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Improving Reliability of Hydrological Flow Estimation using Hydroinformatics Approach

By Md Atiquzzaman

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Doctor of Philosophy

under the supervision of
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CERTIFICATE OF AUTHORSHIP

I certify that the work in this thesis has not previously been submitted for any degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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LIST OF PUBLICATIONS

Journal Publications:

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- Atiquzzaman, M and Kandasamy, J. (2018). "Robustness of Extreme Learning Machine in the prediction of hydrological flow series.", Computers & Geosciences Journal, 120, pp. 105-114, http://dx.doi.org/10.1016/j.cageo.2018.08.003.
- Atiquzzaman, M and Kandasamy, J. (2019). "Kernel and node based extreme learning machines to predict hydrological time-series.", Paper prepared for the submission to a journal.

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NOMENCLATURE

$(Q_m)_t$ = "Modelled flow at time t";

$(Q_o)_t$ = "Observed flow at time t";

a_i = "Weight vector connecting the i^{th} hidden node and the input variables";

b_i = "Bias of the i^{th} hidden node";

t_j = "Target at time j";

y_j = "Output at time j";

$\Delta w_{ij}(s)$ = "Weight adjustment between node j in layer s and node i in layer (s-1)";

$F_j(s)$ = "Output of the neuron j in layer s";

H = "Hidden layer output matrix";

$H^{'}$ = "Moore-Penrose generalized inverse of hidden layer output matrix";

L = "Number of random hidden nodes;

Qgp = "Predicted flow by GP";

Qnam = "Predicted flow by NAM";

Q_t = "Flow at time t";

R_t = "Rainfall at time t";

$w_{ij}(s\text{-}1)$= "Weight in the link between neuron j in layer s and neuron i in layer (s-1)";

$x_{\mathrm{i}}(s)$ = "Iinput of neuron j from previous layer's neuron I";

$x_i(s\text{-}1)$ = "Input from neuron i in layer s-1";

$Y_j(s)$ = "Weighted sum for neuron j in layer s";

β_i = "Weight connecting the hidden node and the output node";

$g(x)$ = "Activation function (example, sigmoidal function)";

$\delta_j(s)$ = “Local or instantaneous gradient”; and

ε = “Error Value”.

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ABSTRACT

Application of hydroinformatics tools in water resources has been very common in water industry due to the rapid advancement of digital computer. Over the last few decades, there are several tools have been developed and applied with success. The most commonly used Artificial Intelligence (AI) based hydroinformatics tools in hydrology are Genetic Programming (GP), Artificial Neural Network (ANN), Fuzzy Logic (FL), Standard Chaos Technique, Inverse Approach, Support Vector Machine (SVM) and Evolutionary Computation (Genetic Algorithm (GA), Shuffled Complex Evolution (SCE), Particle Swarm Optimization (PSO), Ant Colony Optimization Algorithm (ACOA)) based AI techniques including SVM (EC-SVM). These tools including Genetic Programming (GP) have been proven to be efficient in prediction of flows from event based rainfalls series.

The driving factor behind the application of hydroinformatics tools was to ease the complex numerical modelling process. In principal, both conceptual and physically based distributed models require a large number of parameters such as catchment characteristics, losses, flow paths, meteorological and flow data. The values of some of these parameters are evaluated through calibration. The calibration process of complex models may be cumbersome and requires considerable effort and experience particularly when the number of the calibration parameters is large. Even though the model is calibrated, the application of the parameters is catchment specific. Model parameters from one catchment may not be representative for the other catchment. In this case, hydroinformatics tools like GP and/or ANN can be used where no parameters associated with catchment and soil characteristic are necessary. GP has been successfully applied for calibration of numerous event based rainfall and runoff models. However, application of GP for the prediction of long term time series is

limited.

The application of GP for long term runoff prediction from a dam catchment is demonstrated. The model is developed and calibrated for a dam catchment located in New South Wales, Australia. The calibration shows excellent agreement between the observed and simulated flows recorded over thirty years and the results are better than traditional Sacramento model and ANN. GP is also linked to MIKE11-NAM to build a hybrid model. The concept of this hybrid model is to fill the data gaps and generate long term (100 years) predictions. The calibrated GP model is then applied for the assessment of two future rainfall scenarios where future hundred year flows are predicted using rainfall input generated from different assumed climatic conditions. The analysis results provide some basis for making future water management plans including water supply from alternative sources. While the application was successful and produced better results, it was found that GP suffered from computational overhead in the learning process from input data. To improve the prediction accuracy, relatively new AI technique, called Extreme Learning Machine (ELM) is proposed.

ELM is applied to partly overcome the slow learning problems of GP and ANN and to predict the hydrological time-series very quickly. ELM, which is also called single-hidden layer feed-forward neural networks (SLFNs), is able to well generalize the performance for extremely complex problems. ELM randomly chooses a single hidden layer and analytically determines the weights to predict the output. The ELM method was applied to predict hydrological flow series for the Tryggevælde Catchment, Denmark and for the Mississippi River at Vicksburg, USA. The results confirmed that ELM's performance was similar or better in terms of Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE) compared to ANN and other previously published techniques, namely

Evolutionary Computation based Support Vector Machine (EC-SVM), Standard Chaotic Approach and Inverse Approach. In this analysis, the sensitivity of ELM's input parameters on the prediction accuracy were not investigated. The influence of input parameters was then analysed to further improve the model results.

