DAILY STREAMFLOW FORECASTING USING SIMPLIFIED RULE-BASED FUZZY LOGIC SYSTEM

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ABSTRACT

In this study, a simplified fuzzy logic system with uniform partitions in the input space is proposed for forecasting the daily streamflow of four river systems in Malaysia. The proposed simplified fuzzy logic system was calibrated (trained) using back-propagation (BP) and recursive prediction error (RPE) algorithms. For each catchment, the calibration data set consisted of three consecutive years of daily rainfall and streamflow records. Verifications of the calibrated models were done using the data set of the following year. The performances of the simplified fuzzy logic system and the normal fuzzy logic system are compared, with each model having the same number of adjustable parameters. The results are also compared with the auto-regressive with exogenous input model. This study has shown that the proposed RPE algorithm performed better than the more popular BP algorithm. The results show that all the simplified fuzzy logic system models registered better performance measures for the calibration data sets. However, variable results were obtained for the predictions of the verification data sets.

Keywords : *Fuzzy Systems, Rainfall-runoff Modelling, Time Series Forecasting, Training Algorithms*

1 INTRODUCTION

Daily streamflow forecasting model is essential in estimating the potential flood event that can possibly occur in the following day. The previous rainfall and streamflow records can be utilised as model inputs for forecasting the next time step ahead of the streamflow. Normally, the rainfall-runoff model is developed to formulate the relationship between the rainfall and the runoff. Consequently, the runoff is predicted based on estimated or designed rainfall using the rainfall-runoff model. However, this study employs the previous rainfall and streamflow records to forecast the streamflow discharge of the following day. In the analysis, the daily streamflow discharge is assumed to be equivalent to the daily runoff.

Various rainfall-runoff models have been developed and applied for flood forecasting [1, 2]. In general, these models can be divided into (1) conceptual rainfall-runoff (CRR) models, retaining some of the physical laws in their mathematical formulation and (2) system theoretic models (sometimes referred to as black box models), that establishes an input-output mapping without physical considerations [3, 4]. The CRR models are important for understanding the nature of hydrologic processes. In some situations, the theoretic models are preferred when accurate predictions are required for specific watershed locations. The linear time series models such as the auto-regressive moving average with exogenous inputs (ARMAX) have been most commonly used in these situations because they are relatively easy to develop and implement. ARMAX models have been found to provide satisfactory predictions in many applications [5, 6]. However, regardless of the complexity and sophistication, no single model has been found to work satisfactorily for simulating and forecasting all flood events in all watersheds [2, 7].

Recently, artificial neural networks (ANN) have made significant progress in the field of hydrology, specifically for modelling of rainfall-runoff processes [3, 4, 7–10]. This is partly due to excellent capabilities of ANN models in mapping the inputs and outputs of any arbitrarily complex non-linear processes. Another principal advantage of ANN models is their adaptive nature, which learns from historical data to automatically adjust the parameters without the need of physical models. Apart from ANN models, although not as widely applied, fuzzy logic system (FLS) has also made some impact in modelling of rainfall-runoff processes [2, 11–13]. Similar to ANN models, FLSs are function approximators that can approximate any real non-linear function to any arbitrary degree of accuracy if enough fuzzy rules are used [14]. However, since rainfall-runoff models usually require large number of input variables, FLS model suffers a great deal from the problem of rule explosion. It is commonly to expected that the number of input variables for any rainfall-runoff models to be in the range from 5 to 10 [4] and sometimes it can be more than 20 [15, 16]. Most fuzzy applications use just two or three inputs, and each input space is partitioned into 5 or 7 fuzzy sets [17]. For a rainfall-runoff model that requires 5 inputs, to completely represent the model, FLS with 7 partitions would require 16,807 rules!

