Co-Active Neuro Fuzzy Inference System for Regional Flood Estimation in Australia[1]

K. Aziz[a*], A. Rahman[a], A. Y. Shamseldin[b] and M. Shoaib[b]
[a]School of Computing, Engineering and Mathematics, University of Western Sydney, Australia
[b]Department of Civil and Environmental Engineering, University of Auckland, New Zealand

Abstract

Regional flood frequency analysis (RFFA) involves transfer of flood characteristics from gauged to ungauged catchments. In Australia, RFFA methods generally focus on the application of empirical methods based on linear forms of model such as the Probabilistic Rational Method, the Index Flood Method and the regression-based techniques. There have been successful applications of non-linear models in RFFA in some other countries such as Co-Active Neuro Fuzzy Inference System (CANFIS), Gene-Expression Programming (GEP) and Artificial Neural Network (ANN). The application of these non-linear RFFA methods in Australia is limited. This study focuses on the application of Co-Active Neuro Fuzzy Inference System (CANFIS) based RFFA models to Australian data. Using data from 452 catchments in eastern Australia (a part of Australian Rainfall and Runoff Revision Project 5 Regional flood methods database), it has been found that the CANFIS based RFFA provides quite accurate regional flood quantile estimates. However, the Bayesian generalised least squares based QRT coupled with the region of influence approach outperforms the CANFIS based RFFA models.

Keywords: ANN, CANFIS, QRT, RFFA, Floods, ARR, GLS regression

1 Introduction

A design flood estimate is needed in the planning and design of hydraulic structures and in many other water resources management tasks such as flood control measures, flood plain mapping and flood insurance studies. The most direct method of flood estimation is the flood frequency analysis, which requires long period of recorded streamflow data at the site of interest. In the case of Australia, many catchments are ungauged or poorly gauged and hence regional flood frequency analysis (RFFA) methods are widely used in Australia. RFFA is the generic name given to describe techniques which utilises streamflow data from gauged catchments in a region to estimate design floods for poorly gauged or ungauged catchments. The use of RFFA enables the "transfer" of flood characteristics information from gauged to ungauged catchments (Bloschl and Sivapalan, 1997; Pallard et al., 2009). The most commonly adopted RFFA methods have been described in Cunnane (1988) and Hosking and Wallis (1997). RFFA essentially involves two important stages: (1) formation of regions; and (2) development of prediction equations. Traditionally these regions have been formed based on geographic, political, administrative or physiographic boundaries (e.g. NERC, 1975; I. E. Aust., 1987); however, they can also be formed in catchment characteristics data space using multivariate statistical techniques (e.g. Acreman and Sinclair, 1986; Nathan and McMahon, 1990; Rao and Srinivas, 2008; Guse et al., 2010). Moreover, regions can also be formed using a region-of-influence approach where a certain number of catchments based on proximity in geographic or catchment attributes space are pooled together based on some objective function to form an optimum region in RFFA (e.g. Burn, 1990; Zrinji and Burn, 1994; Kjeldsen and Jones, 2009; Haddad and Rahman, 2012).

To develop the regional flood prediction equations, the commonly used techniques include the rational method, index flood method (IFM) and Quantile Regression Technique (QRT). The rational method has widely been adopted in estimating design floods for small ungauged catchments (e.g. Mulvany, 1851; I. E. Aust., 1987; Jiapeng et al., 2003; Pegram and Parak, 2004; Rahman et al., 2011). IFM has widely been adopted in many countries which rely on the identification of homogeneous regions (Dalrymple, 1960; Hosking and Wallis, 1993; Bates et al., 1998; Rahman et al., 1999; Kjeldsen and Jones, 2010; Ishak et al., 2011). The QRT, proposed by the United States Geological Survey (USGS) has been applied by many researchers using either an Ordinary Least Square (OLS) or Generalised Least Square (GLS) regression technique (e.g. Benson, 1962; Thomas and Benson, 1970; Stedinger and Tasker, 1985; Tasker et al., 1986; Pandey and Nguyen, 1999; Bayazit and Onoz, 2004; Rahman, 2005; Griffis and Stedinger, 2007; Ouarda et al., 2008; Kjeldsen and Jones, 2009; Haddad and Rahman, 2011; Haddad et al., 2011, 2012).

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Corresponding author may be contacted at k.aziz@uws.edu.au

In case of Australia, the diversity of climatic conditions, site characteristics and a vast area have encouraged the hydrologists to emphasize on different aspects of RFFA. Furthermore, increased computing power and the research in statistical methods have enabled the hydrologists to develop new techniques such as non-linear models for the solution of many complex hydrological problems. Neuro fuzzy based techniques e.g., Co-Active Neuro Fuzzy Inference System (CANFIS) presents more flexible model structure that can easily account for non-linearities between the model input and output and their complex interactions. Neuro-fuzzy modelling refers to the way of applying various learning techniques developed in the neural network literature to fuzzy modelling or a fuzzy inference system. This approach adds the advantage of reduced training time not only due to its smaller dimensions but also because the network can be initialised with parameters relating to the problem domain (Maguire et al, 1998).

From the early application of fuzzy logic to hydrology, a large amount of research has been pursued and, at present, fuzzy logic has become a practical tool in many hydrologic analyses and water resources decision making. Fuzzy logic can easily incorporate expert knowledge into standard mathematical models in the form of a fuzzy inference system. A judicious integration of fuzzy system and ANN can produce a functional neural fuzzy system capable of learning, high-level thinking, and reasoning (Loukas, 2001). The hybrid neuro fuzzy models are becoming popular as they gets the benefits of neural networks and fuzzy logic systems and removes the individual disadvantages by combining them on the common features.