The robustness of ELM's performances based on number of lagged input variables, the number of hidden nodes in ELM, higher lead days prediction and extrapolation capability using four goodness-of-fit measures is demonstrated. The results show that (1) ELM yields reasonable results with all combinations of lagged input variables (flows) for 1-day lead prediction. The minimum errors were obtained when 4-day lagged flows were applied as input variables; (2) ELM produced satisfactory results very rapidly for any number of hidden nodes ranging from ten to six thousand in the hidden layer. The time required to train ELM varies from less than a second to two minutes as only single iteration is required. A larger number of hidden nodes generally gives slightly better results; (3) ELM generated reasonable results for higher number of lead days (second and third) predictions; (4) ELM was able to extrapolate when the highest magnitude of input variables were excluded from training dataset; (5) ELM was shown to be computationally much faster and capable of producing better results compared with GP and EC-SVM for prediction of flow series from the same catchment. This demonstrates ELM potential for forecasting real-time hydrological time-series. This analysis was based on node based ELM (NELM) method. The performance of ELM is further improved by introducing Kernel function (KELM) in the learning process in the subsequent analysis.

In addition to node based ELM, Kernel based ELM (KELM) is also applied. The performance of KELM was also compared against hidden node based ELM (NELM). The predictive capabilities of both NELM and KELM were investigated using data from three different catchments located in three different climatic regions (Tryggevælde catchment, Denmark, Mississippi River at Vicksburg, USA and Duckmaloi Weir catchment, Australia). The results were compared with those obtained with Genetic Programming (GP) and evolutionary computation based Support Vector Machine (EC-SVM), the later obtained from literature. The results show that KELM predictions were better than NELM, GP and EC-SVM. KELM ran faster than any other model.

ELM's fast learning capability from a training dataset for the prediction of hydrological flows means that it would be more suitable for on-line and real-time applications where quick processing time is important or vital. The study demonstrates ELM's ability for rapid prediction and has potential application in real-time forecasting and in water resources planning and management.

CHAPTER 1

INTRODUCTION

1. INTRODUCTION

1.1. General

Water is one of the most valuable natural resources in human life. The rapid growth of the population is impacting the water cycle, rainfall and the catchment characteristics. Understanding this water movement, rainfall pattern and influence of catchment response to the rainfall has been one of the major research fields for many decades as hydrological flows generated from rainfall is paramount important for water resources planning and management. For example, heavy rainfall from a developed or urban catchment is a major problem in many parts of the world. The impacts of this urban flooding include public health hazards, deaths, and tremendous economic and environmental damages. The impact of high flows in rural catchment also causes significant impacts to crop, stock and domestic animals. In many countries in Asia, people constantly face minor to catastrophic floods that last even several months. In Bangladesh, flood is an annual phenomenon. Each year, the flood water may cover 75% of the area and resulting huge economic damage. In August 2017, heavy rainfall in India and Nepal resulted in extensive flooding on rivers downstream in Bangladesh. The city of Mumbai experienced a flood in 2002 when all the basic needs for human beings like electric supply, telephone were shut down (Boonya-Aroonnet, 2002). The response to this flood issue is to establish an improved flow forecasting technique for flood mitigation and floodplain management.

Development of conceptual rainfall-runoff models based on engineering hydrology is applied to forecast the flows. In principal, these models generalise the complex hydrological cycle and predict the flow from watershed. Various conceptual methods were developed for the analysis of rainfall-runoff model, with the advent of high performance computers. Some of the traditional methods include MIKE11 NAM (Nillsen and Hansen, 1973), Sacramento Model (Burnash, 1995), Tank Model (Sugawara, 1995), SWMM (Huber et al., 1988; Liong et al., 1991), XPRafts, RORB, URBS and WBNM. These models are used by the water manager for flow forecasting, flood control, impact of urbanisation, management of river operation and reservoir operations. Flow forecasting is essential for reservoir/dam operation as the operators make the planned release decisions based on this forecast to meet the requirement for hydroelectric power generation, irrigation water demand, town water supply etc. For multipurpose reservoir system, inflow prediction plays a significant role in the management as hydroelectric power generation that requires high head water level whereas flood control requires the storage level to be as low as possible. However, the accuracy of the flow predictions (peak as well as hydrograph) provided by the hydrologist is often not enough. Hydrologist needs to understand the level of details of hydrological cycle included in the model. Some parameters must be adjusted to match the model output to those observed from the catchment of interest. These models also need periodic recalibration as the catchment characteristics (topography) changes so rapidly. Modification of model parameters to reflect catchment changes and to predict the flow, is needed within shortest possible time especially during the management of flood. Fine tuning of the model parameters is usually performed by trial-and-error approach. The performance depends upon the users' intuition, experience, skill, and knowledge. Manual approach is inefficient and large number of repetitive simulations is required to arrive at a satisfactory solution particularly for large catchment like Mississippi River (Ibrahim and Liong, 1992). In such real-time forecasting applications, where time, along with high prediction accuracy, is crucial, a much simpler and faster data-driven model that yields accurate runoff from rainfall with shortest possible time is therefore highly desirable.

1.2. Statement of the Problem

Determination of catchment response (hydrological flow) due to a rainfall event is very important especially from a dam catchment for efficient allocation of water in the future to customers/irrigators or management of flood flows or tributary inflows to the river system downstream of the dam. Establishing a noble methodology in determining the accurate magnitude of runoff or inflows to the dam or flood resulting from heavy rainfall has been a research topic since last many decades. Hence, conceptual rainfall-runoff model has been very popular. However, calibration of this model to improve the accuracy of the yield is still under research. Instead of using the cumbersome and computationally long trial-and-error approach, many Artificial Intelligence (AI) based machine learning techniques (data driven modelling) solely or together with a family of population-evolution based search algorithms known as evolutionary algorithms (EAs) have been extensively considered in this field. However, very few of the machine learning techniques have received widespread acceptance in the commercial applications. This is because most techniques require high number of function evaluation and computational time to solve even a simple problem. These techniques may not be suitable during a flood event as quick response from the model is required. The present study applies a machine learning method (data driven modelling technique) to increase the robustness in obtaining reasonably accurate runoff/flood from rainfall events.

