-BASED RAINFALL-RUNOFF MODELING IN A LARGE TROPICAL CATCHMENT

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ABSTRACT

Population growth in fast developing countries such as Malaysia leads to more demand for infrastructures which in turn may gradually transform agricultural or forest landscapes to built-up areas. This change has significant impact on hydrologic processes which can lead to an increase in both magnitude and frequency of floods in urban areas. To date several physically-based models are developed to capture the rainfall-runoff process; however, they require significant number of parameters which could be difficult to be measured or estimated. Recently, neuro-fuzzy systems (NFS) which are well-known for their ability in simulating nonlinear complex systems have been widely used in hydrological time series modeling and prediction. Online learning and rule evolving mechanisms of Dynamic Evolving Neural-Fuzzy Inference Systems (DENFIS) are the two capabilities that make it suitable to be used as a tool for rainfall-runoff modeling. The results obtained by DENFIS model were compared with an autoregressive model with exogenous inputs (ARX) as a bench mark. Results revealed that DENFIS has a good potential to be used as a rainfall-runoff modeling tool.

Keywords: *DENFIS, rainfall-runoff modeling, neuro-fuzzy systems, ARX*

1.0 INTRODUCTION

Modeling the rainfall-runoff process is the most significant hydrologic task as it provides a good understanding of the watershed behavior. Finding the relationship between rainfall and runoff is required to have a better understanding of river management and achieve the satisfactory drainage system [1]. This relationship is known to be highly non-linear and complex. Rainfall-runoff modelling is performed not only to reduce damages occur from flood but also to manage the reservoir operations especially during the drought periods [2]. In addition, rainfall-runoff process is dependent on numerous factors such as initial soil moisture, watershed geomorphology, distribution, intensity, and duration of rainfall, infiltration, evapotranspiration, temperature, land use and so on. The correct estimation of this hydrological phenomenon can provide effective information for planning and management of a watershed. Since 1930's numerous rainfall-runoff models have been developed to forecast streamflow [3]. Most of the hydrological processes have a high degree of temporal and spatial variability, and also are engaged by the issues of non-linearity of physical process, conflicting between spatial and temporal scales, and uncertainty in parameter estimation. Reliable estimates of stream flow generated from catchments are required as part of the information that helps policy makers to make decisions on water resources planning and management. The characteristics of the streamflow time series that influence water resources system modeling and planning can include the sequencing of flows on different time steps, spatial and temporal variability of flows, seasonal distribution and characteristics of high and low flows [4]. Researchers have so far developed many rainfall-runoff models [5-7]. Some of them are physically-based models in which extreme efforts in mathematical analysis is required [8, 9]. On the other hand, some other models are considered as data-driven models from which black box models are commonly used in rainfall-runoff modeling. Black-box models are able to capture the rainfall-runoff relationship without explicit consideration of internal hydrological processes. Although the physically-based models provide reasonable accuracy, but the implementation and calibration of such models typically requires sophisticated mathematical tools, a significant amount of calibration data and some degree of expertise and experience with the model [10]. In many catchments, all physical parameters may not be available; therefore, in that case, hydrologists are dealing with estimation of parameters which could bring in some uncertainties into the problem.

Recently, Artificial Intelligence (AI) techniques have shown promising ability in simulating hydrological time series. AI techniques offer an effective approach for handling large amounts of dynamic, non-linear and noisy data, especially when the underlying physical relationships are not fully understood. In general, the application of AI technique does not require a prior knowledge of the process [11]. Previous studies have confirmed that these models are able to produce results which are at least comparable in term of model accuracy to those obtained from more sophisticated models [12]. Most recently, Neuro-fuzzy systems (NFS) as one of the sophisticated AI tools have attracted many of hydrologists for rainfall-runoff modeling and runoff forecasting. The main objectives of this study are: (1) to develop DENFIS rainfall-runoff model for selected extreme events in a tropical catchment; (2) to assess the capabilities of DENFIS model in rainfall-runoff modeling and compare its results with the ones obtained by an autoregressive model with exogenous inputs (ARX) model.