There have been many applications of neuro fuzzy based techniques in hydrology (Talei et al., 2010a, 2010b; Shiri and Kisi, 2010; Nourani et al., 2011; Nayak and Sudheer, 2004) but their application to RFFA problems is rather limited (Turan and Yurdusev, 2009 and Shu et al., 2008). The hydrological and climatic conditions of Australia are different from rest of the world; hence, it is important to develop new models and techniques based on Australian data for RFFA.

In this paper, an overview of the CANFIS is presented first, which follows the description of study area and data. The adopted methodology is presented next, which follows the results and conclusion from the study. CANFIS based RFFA models have been developed for eastern parts of Australia. The database developed in the Australian Rainfall and Runoff (ARR) Revision Project 5 Regional flood methods has been used in this study. At the beginning, CANFIS and QRT based RFFA models are compared, which is then followed by a comparison of these models with the ordinary least squares (OLS) based QRT. The QRT method developed in the ARR Project 5 (Haddad and Rahman, 2012) has also been used in this comparison.

2 Overview and applications of CANFIS to RFFA

A number of different neuro-fuzzy algorithms are available in the literature: fuzzy inference network (Keller et al., 1992b), fuzzy aggregation networks (Keller et al., 1992a), neural network driven fuzzy reasoning (Takagi and Hayashi, 1991), fuzzy modelling networks (Horikawa et al., 1992), fuzzy associated memory systems (Kosko, 1992) and the most popular neuro fuzzy system ANFIS (Jang, 1993) and CANFIS (Jang, 1997). The CANFIS model integrates the modular neural network with fuzzy inference system in (FIS) in the same topology. The powerful capability of CANFIS stems from pattern-dependent weights between the consequent layer and the fuzzy associate layer. The CANFIS model integrates adaptable fuzzy inputs with a modular neural network to rapidly and accurately approximate complex functions.

In recent years much attention has been given to deriving effective data driven neuro-fuzzy models due to its numerous advantages. ANFIS-based neuro-fuzzy modeling was initially developed by Jang (1993), Jang and Sum (1997), Jin et al. (1995), which has been widely applied in engineering applications. Palit and Popovic (1999, 2000 and 2005) developed and applied neuro-fuzzy network for time series forecasting, Deka and Chandramouli (2003) used a fuzzy neural network model for deriving the river stage-discharge relationship, Kisi (2005) estimated suspended sediment by applying neuro-fuzzy and neural network approaches. Shafie et al. (2007) modeled inflow forecasting of the Nile River at Aswan high dam by using a neuro-fuzzy model.

Jacquin and Shamseldin (2006) developed two types of fuzzy rainfall runoff models based on Takagi-Sugeno fuzzy inference systems. The results of the developed models are compared with those of Simple Linear Model. They found that the fuzzy inference systems are a suitable alternative to the traditional methods of rainfall and runoff modelling. Kisi (2006c) and Kisi and Ozturk (2007) applied adaptive neuro-fuzzy computing technique for pan evaporation and evapotranspiration modeling, and recently, Saemi and Ahmadi (2008) modeled permeability from well logs by using Genetic Algorithms and CANFIS. Talei et al. (2010a) evaluated the rainfall runoff modelling for a sub-catchment of Kranji basin in Singapore by using a neuro-fuzzy computational technique adaptive neuro-fuzzy inference system ANFIS. The result of the ANFIS was compared with those of physically based storm water management model (SWMM). They concluded that ANFIS model is comparable to storm water management model (SWMM) in terms of goodness of fit results.

It was observed that only a few studies existed in the literature related to the use of neuro fuzzy in RFFA e.g. Shu et al. (2008). They applied ANFIS for RFFA at ungauged catchments in Canada and compared the results with nonlinear regression (NLR) and nonlinear regression with regionalisation (NLR-R) approaches and found that the ANFIS approach has a much better generalization capability than the NLR-R approach and comparable to ANN. In 2009, Aytek (2009) adopted CANFIS for evapotranspiration modelling. He found CANFIS based models to be outperforming the conventional model for evapotranspiration (ET_0). Tabari and Talaee (2012) compared the utility of CANFIS for pan evaporation (E_{pan}) modelling with multilayer perception (MLP) and found that MLP provides better results than CANFIS. But to the best knowledge of the authors, a CANFIS based RFFA modeling is not available in literature especially in case of Australia. Hence, this paper applies CANFIS in RFFA in Australia and compares the results with traditional RFFA methods.

3 Working structure of ANFIS and CANFIS

Fuzzy Logic provides a different way to approach a control or classification problem. This method focuses on what the system should do rather than trying to model how it works. An adaptive network is a feed forward network which makes use of a collection of modifiable parameters for determining the output of the network. Like other neural networks, an adaptive network also consists of a set of nodes connected through directional links and each node is a process unit that performs a static node function on its incoming signal to generate the signal output. Unlike other neural networks, the links in an adaptive network only indicate the flow direction of signals between nodes and no weights are associated with these links. As introduced by Jang (1993), ANFIS is a novel architecture that uses a neural network learning algorithm for constructing a set of fuzzy if-then rules with appropriate membership functions (MFs) from the stipulated input-output pairs.