This study proposes the application of the simplified fuzzy logic system (SFLS) with uniform partitions in the input space to forecast the daily streamflow discharge of four river systems in Malaysia, namely the catchments of Sungai Lenggor, Sungai Lui, Sungai Klang, and Sungai Bernam. The forecasting model is designed as a time series model of the rainfall-runoff structure. The SFLS is formulated as a rule-based type with incomplete rule set in order to maintain the number of necessary rules under control. The number of adjustable parameters in the rule base is further reduced by fixing the spreads of each input membership functions. Calibration of the SFLS models employs the back-propagation (BP) and recursive prediction error (RPE) algorithms. Three consecutive years of daily rainfall and runoff records of each catchment are selected as calibration data set. Meanwhile, verifications are carried out using the remaining data set of the following year. The performance of the SFLS in forecasting the daily streamflow is compared to the performance of the model obtained using the normal fuzzy logic system (NFLS) with the same number of adjustable parameters. Comparison on the effectiveness of the BP and RPE algorithms on training the SFLS models were also made. For further insight, the results obtained using the auto-regressive with exogenous input (ARX) model are compared.

2 SIMPLIFIED FUZZY LOGIC SYSTEM

The rule-based fuzzy logic system consists of collection of fuzzy *IF-THEN* rules to determine a mapping from fuzzy sets in the input universe of discourse to fuzzy sets in the output universe of discourse based on fuzzy logic principles. The *fuzzy rule base* is a set of linguistic rules in the form of "*IF* a set of conditions are satisfied, *THEN* a set of consequences are inferred". For a given fuzzy logic system with n input variables $x_1, x_2, \ldots, x_n$ and one output variable y, these rules R^l can be formally written as:

$$R^l: IF\ x_1 \text{ is } A_1^l \text{ and } \ldots\ x_n \text{ is } A_n^l,\ THEN\ y\ is\ G^l \qquad (1)$$

where $l = 1, 2, \ldots, M$ is the rule number, A_n^l and G^l are fuzzy sets in the input and output universe of discourse respectively. When *product-inference* rule, singleton fuzzifier, center average defuzzifier, and Gaussian membership function are used, the functional form of the normal fuzzy logic system (NFLS) can be written as [14]:

$$f(\underline{x}) = \frac{\sum_{l=1}^{M} \bar{y}^l \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{x_i - \bar{x}_i^l}{\sigma_i^l} \right)^2 \right] \right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{x_i - \bar{x}_i^l}{\sigma_i^l} \right)^2 \right] \right)} \qquad (2)$$

Here, $\underline{x} = [x_1\ x_2\ \ldots\ x_n]^T$ is the input vector. The adjustable parameters for the NFLS are $\bar{x}_i^l$ and σ_i^l which represent the centres and the spreads of the input membership functions respectively and y which represent the centres of the output membership functions. In its original form of Equation (2), the number of adjustable parameters for the NFLS is $p = M(2n+1)$, where M is the number of fuzzy rules and n is the number of input variables.

In this study, a SFLS is proposed such that the spreads of the input membership functions σ_i^l in Equation (2) are fixed with some predetermined constants. By doing this, the number of adjustable parameters needed to be trained reduces to $p = M(n+1)$. Although the structure of the SFLS becomes more rigid, both the premise and the consequence part of the fuzzy rules can still be adjusted during training by adjusting the more dominant parameters $\bar{x}_i^l$ and $\bar{y}^l$. In this study, for all M rules, the spreads of the input membership function are chosen to be 15% of their universe of discourses defined as:

$$\sigma_i^l = 0.15(\max(x_i(t)) - \min(x_i(t))) \qquad (3)$$

where $t = 1, 2, \ldots, N$, and N is the number of calibration data pairs.

Since only small number of fuzzy rules M are used in this study at the expense of incomplete rules (the union of the fuzzy sets involved does not cover the entire space of the input variables), it is important that most of them are good rules. It has been reported that the best rules lie at the bumps or extrema of the function [17]. Therefore, to further assists the training process, the calibration data set is divided into *M/2* sections and the initial values of $\bar{x}_i^l$ and $\bar{y}^l$ are chosen to be the exact value of the input-output data pairs at the maximum and minimum of the measured output in each section. In other words, there are two initial rules in each section and the rules are located exactly at the extrema of the function in each of the *M/2* sections. It has been found throughout this study that these are better choices of initial rules in comparison to initial rules that are uniformly spaced in the calibration data set.