1.1 Neuro-fuzzy systems

Fuzzy sets were first developed by [13] which can deliver an inference morphology that allows approximation of human reasoning capabilities applicable to knowledge-based systems. Fuzzy logic theory provides mathematical strength to abduct the uncertainties associated with thinking and reasoning abilities of human cognitive processes. Fuzzy logic development got motivation in large scale for a conceptual framework that can resolve the matter of uncertainty and lexical imprecision [14].The first application of fuzzy logic was made by [15], who designed an experimental fuzzy control for a steam engine. There are two basic fuzzy logic approaches: (1) the expert knowledge based proposed by Mamdani; and (2) the data driven based proposed by [16]. Mamdani approach uses linguistic values in rule consequence while the Takagi-Sugeno approach uses crisp values. On the other hand, the connectionist structure of artificial neural networks can be used as the mathematical tool to find the parameters of the model. The brain-inspired computation methods were started approximately 70 years ago in the work of [17]. The neural computing got attention of researchers again in 1980s: The mathematical foundation was provided by [18] to understand the dynamics of such networks; [19] presented the back-propagation learning algorithm for multi-layer networks. The important factor of neural networks is their adaptivity and their capability in automatically adjusting their weights up to optimize level. Such capability can be utilized for pattern recognition, decision making, system control, prediction, etc. The other advantages of neural networks are learning, fault tolerance and generalization whereas, fuzzy logic performs an inference mechanism under cognitive uncertainty [14]. The combination of these two powerful computational tools; neural networks and fuzzy logic gave birth to neuro-fuzzy systems. Neuro-fuzzy systems have the ability to utilize the advantages of both tools in a single framework. Neuro-fuzzy systems resolved the essential drawback in fuzzy system design (acquiring fuzzy if-then rules) by successfully using the learning capability of neural networks for generating fuzzy if-then rules and parameter optimization. Neuro-fuzzy systems can use expert's linguistic information and the measured data during modeling [20]. Adaptive network-based fuzzy inference system (ANFIS) as one of the NFS was first introduced by [21]. Author presented the architecture and underlying procedure of ANFIS and applied the system in automatic control and signal processing. In hydrological studies, ANFIS was first applied by [22] for modeling hydrological time series. The successful applications of neuro fuzzy systems in various hydrological problems can be found in literature which includes rainfall-runoff simulation [22-30], groundwater modeling [31-33], evaporation estimation[34], Extrapolate missing rainfall data [35], water quality [36, 37] and flood forecasting [38, 39].

1.2 DENFIS model

Dynamic Evolving Neural Fuzzy Inference Systems (DENFIS) evolve through incremental, hybrid (supervised/unsupervised) learning and accommodate new input data, including new features, new classes, etc. through local element tuning. New fuzzy rules are created and updated during the operation of the system. At each time moment the output of DENFIS is calculated through a fuzzy inference system based on m-most activated fuzzy rules which are dynamically chosen from a fuzzy rule set. An approach is proposed for a dynamic creation of a first order Takagi-Sugeno type fuzzy rule set for the DENFIS model. The fuzzy rules can be inserted into DENFIS before, or during its learning process, and the rules can also be extracted from DENFIS during, or after its learning process. DENFIS utilizes an evolving, online clustering method called the Evolving Clustering Method (ECM) which is an online, maximum distance-based clustering method. It is a fast, one-pass algorithm for a dynamic estimation of the number of clusters in a data set and finding their current centers in the input space. For each new input data point the output will be simulated based on the available rules created from training with previous data. DENFIS was first introduced by [40] and have been successfully applied in rainfall-runoff modeling by [23]. This study is an application of DENFIS for event-based rainfall-runoff modeling in a tropical catchment.

1.3 ARX model

Autoregressive model with exogenous inputs (ARX) is a characteristic time-series estimating model, and consequently being used as a bench mark model to assess the competency of any other models. Even though a linear model like ARX is probably not able to simulate the nonlinearity involved in rainfall-runoff process, it is still a frequently used technique for models comparison. In this study, the ARX model was developed using different combinations of rainfall antecedents (up to present time) as well as runoff antecedents (up to t-1) as exogenous inputs to estimate the runoff at present time t. The ARX model was calibrated using the same fifteen events used for DENFIS model to simulate the five testing events.