1.3. Objectives of this Study

The objective of this study is to explore and enhance the use of hydroinformatics tool including machine learning technique in rainfall-runoff modelling (data driven modelling technique), and for real-time flood forecasting. This study also aims to analyse the sensitives of the input parameters and improve the accuracy of the model. Thus, the main contribution of this research can be stated as below:

(i) Evaluate the application of Genetic Programming (GP) for improving the forecasting accuracy of rainfall-runoff model and compare the performance against Artificial Neural Network (ANN) technique.
(ii) Improve the accuracy of traditional conceptual rainfall-runoff model (MIKE11-NAM) by linking with GP if the input data is erroneous or missing.
(iii) Evaluate the performance of GP model for different long term rainfall scenarios where the rainfall pattern is changed over a long period.
(iv) Demonstrate the performance of a relatively new machine learning technique, called Extreme Learning Machine (ELM) in the prediction of hydrological flows
(v) Demonstrate the superiority of ELM's prediction accuracy over other widely available techniques such as Support Vector Machine (SVM), Evolutionary Computation based SVM (EC-SVM), GP, ANN and other techniques.
(vi) Demonstrate the sensitivities of the ELM's (node base ELM) input parameters in the prediction of real-time flood flows.
(vii) Demonstrate the applicability of ELM for up to higher lead-days predication.
(viii) Evaluate the performance of extreme flood prediction when the extreme values are removed from training dataset.
(ix) Investigate the performance ELM using Kernel function (Kernel based ELM) and compare the performance against node based ELM.

The overall flow chart illustrating the overall methodology adopted in the current study is shown in Figure 1. 1.

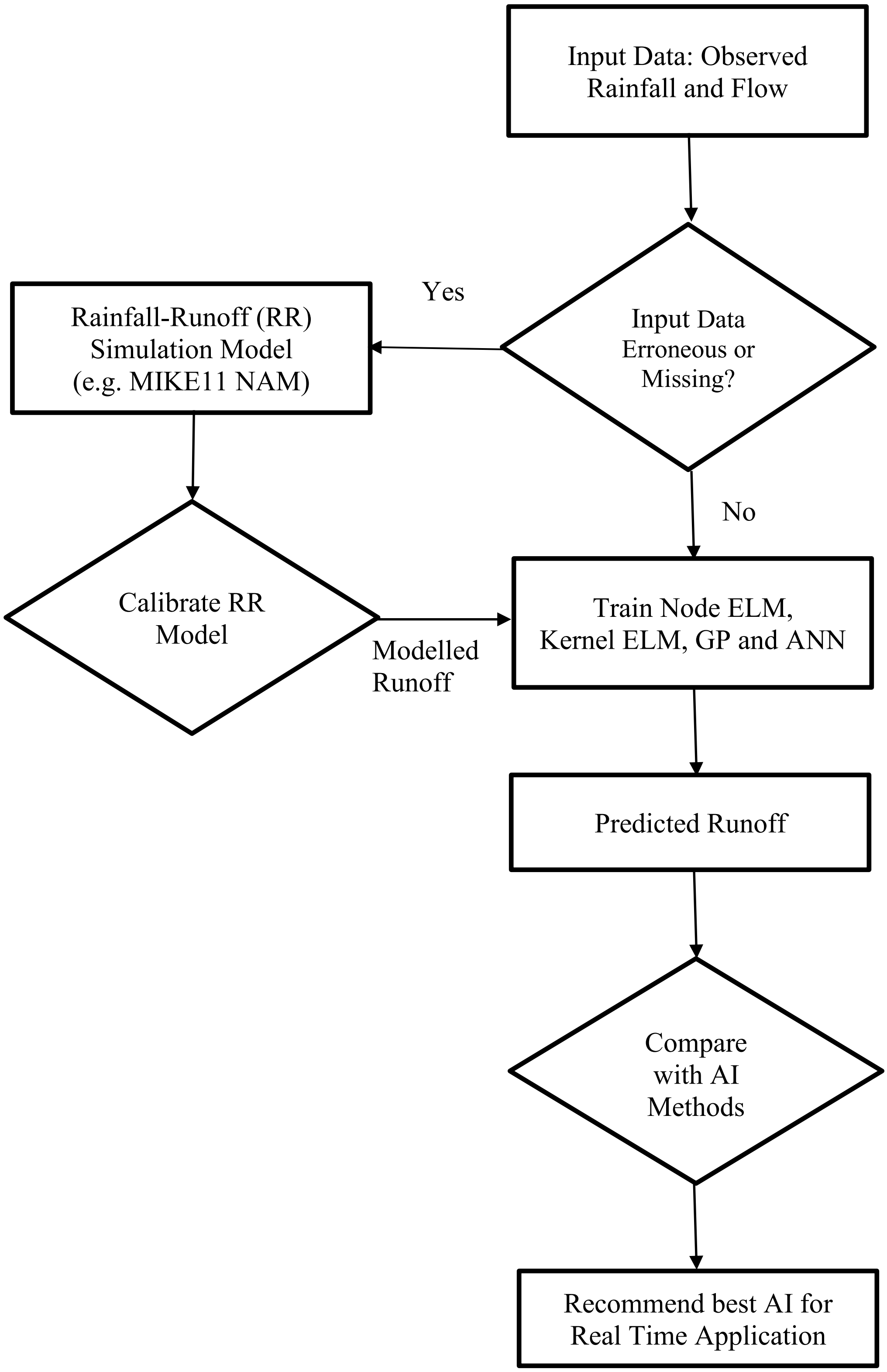


Figure 1. 1: Flow Chart Illustrating the Overall Methodology Adopted in the Current Study.

1.4. Scope of this Study

This study includes the following scope of works to understand the limitations (e.g. prediction accuracies, run time etc) of some of the existing hydroinformatic approaches (e.g. Artificial Intelligence techniques) and how these limitations can be improved using a relatively new machine learning technique.