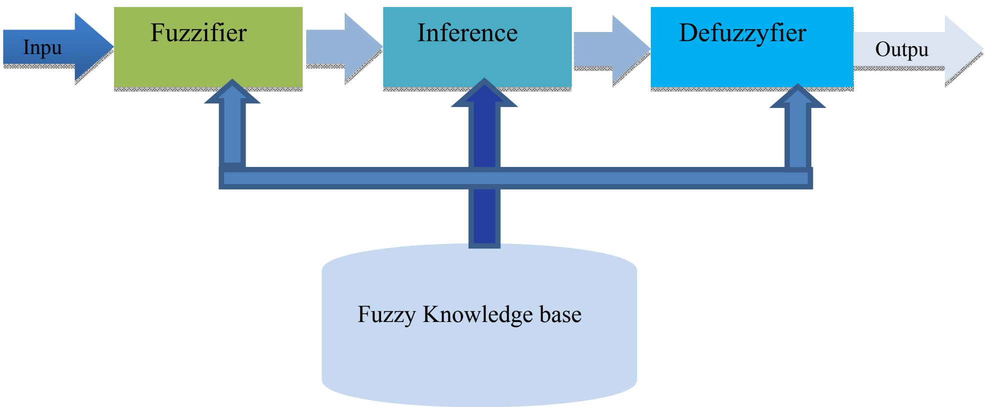

Figure 1 Fuzzy Inference System (FIS)

This procedure of developing a FIS using the framework of adaptive neural networks is called an adaptive neuro fuzzy inference system (ANFIS). Consider the example of simple FIS with only two inputs x and y and one output z. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno (1983).

Rule 1: If x is A_1 *and y is* B_1*, then* $f_1 = p_1x + q_1y + r_1,$
Rule 2: if x is A_2 *and y is* B_2*, then* $f_2 = p_2x + q_2y + r_2$

Where A_1, A_2 and B_1, B_2 are the MFs of input x and y respectively; p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output functions. The node function in the same layer of the same function family is described below:

Layer 1: Each node in this layer performs fuzzification and generates membership grade of linguistic label of an input variable.
Layer 2: Each node in this layer is denoted by determining the MF of the whole input vector by aggregating the fuzzified results of the individual scalar functions of the every input variable. The output of each node in this layer is obtained by multiplying the incoming signals and represents the firing strength of a rule.
Layer 3: Each node in this layer is labelled as N and computes the normalized firing strength.
Layer 4: The output of each node in the fourth layer is calculated by the sum of the signals of the third and second layer of the network.
Layer 5: There is only single node in this layer labelled as $\sum$ that calculates the overall output of the ANFIS or CANFIS as the summation of all incoming signals.

In case of CANFIS, the fuzzy neuron that applies MFs to inputs is the fundamental component of CANFIS. The general Bell and Gaussian functions are the two commonly used MFs (Principe et al., 2000). The bell shaped membership function is used in this study. The normalized axon/neuron in the network is used to expand the output into a range of 0-1. One of the advantages associated with the fuzzy axon is that their MF can be modified through back propagation during network training and results in the expedition of the convergence. The modular neural network that applies functional rules to the inputs is the second major component of CANFIS. The number of modular networks equals the number of network outputs, and the number of processing elements in each network corresponds to the number of MFs. The CANFIS also has a combiner axon that applies the MFs outputs to the modular network outputs (Roger et al., 1997 and Alecsandru et al., 2004). Finally, the combined outputs are channelled through a final output layer and the error is backpropagated to both the MFs and the modular networks.

There are a total of five layers in the CANFIS similar to ANFIS and each layer functions is summarizes as follows. The fuzzification of the input is performed by each node in layer 1. Each node in this layer is the membership grade of a fuzzy set (A1, A2, B1 or B2) and specifies the degree to which the given input belongs to one of the fuzzy sets. The input to the layer 2 is the product of all the output pairs from layer 1. Two components are present in the next third layer in the network. The upper component of this layer applies the membership functions to each of the inputs, while the lower components is a representation of the modular network that computes, for each output, the sum of all the firing strength. The weight normalization of the outputs of the two components of the third layer is performed in the fourth layer of the network and this produces the final output of the network (Ishak and Trifiro, 2007).

The CANFIS model integrates adaptable fuzzy inputs with a modular neural network to rapidly and accurately approximate complex functions. The TSK model fuzzy model proposed by Takagi, Sugeno and Kang (Takagi and Sugeno, 1985; Sugeno and Kang, 1988) is used in the present study, since this type of fuzzy model best fits the multi-input, single output system (Aytek, 2009).

4 Study area and data

This paper focuses on the eastern states of Australia consisting of New South Wales (NSW), Victoria (VIC), Queensland (QLD), and Tasmania (TAS). This part of Australia is selected as the spatial and temporal data of gauged catchments in this region are more comprehensive than other parts of Australia. Data was obtained from 452 stations which was prepared as a part of the ARR Revision Project 5 (Haddad and Rahman, 2012). The data preparation involved filling gaps, checking for trends, outliers and rating curve error in streamflow as detailed in Rahman et al (2012). The selected stations are shown in Figure 2, which include 96 stations from NSW, 131 from VIC, 172 from QLD and 53 from TAS. In this study, the ANFIS and ANN-based models were developed using two catchment characteristics: catchment area (*area*) and design rainfall intensity ($I_{\mathrm{tc\_ARI}}$) (where ARI = 2, 5, 10, 20, 50 and 100 years and t_c = time of concentration (hour), estimated from $t_c = 0.76(area)^{0.38}$). The basic design rainfall intensities (I) data for the selected catchments were obtained from Australian Rainfall and Runoff (ARR) (I. E. Aust., 1987, 2001).