2.0 METHODOLOGY

The study was performed on Semenyih River catchment which is located at Selengor, Malaysia. The catchment has four rainfall stations and one discharge station located at the outlet as can be seen in fig 1.

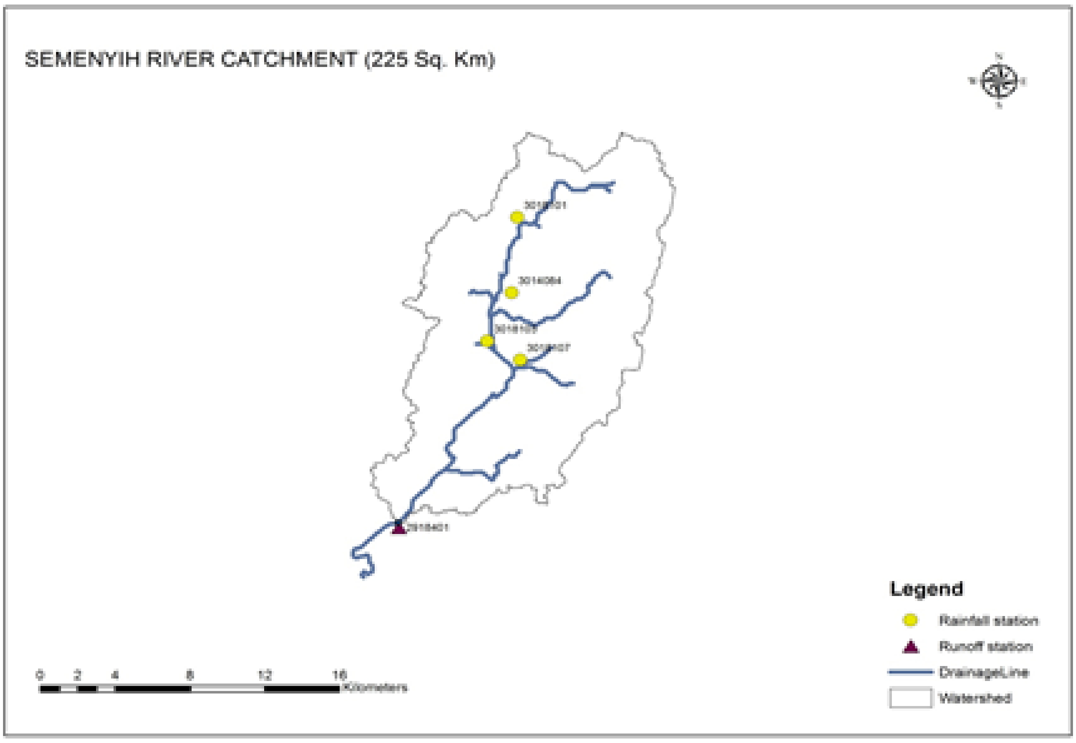

Figure 1: Map of Semenyih River catchment

The rainfall data of the presently active stations was arranged from department of irrigation and drainage (DID). Twelve years (2002-2013) of hourly rainfall and runoff data was provided from the department of irrigation and drainage (DID), Malaysia. Twenty of extreme events were selected from rainfall-runoff time series to be used for this study from which fifteen events were used for training the model and the remaining five for the validation. All the rainfall and runoff data were normalized before analysis. Normalization concentrates the dispersed data into a defined interval. The normalization method used in this study follows [41] which can be given by:

$$x_n = FMIN + \left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}}\right) \times (FMAX - FMIN) \tag{1}$$