3 TRAINING ALGORITHMS

Here, a p-dimensional parameter vector of the SFLS is defined as:

$$\Theta = [\bar{x}_1^1\ \bar{x}_2^1 \ldots \bar{x}_n^1\ \bar{x}_1^1\ \bar{x}_2^2 \ldots \bar{x}_n^2 \ldots \bar{x}_1^M\ \bar{x}_2^M \ldots \bar{x}_n^M\ \bar{y}^1\ \bar{y}^2 \ldots \bar{y}^M]^T \qquad (4)$$

where the number of elements in the parameter vector Θ is $p = M(n+1)$. One of the algorithms used to train the adjustable parameters in the parameter vector is the BP algorithm. The BP algorithm is a gradient descent algorithm designed to minimise the error squared between the SFLS output and the desired output. That is, for a given input-output data pair $(\underline{x}(t), y(t))$, the SFLS is designed such that the error squared:

$$e(t) = \frac{1}{2}[f(\underline{x}(t)) - y(t)]^2 \qquad (5)$$

is minimised. BP algorithm updates each element in the parameter vector using:

$$\theta_j(k+1) = \theta_j(k) - \alpha \left. \frac{\partial e}{\partial \theta_j} \right|_k \qquad (6)$$

where $j = 1, 2, \ldots$ p is the parameter number, $k = 1, 2, \ldots$ is the iteration step, and a is a constant step size known as the learning rate. Detail descriptions of the BP algorithm can be found in the literature [14].

The second algorithm considered here is the RPE algorithm which is based on the class of unified recursive parameter estimation methods that minimises the prediction error over the model set using the Gauss-Newton search direction. The discrepancy of the predicted model $\hat{y}(t)$ from the desired output $y(t)$ is called the prediction error and is given by:

$$\varepsilon(t) = y(t) - \hat{y}(t) \qquad (7)$$

For the quadratic function used as a measure of fit, the RPE algorithm minimises the criterion:

$$V(\Theta) = \frac{1}{2N} \sum_{t=1}^{N} \varepsilon^T(t,\Theta) \Lambda^{-1} \varepsilon(t,\Theta) \qquad (8)$$

where Λ is some symmetric positive definite matrix and is equal to a scalar for the case of single output fuzzy system. The negative gradient vector of with respect to $\varepsilon(t,\Theta)$ can be written as:

$$\Psi(t,\Theta) = \left[-\frac{d\varepsilon(t,\Theta)}{d\Theta}\right]^T = \left[\frac{d\hat{y}(t|\Theta)}{d\Theta}\right]^T \quad (9)$$

The elements of the gradient vector $\Psi(t,\Theta)$ can be obtained by directly differentiating Equation (2). Using the Gauss-Newton search direction, one of the algebraically equivalent variants of the RPE algorithm is given by Ljung and Soderstrom [18] as:

$$P(t) = P(t-1) - P(t-1)\Psi(t)\left[\Psi^T(t)P(t-1)\Psi(t) + \Lambda\right]^{-1}\Psi^T(t)P(t-1) \quad (10)$$

$$\hat{\Theta}(t) = \hat{\Theta}(t\text{-}1) + P(t)\Psi(t)\varepsilon(t) \quad (11)$$

Here, $P(t)$ is a $p \times p$ covariance matrix, and Λ is chosen to be the identity matrix. For a single output fuzzy system, the matrix in the square bracket of Equation (10) is just a scalar. Detail discussions on the use of RPE algorithm and its equivalent variations have been reported in the literature [18].

4 RAINFALL-RUNOFF MODELLING

In this study, the runoff (equivalent to steamflow discharge) $Q(t)$ is assumed to be related to the past inputs, the previous rainfalls $S(t-1)$, $S(t-2)$, … and the past outputs, the runoff $Q(t-1)$, $Q(t-2)$, …. The SFLS(s,q,M) model is the simplified fuzzy logic system representing the predicted runoff in the form of:

$$\hat{Q}(t) = f\,(S(t\text{-}1), S(t\text{-}2),...,S(t\text{-}s), Q(t\text{-}1), Q(t\text{-}2),...,Q(t\text{-}q)) \quad (12)$$

where s and q are the (unknown) number of past inputs and outputs contributing to the present output, and f is the SFLS in the form of Equation (2) consists of M fuzzy rules. $Q(t)$ can also be viewed as the one-day-ahead prediction of the runoff. In some catchments, however, the present rainfall $S(t)$ contributes heavily to the present runoff $Q(t)$ due to shorter time delay and the method of data collection which was done on a daily basis. For this type of catchments, the present rainfall $S(t)$ is added as one of the input variables in Equation (12). In this case, the predicted runoff $\hat{Q}(t)$ is just a one-time delay-ahead prediction.