The *T*-year flood quantile was estimated by fitting the log Pearson Type 3 (LP3) distributions for each of the selected stations using a Bayesian parameter fitting procedure (Kuczera, 1999). If different predictor variables are prioritized in RFFA, it may be noted that catchment area *(A)* is the most important predictor variable for a catchment followed by design rainfall intensity *(I)*, slope *(S)*, mean annual rainfall *(R)* and evaporation *(E)* (Rahman et al., 1999; Haddad et al., 2010). Based on the same data set of the 452 catchments, a study was conducted by Aziz et al. (2010, 2013) using artificial neural network (ANN) and Gene expression programming (GEP) based RFFA techniques. They found that the set of predictor variables giving the best results consisted of A and I_{tc_ARI}. In this study, these two predictor variables were selected for model development. All the eastern states i.e. NSW, VIC, QLD and TAS were considered as one region as this has been found to be producing the best results with the ANN based RFFA models in previous studies by Aziz et al. (2011, 2013).

The catchment sizes of the selected 452 stations range from 1.3 km^2 to 1900 km^2 with the median value of 256 km^2. For the stations of NSW, VIC and QLD, the upper limit of catchment size was 1000 km^2; however, for Tasmania; there were 4 catchments in the range of 1000 km^2 to 1900 km^2. Overall, there are 12% catchments in the range of 1 km^2 to 50 km^2, 11% in the range of 50 km^2 to 100 km^2, 53% in the range of 100 km^2 to 500 km^2 and 24% greater than 500 km^2. The annual maximum flood record lengths of the selected stations range from 25 to 75 years (mean: 33 years).

5. Method

In case of CANFIS, all the 452 catchments were considered to be one region. The 452 catchments were then divided into 80% for training and 20% for independent testing. The training and testing data sets were selected randomly from the region. For each case, the model was built using the 80% model catchments and then used to predict 2, 5, 10, 20, 50 and 100 years ARI flood quantiles for the 20% independent test catchments.

Moreover, the results from CANFIS were compared with two different techniques of QRT. In the first case, all the 452 catchments were considered to be one region to be consistent with the CANFIS based model. Randomly selected 80% of the catchments were used to develop the QRT models and the rest of the catchments (20%) were used for validation of the developed QRT model. An ordinary least squares fitting method was adopted to estimate the QRT model coefficients. This is referred to as 'QRT' in this paper. In the second case, the QRT method developed as a part of Project 5 was also considered in the comparison where a Bayesian generalised least squares (BGLS) regression was applied with a region-of-influence (ROI) approach (for details see Rahman et al., 2012). The relative error reported in Project 5 Stage II report by Rahman et al. (2012) has been used directly without redeveloping these models in this study. This is referred to as 'BGLS-QRT-ROI'.

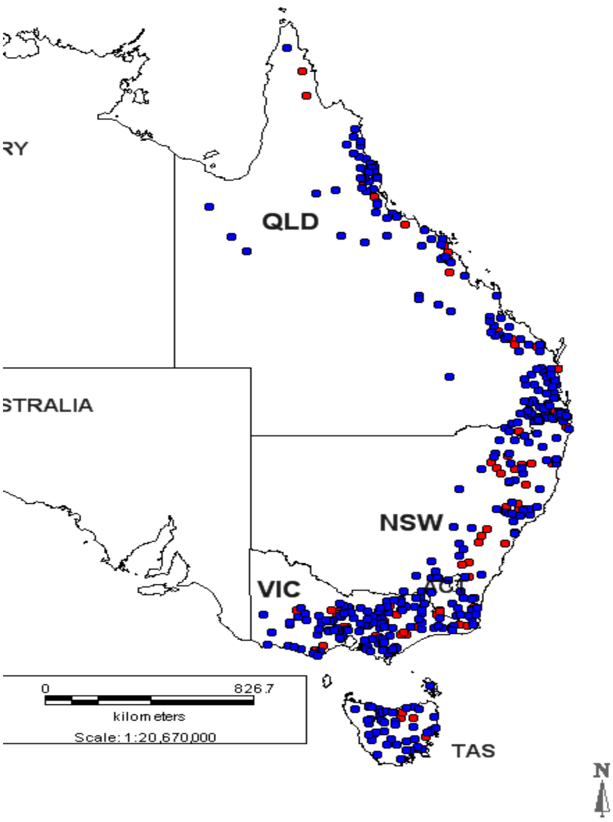

Figure 2 Location of study catchments (Blue colour represents training catchments and red colour represents test catchments)

For the CANFIS model development, model catchments are clustered based on model variables (catchment area and rainfall intensity) into several class values in layer 1 to build up fuzzy rules, and each fuzzy rule was constructed through several parameters of membership function in layer 2. A fuzzy inference system structure was generated from the data using subtractive clustering. This was used in order to establish the rule base relationship between the inputs.