- Literature review.
- Genetic Programming (GP), Artificial Neural Network (ANN) and Extreme Learning Machine (ELM) will be used for rainfall-runoff modelling/flood forecasting.
- Historical rainfall and lagged observed flow will be used to train GP, ANN, and ELM.
- Traditional rainfall-runoff model using MIKE11-NAM will be developed and calibrated using observed flow.
- NAM output and historical rainfall be used as input to train GP for flood forecasting,
- The performance of GP will be improved using base flow parameter.
- Rainfall scenarios using long term historical rainfall time series (100 year) will be generated by extending the drought season and fed into the GP.
- Future rainfall time series generated by varying the rainfall magnitude will be used for flood forecasting for next 100 years.
- GP, ANN and ELM will be applied for the prediction real-time flows from three catchments in Denmark, USA and Australia.
- Two types of ELM (node and Kernel based) techniques will be investigated for the prediction of flood flows and compared with other techniques.
- The best method is recommended for the real-time application as a flood forecasting tool.

1.5. Organisation of the Thesis

Chapter 2 describes the previous research works in the application of evolutionary algorithm and data driven modelling techniques and the problems associated with their application in rainfall-runoff modelling.

Chapter 3 describes the application of Genetic Programming (GP) and Artificial Neural Network (ANN) in predicting flows using the rainfall and past historical observed lagged flow. The long-term (>100years) prediction of flows is also described using hybrid approach where GP is linked with MIKE11-NAM.

Chapter 4 demonstrates the use of a relatively new Artificial Intelligence (AI) technique called, Extreme Learning Machine (ELM) for prediction hydrological flow series. The performance of ELM (node based) is compared with other widely used data driven modelling techniques including Standard Chaos Technique, Inverse Approach, ANN and Evolutionary Computation (EC) based Support Vector Machine (SVM).

Chapter 5 presents the improvement of node based ELM's performance by fine-tuning the input parameters. The sensitivities of input parameters on the flow prediction, higher lead days prediction and ELM's extrapolation capability are also described in this chapter. The performances of some of the best models are compared with GP and EC-SVM.

Chapter 6 applies the application of improved ELM called Kernel based ELM and compares the performance and run time against node based ELM, GP and EC-SVM.

Chapter 7 describes the conclusion of this research works and recommends for further studies.

CHAPTER 2

LITERATURE REVIEW

2. Literature Review

2.1. Introduction

The need for hydrological flow estimation and prediction is quite obvious to complement field measurement especially when the catchment is very large and has scarcity of hydrologic record. Gathering data by installing measurement equipment is sometimes difficult in terms of cost and time as the flow estimation model requires long period of hydrological information. This leads to the analysis of hydrologic response of the catchment to future rainfall occurred on the catchment. Accordingly, research interests have been concentrating on the development of efficient hydroinformatic approach to estimate the flows yield from the catchment.

In this chapter, various techniques known in the rainfall-runoff model are first reviewed especially the applications of conceptual models and data driven models. Review on some recently emerging evolutionary techniques that were linked with data driven model useful to solve complex problems and improve the prediction accuracy is also presented.

2.2. Conceptual Techniques in Rainfall-Runoff Model

In hydrological process, rainfall is converted to flows for the management of catchment. The flow estimation process from the rainfall is reported to be highly non-linear and is not easy to represent in the simple model (Singh, 1964; Kulandaiswamy and Subramanian, 1967; Chiu and Huang, 1970). Usually, two approaches were applied, namely conceptual approach and black box approach (Young and Wallis, 1985; Singh, 1988).

In the analysis of rainfall-runoff model, various conceptual methods were developed with the advent of high performance computational techniques. Such methods include MIKE11 NAM (Nielsen and Hansen, 1973), Sacramento Model (Burnash, 1995), Tank Model (Sugawara, 1995), SWMM (Huber et al., 1988), XPRafts, RORB, URBS and

WBNM. In principal, conceptual methods generalise the hydrological cycle and predict the flow from watershed. Some of these also take into account the soil moisture interconnection with hydrologic cycle (Duan et al., 1992). However, depending on the level of details of hydrological cycle included in the model, some parameters must be adjusted in order to match model output to those observed from the catchment of interest. Fine tuning of these parameters is usually performed manually. However, this manual approach is time consuming to arrive at a satisfactory solution particularly when the calibration parameters are large (Ibrahim and Liong, 1992). In these circumstances, automatic calibration procedures were developed with computer technology. Development of automatic calibrations (Madsen, 2000) schemes which is called optimization techniques, has been an active research endeavours during the past decades.

Several optimization methods have been applied in the calibration process. These traditional optimization techniques include linear, nonlinear, dynamic programming and evolutionary algorithms. The detailed description of evolutionary algorithm is presented in section 2.4.

2.2.1. Linear Programming

A linear programming gradient (LPG) method is presented by Alperovits and Shamir (1977) in the optimal design of water distribution network by linearizing the mathematical formulation (Atiquzzaman, 2004). Quindry et al. (1981), Fujiwara et al. (1987), Kessler and Shamir (1989) and Eiger et al. (1994) also applied LPG successfully and enhanced the functionalities (Morgan and Glulter, 1985; Fujiwara and Khang, 1990). However, linearization of complex non-linear process in LP reduces its performance. It is not always beneficial to linearise the problem as it may suffer losses and distort the original problem (Atiquzzaman, 2004).

A linear programming model was introduced by Tu et al. (2003) for multipurpose reservoir system operation. The reservoir operating rules was proposed to minimize the drought impacts. The model efficiently allocated water to meet the planned demand during normal periods of operation.