where FMIN and FMAX are the required minimum and maximum of the new domain (e.g. 0.1-0.9), x_n is the standardized data, x_{min} and x_{max} are the minimum and maximum observed data, respectively; and x_i is the observed data. As the Semenyih catchment has four rainfall stations therefore, an input selection process based on correlation and mutual information analyses [42] was carried out to identify the suitable input combination for the model. The input selection procedure showed that out of the four available rainfall stations, the rainfall antecedents of only one station show sufficient correlation with output. Moreover, including one discharge antecedent, Q(t-1) in inputs, was found to be effective in enhancing the model performance. Out of different possible combinations between rainfall antecedents, the correlation analysis showed that the input combination of R4(t-2), R4(t-4), and Q(t-1) is the best. After finding the proper input combination, DENFIS model was developed by allocating three Gaussian membership functions to each input. DENFIS model trained by the 15 training events was then validated for the five testing events. Similarly, for the development of ARX model the same input combination was used.

2.1 Model performances

The performances of DENFIS model in this study were evaluated based on several statistical measures such as coefficient of efficiency (CE), coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Relative Peak Error (RPE).

$$CE = 1 - \frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{n}(Q_i - \bar{Q}_i)^2} \tag{2}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(Q_i - \bar{Q})(\hat{Q}_i - \tilde{Q})}{\sqrt{\sum_{i=1}^{n}(Q_i - \bar{Q})^2} \times \sqrt{\sum_{i=1}^{n}(\hat{Q}_i - \tilde{Q})^2}}\right]^2 \tag{3}$$

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$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{n}} \quad (4)$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|Q_i - \hat{Q}_i|}{n} \quad (5)$$

$$\mathrm{RPE} = \frac{|(Q_p) - (\hat{Q}_p)|}{(Q_p)} \quad (6)$$

where $\bar{Q}$ is the average observed discharge and n is the total number of the observations, Q_i is observed flow rate and $\hat{Q}_i$ is the simulated flow rate, Q_p and $\hat{Q}_p$ is the observed peak discharge and simulated peak discharge.

3.0 RESULTS AND DISCUSSION

DENFIS model performance in testing phase was evaluated by CE, R^2, RMSE, MAE, and RPE. Figure 2 illustrates the observed and simulated discharge by DENFIS model for the 5 testing events. As can be seen, DENFIS was able to simulate discharge successfully for all testing events. For further evaluation of the DENFIS model, an ARX model was also developed as a bench mark using the same inputs used for DENFIS. Results showed that DENFIS outperforms ARX models in terms of all statistics. A comparison of different statistics obtained from DENFIS and ARX model can be seen in Figure 3. Table 1 shows the average performances of DENFIS and ARX model for the 05 testing events. In literature, very few studies have been conducted on application of DENFIS in rainfall-runoff modeling. Earlier the study conducted by [17] reported that DENFIS model performance was comparable to the physically-based models for three different sizes of catchments and different modeling complexities. The results of the present study support the previous findings on successful application of DENFIS in rainfall-runoff modeling and also confirm its superiority over ARX model in simulating extreme events.