In order to obtain the best CANFIS models, the mean squared error was used as 'fitness function', which was based on the observed and predicted flood quantiles; the training was undertaken to minimise this error. Lavenberg-Marquardt (LM) method was used as the training algorithm to minimize the mean squared error. CANFIS model was trained with a set of input and output data to adjust the weights and to minimize the mean squared error between the desired outputs and the model outputs. The testing data set was selected randomly to produce a reasonable sample of different catchment types and sizes. Two inputs (A, I_{tc_ARI}) were used in one input layer and one output layer with one output (Q_{pred}).

In the case of CANFIS, the Bell membership function and the TSK neuro fuzzy model are used, as this type of fuzzy model best fits the multi-input single output system (Aytek, 2009). LM algorithm is used for the training of CANFIS model. The stopping criterion for the training of the CANFIS network is a maximum of 1000 epochs and training is set to terminate when the mean squared error (MSE) drops to 0.01 threshold value.

In QRT, flood quantiles (Q_T) are regressed against catchment characteristics (predictor variables) (X) using the power form equation (Thomas and Benson, 1970; and Stedinger and Tasker, 1985; Haddad and Rahman, 2012):

$$Q_T = \beta_0 X_1^{\beta_1} X_2^{\beta_2} \ldots \tag{1}$$

where regression coefficients βs are generally estimated by using an Ordinary Least Square (OLS) or Generalized Least Square (GLS) regression. In this study, in developing the QRT, both the dependent and independent variables were log-transformed to linearise Equation 5. In this study an OLS regression was adopted to develop prediction equations for each of the six flood quantiles using two predictor variables (A, I_{tc_ARI}). The data sets for building and independent testing of the QRT model were the same as with the ANN and GEP models. The MINITAB 14 software was used to develop the QRT models.

Following evaluation statistics were used for model assessment and comparison:

- Ratio between predicted and observed flood quantiles:

$$\text{Ratio } (r) = \frac{Q_{predicted}}{Q_{observed}} \tag{2}$$

- Relative error (RE):

$$\text{RE } (\%) = \text{Abs}\left[\frac{\left(Q_{pred} - Q_{obs}\right)}{Q_{obs}} \times 100\right] \tag{3}$$

Where Q_{pred} is the flood quantile estimate from the ANFIS, CANFIS and QRT models, Q_{obs} is the at-site flood frequency estimate obtained from LP3 distribution using a Bayesian parameter fitting procedure (Kuczera, 1999).

6 Results

Table 2 summarises the median ratio values for the models based on CANFIS and QRT. In case of CANFIS based model, the best results are obtained for Q_5 and Q_{50} with median ratio values of 0.95 and 0.93, respectively. The overall values range from 0.79 to 2.81. All the results based on CANFIS model are within acceptable range except for Q_2 that shows a significant over prediction. The CANFIS based model shows remarkable improvement for ARIs. The QRT shows 19% to 28% overestimation in case of Q_{50} and Q_{100}. Overall, the CANFIS based RFFA model outperforms the QRT based RFFA models in terms of median ratio values.

Table 3 summarises the median relative error values for the CANFIS and QRT. In terms of median relative error, the CANFIS based model provides values from 34% to 59% except for Q_2 which is 180%. In terms of relative error, the CANFIS based model either outperforms the QRT or provides competitive results except for Q_2. Best value is obtained for 20 years ARI which is 34% for CANFIS and 42% for QRT based RFFA model. Although both models provide competitive results, if the RE value for Q_2 is ignored CANFIS based RFFA model can be given a preference over QRT based model for regional flood estimation.

Figure 4 shows the plot of observed and predicted flood quantiles for 20 years ARI from the CANFIS based model, which shows a good fit for the validation data sets. Similar results were found for other ARIs. It should be noted that for majority of the cases the model prediction match very well with the observed quantiles, but there are notable differences in few cases, which is not unexpected in RFFA for Australia as found by similar other studies (e.g. Haddad et al., 2011; Haddad and Rahman, 2012 and Haddad et al., 2011).

Now, the better of the two models i.e. CANFIS is compared with BGLS-QRT-ROI method in Table 3. These BGLS-QRT-ROI relative error values were obtained from Project 5 Stage II report by Rahman et al. (2012). It is found that overall the BGLS-QRT-ROI provides better results than the CANFIS model; however, the CANFIS model provides results which are comparable to the BGLS-QRT-ROI in few cases. For Q_2, CANFIS based model produces higher relative error values for all the states. The results obtained from CANFIS based model are comparable to the QRT-ROI for Victoria. Hence, it can be concluded that the linear QRT model integrated with BGLS and ROI generally outperforms the CANFIS based non-linear RFFA models for eastern Australia.

Table 1 Median Q_{pred}/Q_{obs} ratio values for different models

ARI (years)	CANFIS	QRT
2	2.81	1.15
5	0.95	1.06
10	0.79	1.35
20	1.18	1.13
50	0.93	1.19
100	1.31	1.28