2.2.2. Non-Linear Programming

Chiplunkar et al. (1986) and Lansey and Mays (1989) applied non-linear programming technique (NLP) (Su et al., 1987; Duan et al., 1990). Compared to LP, NLP model can deal with more variables. However, Chiplunkar et al. (1986) often found that the NLP model often converged prematurely to the local minima. In the last few decades, non-linear programming algorithms that use gradient based algorithms, have been applied widely. Gradient based technique can easily identify a relative optimum solution. However, the method does not always provide optimal solution on a non-convex search space (Atiquzzaman, 2004). Simpson et al. (1994) and Savic and Walters (1997) indicated that NLP is also inadequate to deal with discontinuous search space and unable to provide optimal solution (Gupta et al., 1999; Cunha and Sousa, 1999).

2.2.3. Dynamic Programming

Dynamic Programming (DP) has been adapted since 1960s in the water resources engineering and management problem (Wong and Larson, 1968). In DP, the optimization problem is sub-divided into stages where each stage is linked to the previous stage (Atiquzzaman, 2004). The input of current state is transferred to the following stage. A two-stage dynamic programming approach is proposed by Vamvakeridou-Lyroudia (1993). Lall and Percell (1990) developed a dynamic programming based optimizer (GPO) and applied in the gas transmission pipeline systems. They determined the optimized solution (feasible strategy) by minimising the operation cost of the pipeline and satisfying several constraints. DP produced satisfactory results to simple systems. However, the performance DP deteriorated if the system was increased in size and the computational time increased significantly (“the curse of dimensionality”) (Atiquzzaman, 2004).

During the past decade or so, population-evolution-based optimization schemes have been extensively used for model calibration. The successful application of CRR model depends heavily on how well the conceptual model is calibrated (Johnston and Pilgrim, 1976; Duan et al., 1992; Ibrahim and Liong, 1992; Liong et al., 1995a; Gan and Biftu, 1996; Kuczera, 1997; Thyer et al., 1999). Gupta et al. (1999) mentioned that finding optimal parameters for a CRR model may be difficult from the calibration process. Such problems attributable to the data or information available for calibration cannot identify model parameter values with acceptable precision and non-linear structural characteristics of CRR models. Duan et al. (1992, 1293) identified five characteristics complicating the optimization problem which are: (a) existence of several major regions of attraction into which a search strategy may converge; (b) each major region of attraction may contain numerous local optima; (c) the objective function surface in multi parameter space may not be smooth and may not even be continuous; (d) the parameters may exhibit varying degrees of sensitivity and a great deal of interaction. Duan et al. (1992), through their six-parameter conceptual rainfall-runoff model called SIXPAR demonstrated in their study that the conceptual rainfall-runoff model calibration problem is more difficult than had been previously thought. They performed detailed analysis of the response surface of different objective functions on the SIXPAR model and demonstrated the presence of multiple optima complicating the conceptual rainfall-runoff model calibration. Finally, they stated that calibration of such model requires sophisticated mathematical tools and some degree of expertise and experience with the model.

2.3. Artificial Intelligence (AI) Technique

The AI approach is based on identifying a relationship between input and output from the historical observed data without attempting to describe any of the internal mechanisms. Professionals, researchers in water resources have been interested in data driven modelling using AI approaches which are assumed to overcome some of the drawbacks associated with conventional techniques (conceptual model). Such techniques are proven to be an effective and efficient way to model the complex process (e.g. RR) where the knowledge of the hydrological process is not required. Over the last few decades, these tools have been useful operation tools in case of the absence of hydrologic data such as evaporation data, catchment characteristics, etc. This has attracted to the attention of researchers where accurate and timely estimation of flow and flood forecasting is an extremely important issue in water industry as the existing structural protection system is not adequate to reduce the flood risk. AI (also called Black box model), according to Toth et al. (1999), is sometimes essential to predict the flow in shortest possible time which will allow sufficient time for flood warning and evacuation plan. Black box models for flood forecasting are most suitable tools, especially when the catchment size is large. Application of AI technique has been very popular as conceptual and physically based distributed models in the prediction of dam inflows or natural catchment yield requires many parameters including catchment area, slope, soil type, infiltration, drainage networks and their layout or their representations in the model and meteorological data (rainfall and runoff data). The values of some of these parameters, like infiltration rates, can only be determined through calibration. Calibration of such models using a trial and error method, or optimization algorithm needs knowledge and experience about the catchment, extensive effort specially for larger catchment with lots of calibration parameters to be determined (Atiquzzaman and Kandasamy, 2016a). Artificial intelligence (AI) based machine learning techniques have proven superior in this modelling process (e.g flow prediction) compared to other stochastic models including “Autoregressive (AR)”, “Autoregressive Moving Average (ARMA)”, “Autoregressive Integrated Moving Average (ARIMA)” and “Autoregressive moving average with Exogenous Inputs (ARMAX)” (Hsu et al., 1995 and Lohani et al., 2012). Over the last decades, AI techniques including Artificial Neural Network (ANN) (Funahashi, 1989; Furundzic, 1998; Gallant and White, 1992; Anctil et al., 2004; Jeevaragagam and Simonovic, 2012), Fuzzy Logic (FL) (Tayfur and Sing, 2006; Adeli and Sarma, 2006), Support Vector Machine (SVM) (Sivapragasam and Liong, 2002, Yu and Liong, 2004), Chaos Theory (Yu et al., 2002), and Genetic Programming (GP) (Lee and Suzuki, 1995; Rodriguez-Vazquez and Flemming, 1997; Keijzer and Babovic, 1999; Jayawardena et al., 2005; Meshgi et al., 2015) have been successfully utilized in many application around the world for their ability to recognize non-linearity in complex hydrological process.