The model performances are evaluated using the root mean square error (RMSE), the percent bias (PBIAS), and the Nash-Sutcliffe efficiency criterion (R^2). These criteria are defined as [13]:

$$\text{RMSE} = \sqrt{\tfrac{1}{N}\sum_{t=1}^{N}(Q(t)-\hat{Q}(t))^2} \quad (13)$$

$$\text{PBIAS} = \frac{\sum_{t=1}^{N}(Q(t)-\hat{Q}(t))}{\sum_{t=1}^{N}Q(t)} \times 100\,\% \quad (14)$$

$$R^2 = \left(1 - \frac{\sum_{t=1}^{N}(Q(t)-\hat{Q}(t))^2}{\sum_{t=1}^{N}(Q(t)-\overline{Q}(t))^2}\right) \times 100\,\% \quad (15)$$

where $\overline{Q}(t)$ is the mean observed daily runoff. Smaller RMSE obviously indicates better model performance. The optimal value for PBIAS is 0.0, which mean that the model has an unbiased flow simulation. Positive values indicate a tendency of overestimation and negative values indicate a tendency of underestimation. The R^2 criterion is a measure of the performance of the model with respect to the mean observed daily runoff $\overline{Q}(t)$. A value of R^2 of 90% indicates a very satisfactory model performance while a value in the range 80-90% indicates a fairly good model [7].

Comparisons were made between the models obtained using the SFLS and the models obtained using the NFLS that contain the same number of adjustable parameters. For further insight, comparisons were also made with the predictions given by the ARX model trained by recursive least square (RLS) algorithm. The model ARX(s,q) indicates that the model uses s past inputs and q past outputs to model the predicted runoff as:

$$R^2 = \left(1 - \frac{\sum_{t=1}^{N}(Q(t)-\hat{Q}(t))^2}{\sum_{t=1}^{N}(Q(t)-\overline{Q}(t))^2}\right) \times 100\,\% \quad (16)$$

where a_i and b_i are the model parameters.

5 DESIGN OF TEST EXPERIMENTS

Four consecutive years of the daily rainfall-runoff data from four river systems in Malaysia were used to demonstrate the modelling capability of the SFLS. These four catchments are Sungai Lenggor (207 km^2), Sungai Lui (68 km^2), Sungai Klang (468 km^2), and Sungai Bernam (1090 km^2). These data sets were obtained from the Department of Irrigation and Drainage (DID), Kuala Lumpur, and they are for the period of 1986-1989 for Sungai Lenggor, 1983-1986 for Sungai Lui, 1996-1999 for Sungai Klang, and 1997-2000 for Sungai Bernam. The first three years of each data set was used as the calibration set and the remaining year was for verification.

In order to develop the SFLS rainfall-runoff model, the input variables and the number of fuzzy rules must be selected. In this study, the unknown number of input variables s and q were each varied over the range from 1 to 4. For each of these 16 combinations of s and q, using a specific number of fuzzy rules M, the SFLS were trained and the model performances were evaluated. Two combinations of s and q that gave the best model performance were chosen for each rainfall-runoff data set. For each selected combination of s and q, the SFLS were retrained but the number of fuzzy rules M was varied from 6 to 40. For the maximum number of 8 input variables and 40 fuzzy rules, the maximum number of adjustable model parameters in the SFLS is a manageable 360. Meanwhile, for the same number of input variables and fuzzy rules, the number of adjustable model parameters in the NFLS would be 680.