Table 2 Median relative error (%) values for different models

ARI (years)	CANFIS	QRT
2	180	65
5	48	45
10	51	57
20	34	42
50	59	48
100	42	51

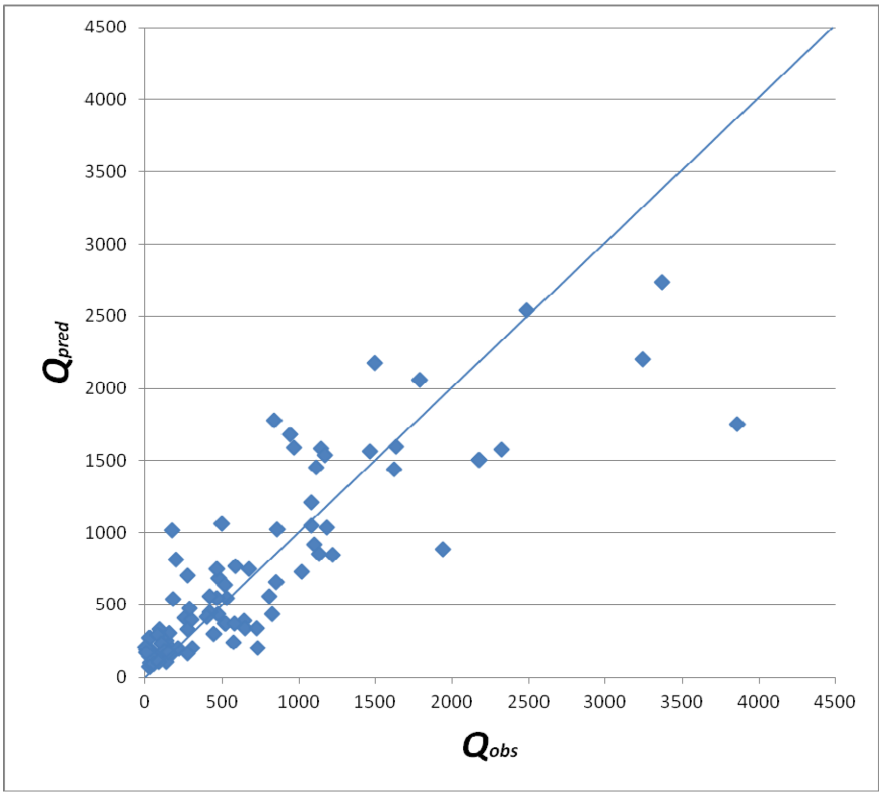

Figure 3 Plot of observed (target) and predicted (output) quantiles for Q_{20} (CANFIS based model) for 90 independent test catchments

Table 3 Median relative error (%) values for the CANFIS model and best QRT model from ARR Project 5 (BGLS-QRT-ROI, Rahman et al., 2012)

ARI (Years)	CANFIS	BGLS-QRT-ROI (from Rahman et al., 2012)			
		NSW+ ACT	VIC	QLD	TAS
2	188	40	37	39	30
5	48	36	35	32	25
10	51	36	35	31	24
20	34	31	33	29	27
50	59	32	40	31	28
100	42	35	44	31	29

6 Conclusions

The paper examines the application of Co-Active Neuro Fuzzy Inference System (CANFIS) based regional flood frequency analysis (RFFA) method in eastern states of Australia. The data from four states (NSW, VIC, TAS and QLD) were combined to form one region consisting of 452 stations. The

CANFIS presents better model than the OLS-based QRT method where the CANFIS shows the median relative error values in the range of 34% to 59% (except for Q_2) and median ratio of predicted and observed flood quantiles in the range of 0.79 to 1.31 (except for Q_2). This study also compares the results obtained from the CANFIS with the BGLS-QRT-ROI method (ARR Project 5 model) and it has been found that the BGLS-QRT-ROI model outperforms the CANFIS based RFFA models. This is important to note that the results obtained from BGLS-QRT-ROI model are based on individual states whereas the results obtained by CANFIS are obtained when the data from all states are combined to form one region. Hence, the ANFIS model is likely to perform better when the larger data set is used. This model may also be used in other parts of the world with larger and good quality data set.

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References

Acreman MC, Sinclair CD (1986). Classification of drainage basins according to their physical characteristics and application for flood frequency analysis in Scotland, *Journal of Hydrology,* 84(3), 365-380.

Alecsandru C and Ishak S (2004). Hybrid model-based and memory-based traffic prediction system. Transportation Research Record*: Journal of the Transportation Research* Board 1879(1), 59-70.

Aytek A (2009). Co-Active neuro-fuzzy inference system for evapotranspiration modelling. *Soft Computing,* 13(7), 691-700.

Aziz K, Rahman A, Fang G, Shreshtha S (2013). Application of Artificial Neural Networks in Regional Flood Frequency Analysis: A Case Study for Australia, *Stochastic Environment Research & Risk Assessment.* DOI 10.1007/s00477-013-0771-5.

Aziz K, Rahman A, Fang G, Haddad K, Shrestha S (2010). Design flood estimation for ungauged catchments: Application of Artificial Neural Networks for eastern Australia. World Environment and Water Resource Congress, ASCE, Providence, Rhodes Island, USA.

Aziz K, Rahman A, Fang G, Shrestha S (2011). Artificial Neural Networks Based Regional Flood Estimation Methods for Eastern Australia: Identification of Optimum Regions. 33rd Hydrology and Water Resources Symposium, 26 June-1 July 2011, Brisbane, Australia.

Bates BC, Rahman A, Mein RG, Weinmann PE (1998). Climatic and physical factors that influence the homogeneity of regional floods in south-eastern Australia. *Water Resources Research,* 34(12), 3369-3382.

Benson MA (1962). Evolution of methods for evaluating the occurrence of floods. U.S. Geological Surveying Water Supply Paper, 1580-A, 30pp.

Blöschl G, Sivapalan M (1997). Process controls on regional flood frequency: Coefficient of variation and basin scale, *Water Resources Research,* 33, 2967-2980.