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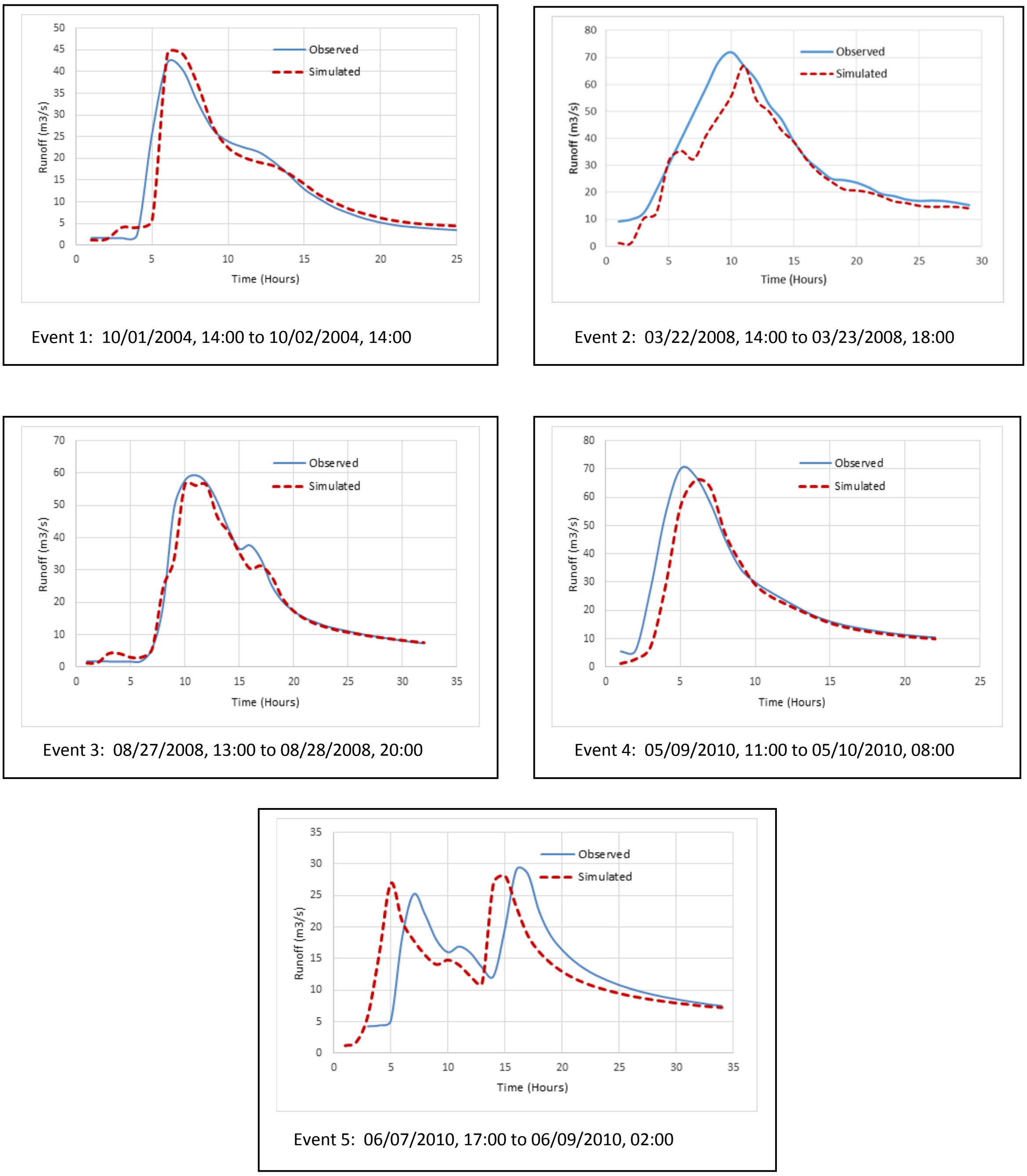

Event 1: 10/01/2004, 14:00 to 10/02/2004, 14:00

Event 2: 03/22/2008, 14:00 to 03/23/2008, 18:00

Event 3: 08/27/2008, 13:00 to 08/28/2008, 20:00

Event 4: 05/09/2010, 11:00 to 05/10/2010, 08:00

Event 5: 06/07/2010, 17:00 to 06/09/2010, 02:00

Figure 2: Observed and simulated discharge by DENFIS model for the 5 testing events.