In this study, the BP algorithm and RPE algorithm were used separately to train the SFLS. The application of BP algorithm requires the selection of the learning rate α. After several values of α over the range from 0.05 to 0.5 were tested, it was found that $\alpha = 0.1$ was suitable for modelling all four data sets. Since the BP algorithm is a slower algorithm, 20 passes were made through the calibration data set each time the SFLS was trained. The application of RPE algorithm requires the selection of the initial covariance matrix $P(0)$. The values of $P(0)$ tested here were within the range from 1 to 1000, and it was found that $P(0) = 10$ was suitable for all four data sets. For the more powerful RPE algorithm, only 6 passes were made through the calibration data set each time the SFLS was trained. Comparisons are made between SFLS and NFLS by maintaining the same number of adjustable parameters. For the purpose of a fair comparison, all models used the same method of choosing the initial fuzzy rules as described in Section 2. In addition, the initial spreads of the input membership function of the NFLS are the same as the fixed spreads of the SFLS given by Equation (3).

6 RESULTS AND DISCUSSIONS

The viability of the SFLS in modelling the rainfall-runoff process was demonstrated by choosing a particular set of input variables for each data set and the model was trained using various numbers of fuzzy rules M. Both the BP algorithm and RPE algorithm were used separately to train the SFLS. The results presented here are for the SFLS(2,2,M) model for Sungai Lenggor, SFLS(2,2,M) model for Sungai Lui, SFLS(1,2,M) model for Sungai Klang, and SFLS(2,3,M) model for Sungai Bernam. Comparisons were also made with the NFLS trained by BP algorithm using the same input variables. All models were trained under the same conditions as described in Section 5. For each model, the RMSE of the predicted runoff $\hat{Q}$ for the calibration set was evaluated and plotted as a function of the number of adjustable parameters in the given model. Figures 1, 2, 3, and 4 show the RMSE of all models for Sungai Lenggor, Sungai Lui, Sungai Klang, and Sungai Bernam respectively.