Generally, application of data driven models to predict hydrological flow series (future discharges) requires an input of lagged discharges or meteorological data (Akhtar et al., 2009). Prediction of hydrological flow at a location in a river was performed by Karunanithi et al. (1994) using a cascade correlation algorithm. Flow data at different locations along the river and along its tributaries was as input. The model performed better than the commonly used conventional technique. Appropriate network structure, presenting data to “Artificial Neural Network (ANN)” and training algorithms were also presented. The study outcome revealed that lag time is more important in predicting stream flows. Hsu et al. (1995) demonstrated that non-linear ANN models provided a more representative rainfall-runoff relationship. They compared ANN results with ARMAX and the conceptual Sacramento soil moisture accounting model. It was reported that the models tend to fit the higher flows quite well. However, the low flow prediction is not so good for a one-step ahead prediction. Fernando and Jayawardena (1998) also modelled this by using Radial Basis Function neural network (RBF-NN). They showed it performed better than the ARMAX. ANN with multi-layer perceptron (MLP) networks trained with gradient-based methods has been used in many applications. Traditionally, the weight vectors in ANN models is determined using back-propagation (BP) algorithm by minimizing the mean square error between the measured and forecasted discharges of the hydrological process. However, the performance of ANN depends on network architecture (e.g. number of hidden layers, the number of neurons, activation functions etc), performance criteria, division and pre-processing of data, and determining appropriate model inputs (Maier and Dandy, 2000). Cigizoglu (2003) studied the application of ANN for forecasting of daily flows for a river in Turkey. Their analysis demonstrated ANN’s superior capability compared to conventional models (e.g. AR and regression models). Application of data-driven modelling methods has been made to quantify the uncertainty associated with the prediction. Kingston et al. (2005) highlighted ANN’s failure to account for prediction uncertainty as the quantification of uncertainty associated with ANN’s parameter, namely, weights is complex and difficult. They proposed Bayesian training method to assess ANN’s weight uncertainty. Peters et al. (2006) used HEC-RAS model to train the multilayer feed forward ANN and to replace one-dimensional hydrodynamic modelling system with ANN. They showed that ANN model performed well in terms of decrease in computational time especially for online flood forecasting. Wang et al. (2005) improved the performance of ANN with self-organising polynomial neural network (SOPNN). They demonstrated the capability of SOPNN in selection of appropriate model inputs, optimization of the network structure and error minimisation. SOPNN was applied to runoff prediction and it was found that SOPNN performed better than the group method of data handling (GMDH) and the traditional back-propagation network (BPN). Mittal et al. (2012) proposed a dual (combined and paralleled) artificial neural network (D-ANN) to estimate the extreme runoff values. They compared the performance of D-ANN with common feed forward ANN (FF-ANN). D-ANN performed better than FF-ANN. The relationship between input and output vectors were established using three steps: (1) compilation of the statistics of rainfall and the corresponding runoff $\{Q_t = f(R_{t-9}, R_{t-8}, R_{t-7}, Q_{t-1}, Q_{t-2})\}$, where R and Q represent the rainfall and runoff values at time "t"; (2) estimation of predicted values and errors of the runoff values ($\varepsilon = y - \hat{y}$), where y is observed value of runoff, $\hat{y}$ predicted value of runoff and ε value of error; (3) estimation of error corresponding to the predicted runoff $\{\varepsilon_t = f(R_{t-9}, \mathrm{R}_{t-8}, R_{t-7}, Q_{t-1}, Q_{t-2})\}$. The ultimate predicted value of runoff was derived by summing the predicted value and the error. The model was applied on a real case study on Kolar River basin in India. In the application, it was demonstrated that though both D-ANN and FF-ANN produced similar behaviour but D-ANN was able to predict the peak value better than FF-ANN. According to Chen and Chang (2009), a very simple ANN network architecture may not accurately predict while too complex architecture may reduce its generalization ability due to over-fitting. Uncertainty in streamflow prediction was assessed by Boucher et al. (2009) based on ensemble forecasts using stacked neural network. Instead of forecasting a single value (e.g. one-day-lead prediction), they predicted an ensemble of stream flows which was then used to fit a probability density function to assess the confidence interval as well as other measures of forecasts uncertainty. The uncertainty associated with prediction of water levels (or discharges) was analyzed by Alvisi and Franchini (2011). They introduced fuzzy numbers to determine the weights and biases of neural network to estimate prediction uncertainty of water levels and discharges. The comparison of this fuzzy neural network method with Bayesian neural network and the local uncertainty estimation model demonstrated the effectiveness of the proposed method where the uncertainty bands had slightly smaller widths than other data-driven models. Alvisi and Franchini (2012) found better accuracy in forecasting water levels and narrower uncertainty band width compared to Bayesian neural network using Grey neural network (GNN). Here the parameters are represented by unknown grey numbers that lie within known upper and lower limits. The grey parameters are searched in way that the grey forecasted river stages include at least a preselected percentage of observed river stages. Sing et al. (2015) applied ANN to establish relationships between rainfall and temperature data with runoff from an agricultural catchment (973 ha) in Kapgari (India). Several resampling of short length training datasets using bootstrap resampling based ANN (BANN), found solutions without over-fitting. A ten-fold cross-validation (CV) technique based ANN was also applied to obtain unbiased reliable testing results. Sing et al. (2015) demonstrated that BANN provides more stable solutions and was able to solve problems of over-fitting and under-fitting than ten-fold CV based ANN. Gholami et al. (2015) achieved high degree of accuracy in the prediction groundwater fluctuation using dendrochronology (tree-ring diameter) and ANN (multilayer perceptron, MLP). Rasouli et al. (2012) applied three machine learning methods including Bayesian Neural Network (BNN) for streamflow forecasting using different combination of local meteo-hydrologic observations and climate indices. They found that BNN outperformed the other nonlinear models. Chen and Chang (2009) proposed an evolutionary algorithm (Genetic Algorithm (GA)) based ANN (EANN) to define the optimal network architecture and for prediction of real-time inflows to the Shihmen Reservoir in Taiwan. They demonstrated that EANN performed better than the ARMAX stochastic model. Chen and Chang (2009) also stated that the performance of ANN depends on network architecture (e.g. inputs, number of hidden layers, the number of neurons and activation functions) and noted that very simple network architecture of ANN may not accurately predict while too complex architecture may reduce its generalization ability due to over-fitting. Wu and Chau (2011) found that the performance of ANN can be improved significantly if the input data is preprocessed with Singular Spectrum Analysis (SSA).