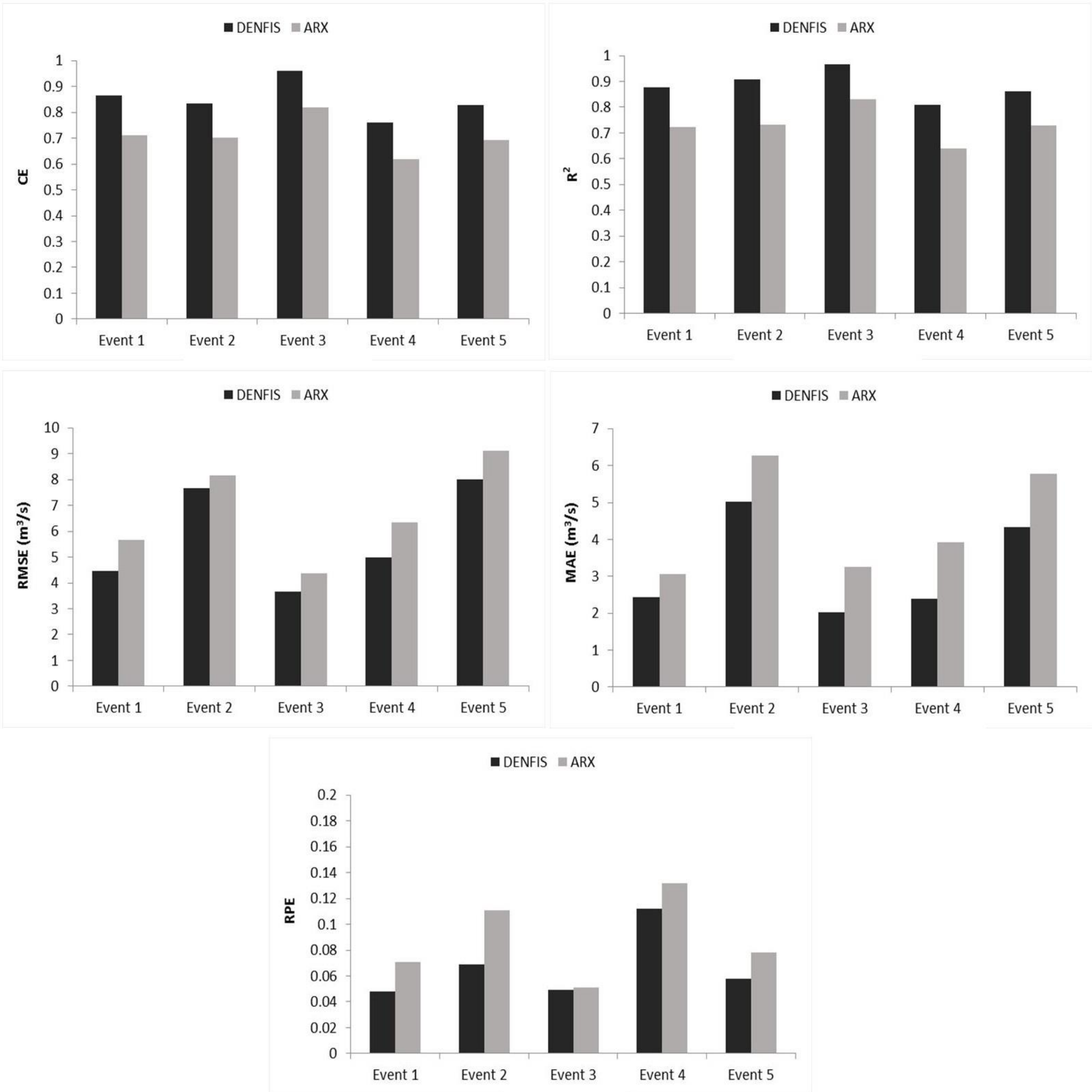

Figure 3: Comparison of performances obtained by DENFIS and ARX models for the 05 testing events.

Table 1: Average performances of DENFIS and ARX model for the 5 testing events.

Model	Average model performances				
	CE	**R^2**	**RMSE**	**MAE**	**RPE**
DENFIS	0.850	0.885	5.764	3.239	0.068
ARX	0.709	0.731	6.728	4.452	0.089

4.0 CONCLUSION

This study presented a successful application of the DENFIS for event-based rainfall-runoff modeling in a tropical catchment. Twenty extreme events were extracted from the twelve-year hourly data. Out of twenty events fifteen were used to train the DENFIS model and remaining five were used to test the model performances. DENFIS was able to simulate runoff of all testing events well in terms of all statistics. Moreover, DENFIS was found to be superior to ARX model. In general, DENFIS model was found to be a good potential to be used as a reliable computing tool in hydrologic modeling specifically for rainfall-runoff modeling. It is also concluded that more investigation on DENFIS model for simulation of rainfall-runoff processes is needed to attain the attraction of hydrologists.

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