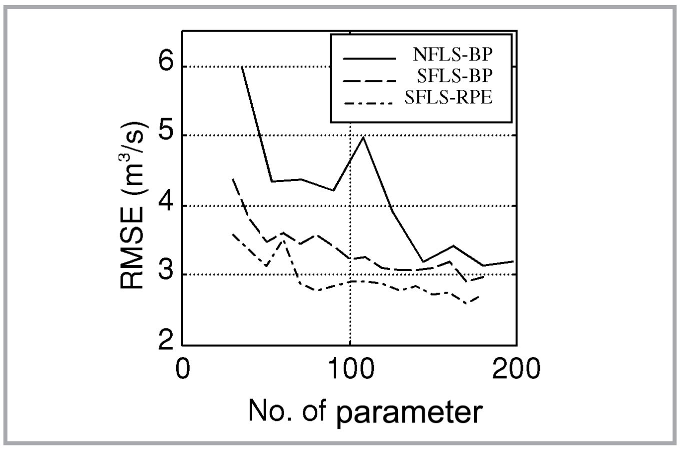

Figure 1: RMSE of the predicted runoff for Sungai Lenggor catchment

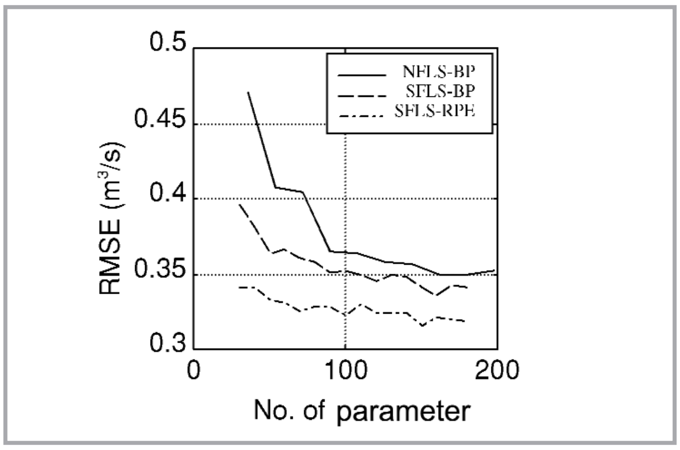

Figure 2: RMSE of the predicted runoff for Sungai Lui catchment

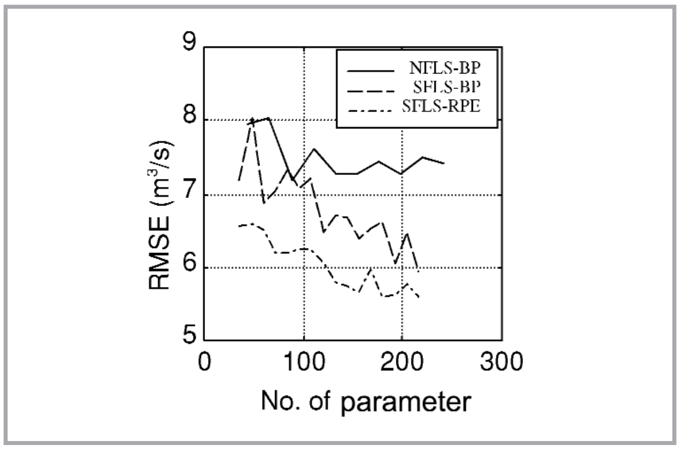

Figure 3: RMSE of the predicted runoff for Sungai Klang catchment

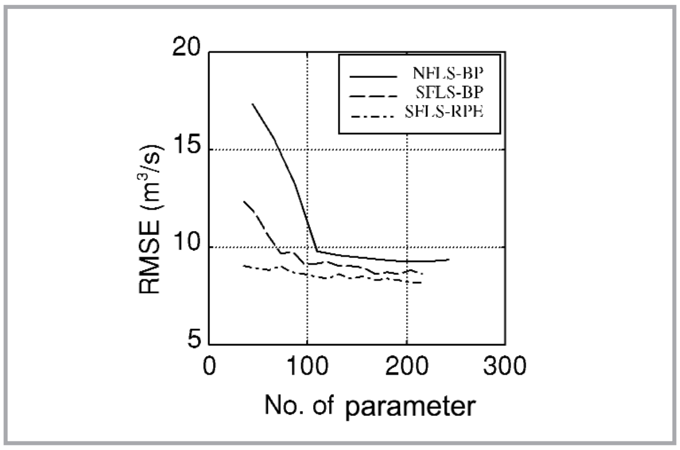

Figure 4: RMSE of the predicted runoff for Sungai Bernam catchment

In general, these results show that the predictive accuracy of all fuzzy models improves when the number of adjustable parameters increases. For a given number of adjustable parameters, the SFLS can utilise more fuzzy rules since only the centres of the input and output membership functions were trained. However, the NFLS utilises less number of fuzzy rules since all parameters including the spreads of the input membership function in the rule base must be trained. With respect to the number of adjustable parameters, results here show that all SFLS performs better than the NFLS. It is obvious that the SFLS is more efficient since it concerns only with what is believed here to be the more dominant parameters. It is also proven here that the proposed RPE algorithm is more powerful than the more popular BP algorithm. Here, the RPE algorithm was stopped after 6 passes were made through the calibration data set compared to 20 passes made by the BP algorithm. Not only that the model with RPE algorithm converges faster but it also yields a smaller value of RMSE.

Next, two sets of input variables that gave the best model performance were chosen for each rainfall-runoff data set. For each selected combination of s and q, the SFLS were trained using the RPE algorithm. Although the accuracy of the predicted runoff for the calibration data set can be improved by increasing the number of fuzzy rules, it does not guarantee a good prediction for the verification data set. An increase in the complexity of the models might mislead the modeller to overfit the training data and lead to poor forecast [8]. Results presented here are for the SFLS models that utilised enough number of fuzzy rules and gave reasonable accuracy for both calibration and verification data sets. Comparisons are also made with the ARX models trained by RLS algorithm. Table 1 shows the performance measures of those selected models for all catchments. It should be noted that additional input $S(t)$ was added for modelling the rainfall-runoff of Sungai Klang catchment.