The performance of ANN was improved by combining with other techniques (e.g. hybrid methods) (Chen et al., 2915). For example, Deka and Chandramouli (2009) proposed Fuzzy Neural Network (FNN) hybrid model to study the operation of a proposed multipurpose reservoir system and found that FNN is highly adaptive, flexible, easy to build. Adaptive Neural-based Fuzzy Inference System (ANFIS) significantly improved on ANN predictions for reservoir prediction (Bhakra Dam, India, Lohani et al., 2012); for forecast of daily flood discharge (Yom River Basin, Thailand, Tingsanchali and Quang, 2004; and Ajay River Basin in Jharkhand, India, Mukerji et al. 2009), and for event-based rainfall-runoff modeling using lag time (Talei and Chua, 2012).

Fuzzy rule based models are based upon the fuzzy set theory. Fuzzy set theory differs from the classical theory of crisp sets. A fuzzy set is a class of objects which is characterised by a membership function. The membership functions for each object assign a grade ranging between zero and one (Zadeh, 1965). Fuzzy set comprises of ordered pairs of values, $(x,\ \mu_a(x))$, where x is an element of numerical basic set A and where $\mu_a(x)$ is the degree of membership of x. If the grade for membership function is 1, this means that x entirely belongs to the fuzzy set. Zero grade, on other hand indicates that x does not belong to the fuzzy set at all. Values in between mean that x belongs to the set to some degree. Tayfur and Singh (2006) described a general fuzzy system consists of four steps – fuzzification, fuzzy rule base, fuzzy output engine, and defuzzification. In fuzzy logic application, firstly the input data are converted to degree of membership functions. Secondly, fuzzy rule base defines a list of rules that include all possible relations between inputs and outputs. These rules are generally expressed in the IF-THEN format. There are two types of expression of rules used in fuzzy application which are called ‘Mamdani’ and ‘Sugeno’. In Mamdani rule system, the consequent of the input variable is expressed as verbally. However, in Sugeno rule system, the consequent part of the fuzzy rule is expressed as a mathematical function of the input variable. Thirdly, the fuzzy inference system engine take into account of all the fuzzy rules in the fuzzy rule base and transform them to a set of output. Finally, defuzzification converts the resulting fuzzy outputs from the fuzzy inference engine to a number. There are several defuzzification methods available which are centre of gravity (COG), bisector of area (BOA), mean of maxima (MOM), left-most maximum (LM), and right most maxima (RM) etc. Fuzzy logic has been widely applied in hydrological modelling for the last two decades. Fuzzy conceptual rainfall-runoff framework was proposed by Ozelkan and Duckstein (2001) where every element of the rainfall-runoff model was assumed to be uncertain. Fuzzy rules, applied to different operational modes and the parameter identification process was examined using fuzzy regression techniques. The methodology was applied to different types of conceptual models including linear, experimental two parameters and Sacramento Soil Moisture Accounting Model that enabled the decision maker to understand the model sensitivity and the uncertainty stemming from the elements of the model. Tayfur and Sing (2006) applied ANN and fuzzy logic (FL) for predicting event based rainfall-runoff and the results were compared against the “kinematic wave approximation (KWA)”. A three layered “feed-forward ANN” was developed using the “sigmoid function” and the “backpropagation algorithm”. The triangular fuzzy membership functions were applied to develop the fuzzy logic model for the input and output variables. They described that ANN and FL require long historical data compared to KWA. But KWA model involves many parameters for which field estimation is needed. Adaptive Neuro-Fuzzy Inference System (ANFIS) and ANN were applied by Tingsanchali and Quang (2004) to forecast the daily flood flow of the Yom River Basin in Thailand. They demonstrated that ANFIS performed better than ANN multilayer perceptron model. Though different types of ANN together with Fuzzy Logic have been successfully applied to solve complex hydrological processes, it suffers from some major limitations (ASCE Task Committee, 2000 a and b), for example,

- choosing optimal network architecture is an issue;
- does not provide a direct relationship between the input and output variables; and
- does not help in advancing the scientific understanding of hydrological process.

Cui et al. (2014) examined the impact of topographic uncertainty in their rainfall-runoff model (TOPMODEL). The performance of TOPMODEL is influenced by the grid size of the digital elevation model (DEM) that defines the topography. The relationship between DEM resolution and TOPMODEL performance was investigated using fuzzy analysis technique. Different grid sizes of the DEM ranging from 30m to 200m were used in TOPMODEL. It revealed that the best results were produced with fuzzy technique for the 30m resolution. Cheng et al. (2002) adopted a parallel Genetic Algorithms (GA) with Fuzzy Optimal model in a cluster of computers to reduce the computational run time required to optimize the rainfall-runoff model (Xinanjiang) and to improve the quality of the results. As the problem was partitioned into smaller pieces, their proposed hybrid approach achieved the superior results quicker than GAs.