Burn DH (1990). Evaluation of regional flood frequency analysis with a region of influence approach, *Water Resources Research,* 26(10), 2257-2265.

Cunnane C (1988). Methods and merits of regional flood frequency analysis, *Journal of Hydrology,* 100, 269-290.

Dalrymple T (1960). Flood frequency analyses. *U.S. Geological Survey Water Supply Paper* 1543-A, 11-51.

Deka P Chandramouli V (2003). A fuzzy neural network model for deriving the river stage–discharge relationship. *Hydrol Sci J* 48(2):197–209.

Griffis VW, Stedinger JR (2007). The use of GLS regression in regional hydrologic analyses. *Journal of Hydrology,* 344, 82-95.

Guse B, Thieken AH, Castellarin A, Merz B (2010). Deriving probabilistic regional envelope curves with two pooling methods, *Journal of Hydrology,* 380(1-2), 14-26.

Haddad K, Rahman A, Weinmann PE, Kuczera G, Ball JE (2010). Streamflow data preparation for regional flood frequency analysis: Lessons from south-east Australia. *Australian Journal of Water Resources,* 14(1), 17-32.

Haddad K, Rahman A, Stedinger JR (2011). Regional Flood Frequency Analysis using Bayesian Generalized Least Squares: A Comparison between Quantile and Parameter Regression Techniques, *Hydrological Processes,* 25, 1-14, DOI: 10.1002/hyp.8189.

Haddad K and Rahman A (2011). Regional flood estimation in New South Wales Australia using Generalised Least Squares Quantile Regression. *Journal of Hydrologic Engineering,* ASCE, 16, 11, 920-925.

Haddad K, Rahman A (2012). Regional flood frequency analysis in eastern Australia: Bayesian GLS regression-based methods within fixed region and ROI framework – Quantile Regression vs. Parameter Regression Technique, *Journal of Hydrology,* (2012), doi:10.1016/j.jhydrol.2012.02.012.

Horikawa S, Furuhashi T, Uchikawa Y (1992). On fuzzy modelling using fuzzy networks with back-propagation algorithm. IEEE Trans, Neural Network, 3(5), 801-806.

Hosking JRM, Wallis JR (1993). Some statistics useful in regional frequency analysis, *Water Resources Research,* 29(2), 271-281.

Institution of Engineers Australia (I. E. Aust.) (1987, 2001). Australian Rainfall and Runoff: A Guide to Flood Estimation. Editor: D.H. Pilgrim, Vol.1, I. E. Aust., Canberra.

Ishak E, Haddad K, Zaman M, Rahman A (2011). Scaling property of regional floods in New South Wales Australia, Natural Hazards, 58, 1155-1167. DOI: 10.1007/s11069-011-9719-6.

Jacquin AP, Shamseldin AY, 2006. Development of rainfall– runoff models using Takagi–Sugeno fuzzy inference systems. *Journal of Hydrology* 329, 154–173.

Jang JSR (1993). ANFIS: adaptive-network-based fuzzy inference system. IEE Transactions on Systems, Man and Cybernetics, 23(3), 665-685.

Jang JSR, Sum CT, Mizutani E (1997). Neuro-fuzzy and soft computing, Prentice-Hall, New Jersey.

Jin Y, Jiang J, Zhu J (1995). Neural network based fuzzy identification and its applications to modeling and control of complex systems. IEEE Trans Syst Man Cybern 25(6), 990–997.

Jiapeng H, Zhongmin L, Zhongbo Y (2003). A modified rational formula for flood design in small basins, *Journal of the American Water Resources Association,* 39(5), 1017-1025.

Keller JM, Krishnapuram R, Rhee FCH (1992a). Evidence aggregation networks for fuzzy logic inference. IEEE Trans, Neural Network, 3(5), 761-769.

Keller JM, Yager RR, Tahani H (1992b). Neural network implementation of fuzzy logic rules with neural networks. International *Journal of Approximate Reasoning,* 6, 221-240.

Kjeldsen TR, Jones D (2009). An exploratory analysis of error components in hydrological regression modelling. *Water Resources Research,* 45, W02407, doi:10.1029/2007WR006283.

Kjeldsen TR, Jones DA (2010). Predicting the index flood in ungauged UK catchments: On the link between data-transfer and spatial model error structure, *Journal of Hydrology,* 387(1-2), 1-9, doi:10.1016/j.jhydrol.2010.03.024.

Kisi O (2005). Suspended sediment estimation using neuro-fuzzy and neural network approaches. *Hydrol Sci J* 50(4):683–696.

Kosko B (1992). Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence., Prentice-Hall, Inc., Englewood Cliffs, NJ.

Kuczera G (1999). Comprehensive at-site flood frequency analysis using Monte Carlo Bayesian inference. *Water Resources Research,* 35, 5, 1551-1557.

Loukas YL (2001). Adaptive neuro-fuzzy inference system: an instant and architecture-free predictor for improved QSAR studies. *Journal of Medicinal Chemistry,* 44, 2772–2783.

Maguire LP, Roche B, McGinnity TT, McDaid LJ (1998). Predicting a chaotic time series using a fuzzy neural network. Information Sciences, 112, 125–136.

Mulvany TJ (1851). On the use of self-registering rain and flood gauges, Inst. Civ. Eng. (Ireland) Trans, 4(2), 1-8.

Nathan RJ, McMahon TA (1990). Identification of homogeneous regions for the purpose of regionalisation, *Journal of Hydrology,* 121, 217-238.