Table 1: Performance measures of selected models

Sungai Lenggor		Calibration Set (1986-1988)			Verification Set (1989)		
Model	Training algorithm	RMSE m^3/s	PBIAS %	R^2 %	RMSE m^3/s	PBIAS %	R^2 %
ARX(3,3)	RLS	4.457	1.669	83.60	6.553	-4.842	70.97
SFLS(1,2,28)	RPE	2.898	0.307	93.21	4.829	-6.128	84.23
SFLS(2,2,28)	RPE	2.841	0.141	93.33	5.286	-1.395	81.11
Sungai Lui		Calibration Set (1983-1985)			Verification Set (1986)		
Model	Training algorithm	RMSE m^3/s	PBIAS %	R^2 %	RMSE m^3/s	PBIAS %	R^2 %
ARX(3,3)	RLS	0.3610	-1.594	83.23	0.4511	-2.245	68.62
SFLS(2,2,24)	RPE	0.3235	-0.155	86.52	0.4348	-0.913	70.84
SFLS(2,3,24)	RPE	0.3208	-0.144	86.76	0.4296	-0.804	71.55
Sungai Klang		Calibration Set (1996-1998)			Verification Set (1999)		
Model	Training algorithm	RMSE m^3/s	PBIAS %	R^2 %	RMSE m^3/s	PBIAS %	R^2 %
ARX(3,3)	RLS	6.806	-2.067	76.53	8.680	-4.095	62.52
SFLS(1,2,28)	RPE	6.150	0.006	80.82	8.538	-7.863	63.74
SFLS(2,3,28)	RPE	5.966	0.222	81.97	8.463	-5.485	64.38
Sungai Bernam		Calibration Set (1997-1999)			Verification Set (2000)		
Model	Training algorithm	RMSE m^3/s	PBIAS %	R^2 %	RMSE m^3/s	PBIAS %	R^2 %
ARX(3,3)	RLS	9.202	-1.059	91.18	9.747	-1.403	88.79

From Table 1, all models obtained using the SFLS registered good performance measures for the calibration set of all catchments. The Nash-Sutcliffe efficiency criterion R^2 for the calibration data set exceeds 80% for all models obtained using the SFLS. Furthermore, the PBIAS of the predicted discharge in the calibration data sets are less than ± 1% for all SFLS models. It is observed here, at least for the calibration data set, the SFLS mapped the input-output data better than the ARX model. However, variable results are obtained for the predictions of the verification data sets. In general, the predictive accuracy for the verification set, given by both SFLS and ARX models, is not as good as that of the calibration set. The RMSE and R^2 performance criteria for the verification set show that the SFLS performed better than ARX models in three out of four catchments. The ARX model, however, gave better forecast for the Sungai Bernam catchment with R^2 value of 88.8% in the verification set, while the SFLS only registered a value of 86.4%, which is also a good R^2 value. Figures 5, 6, 7, and 8 show the observed runoff and the predicted runoff given by selected SFLS for Sungai Lenggor, Sungai Lui, Sungai Klang, and Sungai Bernam respectively. The results show a good agreement between the predicted and observed runoff. Despite using a set of incomplete fuzzy rules, the SFLS did not face any computational problem in forecasting the verification data sets. Apparently, the proposed method of identification managed to identify enough good 'active' fuzzy rules.

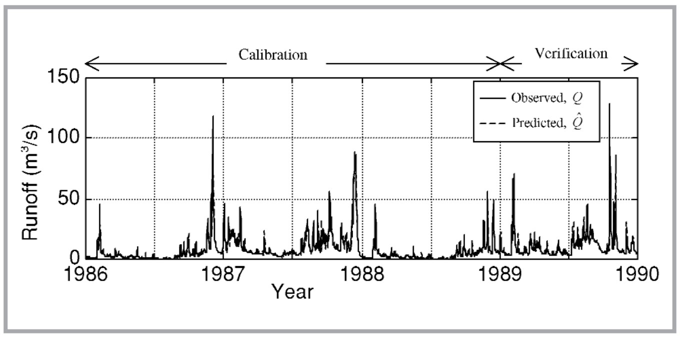

Figure 5: Observed and predicted hydrographs of the SFLS(2,2,28) model trained by RPE algorithm for the catchment of Sungai Lenggor

7 CONCLUSION

In this study, a SFLS with uniform partitions in the input space was proposed for forecasting the daily streamflow of four river systems in Malaysia. The performance of the SFLS was compared with the performance of the model obtained using the NFLS with the same number of adjustable parameters. With respect to the number of adjustable parameters, results in this study indicate that all SFLS performs better than the NFLS. The SFLS is more efficient since it concerns only with what is believed here to be the more dominant parameters. The proposed RPE algorithm has been proven to be more powerful than the more popular BP algorithm. Comparisons between the SFLS and the ARX model indicate that all SFLS models registered better performance measures at least for the calibration sets. However, variable results are obtained for the predictions of the verification data sets, which again confirmed the findings by other researchers that no single model has been found to work satisfactorily for simulating and forecasting all flood events in all watersheds.

It was further shown that the input data for the rainfall-runoff processes do not necessarily cover the whole premise space. Despite using a set of incomplete fuzzy rules, the SFLS did not face any computational problem in forecasting the

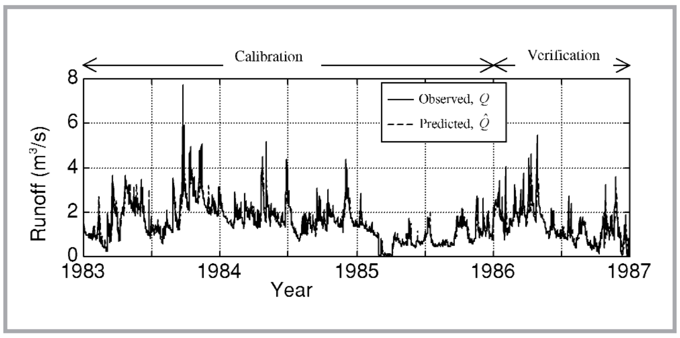

Figure 6: Observed and predicted hydrographs of the SFLS(2,3,24) model trained by RPE algorithm for the catchment of Sungai Lui

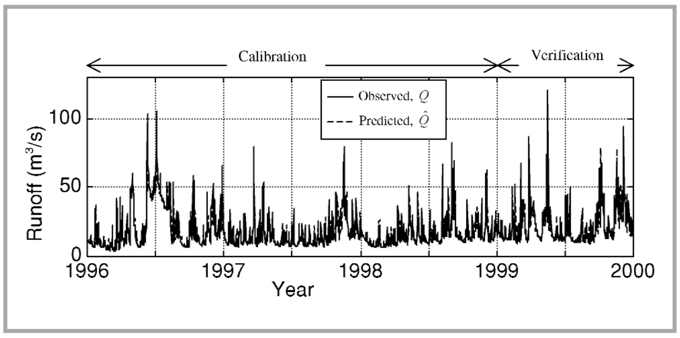

Figure 7: Observed and predicted hydrographs of the SFLS(1,3,28) model trained by RPE algorithm for the catchment of Sungai Klang

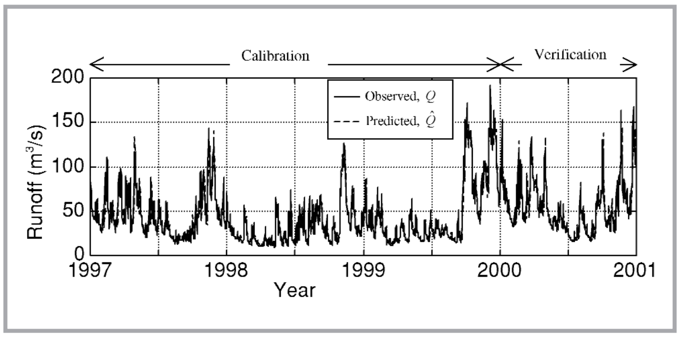

Figure 8: Observed and predicted hydrographs of the SFLS(2,3,24) model trained by RPE algorithm for the catchment of Sungai Bernam

verification data sets. In conclusion, using the identification method proposed in this study, the SFLS can be considered as a good viable alternative for forecasting the rainfall-runoff process. ■

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