Nayak PC, Sudheer KP et al. (2004). A neuro-fuzzy computing technique for modelling hydrological time series. *Journal of Hydrology,* 291(1–2), 52-66.

NERC (1975). Flood studies report, 5 Volumes, Natural Environment Research Centre (NERC), London.

Nourani V, Kisi O et al. (2011). Two hybrid Artificial Intelligence approaches for modelling rainfall–runoff process. *Journal of Hydrology,* 402(1–2), 41-59.

Ouarda TBMJ, Ba KM, Diaz-Delgado C, Carsteanu C, Chokmani K, Gingras H, Quentin E, Trujillo E, Bobee B (2008). Intercomparison of regional flood frequency estimation methods at ungauged sites for a Mexican case study, *Journal of Hydrology,* 348, 40-58.

Pallard B, Castellarin A, Montanari A (2009). A look at the links between drainage density and flood statistics, Hydrology and Earth System Sciences (HESS), 13, 1019-1029.

Palit AK, Popovic D (1999). Forecasting chaotic time series using neurofuzzy approach. In: Proc IEEE IJCNN Washington DC, vol 3, pp 1538–1543.

Palit AK, Popovic D (2000). Intelligent processing of time series using neuro-fuzzy adaptive genetic approach. In: Proc. of IEEE-ICIT Conference, Goa, India, vol 1, pp 141–146.

Palit AK, Popovic D (2005). Computational intelligence in time series forecasting; theory and engineering applications. Springer, Heidelberg, 363 p.

Pandey GR, Nguyen VTV (1999). A comparative study of regression based methods in regional flood frequency analysis. *Journal of Hydrology,* 225, 92-101.

Pegram GGS, Parak M (2004). A review of the regional maximum flood and rational formula using geomorphological information and observed floods, *Water South Africa,* 30(3), 377-392.

Principe JC, Euliano NR, Lefebvre, WC (2000). Neural and Adaptive Systems, John Wiley & Sons, Inc.

Rao AR, Srinivas VV (2008). Regionalization of Watersheds: An Approach Based on Cluster Analysis, Springer.

Roger JSCTS, Eiji M (1997). Neuro-fuzzy and soft computing, Englewood Cliffs, Prentice Hall.

Rahman A, Bates BC, Mein RG, Weinmann PE (1999). Regional flood frequency analysis for ungauged basins in south–eastern Australia. *Australian Journal of Water Resources,* 3, 2, 199-207.

Rahman A, Haddad K, Zaman M, Kuczera G, Weinmann PE (2011). Design flood estimation in ungauged catchments: A comparison between the Probabilistic Rational Method and Quantile Regression Technique for NSW. *Australian Journal of Water Resources,* 14, 2, 127-137.

Shafie EA, Taha RM, Noureldin A (2007). A neuro-fuzzy model for inflow forecasting of the Nile river at Aswan high dam,Water Res. Management. doi:10.1007/s11269-006-9027.

Shiri J and Kisi O (2010). Short-term and long-term streamflow forecasting using a wavelet and neuro-fuzzy conjunction model. *Journal of Hydrology,* 394(3), 486-493.

Shu C, Ouarda TBMJ (2008). Regional flood frequency analysis at ungauged sites using the adaptive neuro-fuzzy inference system, *Journal of Hydrology,* 349, 31-43.

Stedinger JR, Tasker GD (1985). Regional hydrologic analysis - 1. Ordinary, weighted and generalized least squares compared, *Water Resources Research,* 21, 1421-1432.

Tabari H, Talaee PH, Abghari H (2012). Utility of coactive neuro-fuzzy inference system for pan evaporation modeling in comparison with multilayer perceptron. Meteorol Atmos Phys, (2012) 116:147–154.

Takagi H, Hayashi I (1991). Neural Network driven fuzzy reasoning, *International Journal of Approximate Reasoning,* 5(3), 191-212.

Takagi T, Sugeno M (1983). Derivation of fuzzy control rules from human operator's control actions. Proceedings of the IFAC symposium on fuzzy information, knowledge representation and decision analysis.

Takagi T, Sugeno M (1985). Fuzzy identification of systems and its applications to modeling and control. Systems, Man and Cybernetics, IEEE Transactions, (1), 116-132.

Talei A, Chua LHC et al. (2010a). A novel application of a neuro-fuzzy computational technique in event-based rainfall–runoff modelling. Expert Systems with Applications 37(12), 7456-7468.

Talei A, Chua LHC et al. (2010b). Evaluation of rainfall and discharge inputs used by Adaptive Network-based Fuzzy Inference Systems (ANFIS) in rainfall–runoff modeling. *Journal of Hydrology* 391(3): 248-262.

Tasker GD, Eychaner JH, Stedinger JR (1986). Application of generalised least squares in regional hydrologic regression analysis. US Geological Survey Water Supply Paper 2310: 107–115.

Thomas DM, Benson MA (1970). Generalization of streamflow characteristics from drainage-basin characteristics, U.S. Geological Survey Water Supply Paper 1975, US Governmental Printing Office.

Turan ME, Yurdusev MA (2009). River flow estimation from upstream flow records by artificial intelligence methods, *Journal of Hydrology,* 369, 71–77.

Zrinji Z, Burn DH (1994). Flood frequency analysis for ungauged sites using a region of influence approach, *Journal of Hydrology,* 153(1-4), 1-21.