Over the last several decades, parallel to ANN and Fuzzy Logic, Genetic Programming (GP) has been applied to solve various hydrological/hydraulic problems, such as rainfall-runoff relationship from synthetic data, sediment transport modelling, prediction of bridge pier scouring (Azamathulla et al., 2010), salt intrusion in estuaries and flow over a flexible vegetated bed (Babovic, 1996; Babovic and Abbott, 1997). Babovic and Abbott (1997) mentioned that GP can be used to model single non-linear reservoir behaviour of a hypothetical catchment simulated by RORB. Whigham and Crapper (2001) applied Genetic Programming to predict the runoff from 2 catchments using only previous rainfall data. One of the catchments is a moderately fast response catchment and the other, a rapid response catchment. They found that Genetic Programming was able to distinguish the slow response from the rapid response of the catchment and reacted accordingly by incorporating the average rainfall terms in the resultant expression. Makkeasorn et al. (2008) showed GP performed better than neural networks (NN) for forecasting discharges in a semi-arid watershed in South Texas, USA by including sea surface temperature, spatio-temporal rainfall distribution, meteorological data and historical streamflow data. The application of GP in real-time runoff forecasting was also demonstrated by Liong et al. (2002). Liong et al. (2002) applied GP as a forecasting tool in a catchment with a drainage area of 6 km^2. Different storm intensities and durations were considered to train and verify GP results. The functional relationship between rainfall and runoff derived from GP showed that the prediction accuracy of GP in terms of RMSE is reasonably good. Savic et al. (1999) found in their study that GP performed better compared to conceptual hydrological model (e.g. HYRROM). Application of GP demonstrated by Khu et al. (2001) in real-time runoff forecasting showed that GP played as an error updating scheme to complement traditional hydrological model (MIKE11/NAM). GP was able to predict the runoff for all updating intervals not exceeding the time of concentration of the catchment. They also found that non-dimensionalising the variables enhanced the prediction accuracy. Ten storm events were considered to infer the performance of GP in updating NAM output. The best functional form with minimum RMSE is as follows:

$$\boldsymbol{QIMP_{t+1} = QSIM_t + 0.009 + 1.61\varepsilon_t - 0.644\varepsilon_{t-1} + 0.087\varepsilon_t(QSIM_{t-2} - QSIM_{t-1}}$$

Where, $\boldsymbol{QIMP_{t+1}}$ is improved discharge at time $\boldsymbol{t+1}$; $\boldsymbol{QSIM_t}$ is simulated discharge at time $\boldsymbol{t}$; $\boldsymbol{\varepsilon_t}$ is prediction error at time $\boldsymbol{t}$. GP also produced comparable results with two other updating methods such as the auto-regression and Kalman Filter. In applied engineering, GP is frequently used to recognise the relationship between the complex hydrological parameters. Rodriguez-Vazquez et al. (2012) proposed GP and Genetic Algorithm (GA) for rainfall-runoff modelling of a sub-basin located near Mexico City. They developed two different models for the analysis. The first was a multi-objective optimization based GP model for determining the structures and parameters of non-linear auto-regressive models (NARMAX). The second was a GA based model that optimized the parameters of a non-conventional rainfall-runoff model. Their analysis concluded that the multi-objective optimization based GP model best fitted the analysed storms of interest. Recently, Nourani et al. (2013) included watershed geomorphological features as spatial data together with temporal data in GP for rainfall-runoff modelling. Two separate scenarios, namely separated gemorphological GP (SGGP) and integrated gemorphological GP (IGGP) models and their application were described. The geomorphological parameters or the spatial data includes area, slope and curve number for sub-basin were considered in addition rainfall and runoff time series. Separate GP models were developed for each sub-catchment in SGGP where as all the sub-catchment spatial and temporal parameters were integrated in IGGP. From the application of these techniques to Eel River Watershed, they found these models could compensate the lack of temporal data. Specifically, SGGP model for the sub-basins could distinguish the dominant variables of the sub-basins in the process and IGGP can be a reliable tool for spatial and temporal interpolation of runoff through the watershed. IGGP was able to fill up the data gaps in other stations.

SVM is another powerful AI technique that has been successfully applied in flow forecasting, rainfall-runoff modeling (Sivapragasam et al. 2001) and streamflow forecasting (Chiogna et al., 2018). SVM is a statistical method that resolves the problem similar to a NN but the nature of its underlying functional form is not assumed a priori. In other words, SVM can be seen as an approximate implementation of the method of structural risk minimisation. In this process, learning from data is actually to choose from the given set of functions which best approximate the measured output. The best approximation represents the smallest value of the risk. However, if the training examples are limited, this approach does not guarantee a small actual risk. To overcome this limitation, statistical learning theory has been introduced. In this method, the structural risk is minimised by controlling the estimate of risk and the confidence interval of this estimate (Vapnik, 1999). Chiogna et al. (2018) proposed SVM with hydrological model (Soil Water Assessment Tool) output, the hydropower energy price and the day of the week to capture sudden fluctuations in river stage caused by the hydropower production company in Upper Adige River basin in North-East Italy. They found that that SVM was able to reproduce the hydropeaking and performed better than SWAT under low flow condition when the streamflow was impacted by the hydropower. SVM was applied by Sivapragasam (2002) and Liong and Sivapragasam (2002) to predict the stage in the city of Dhaka, Bangladesh using daily water level data measured at five gauging stations (Liong et al., 1999). The results showed that SVM performed better than ANN (Liong et al., 1999) in terms of RSME and R^2. Similarly, SVM was shown to be comparable or better than ANFIS and GP, for application in forecast of monthly river flow (Wang et al. 2009) and short term river flow (Heihe River, Northern China, He et al. 2014). Sivapragasam (2002) applied SVM to rainfall-runoff modelling using six storm events that occurred in Upper Bukit Timah catchment, Singapore. The results showed the robustness of SVM compared to multi-layered feed-forward ANN.

SVM was further improved by reducing the noise from input data using Singular Spectrum Analysis (Sivapragasam et al., 2001), optimization of SVM parameters using Evolutionary Computation based Algorithm (EC-SVM) (Yu et al., 2004) and Particle Swarm Optimization algorithm (Wang et al. 2013). Lin et al. (2006) reported SVM as a powerful tool that could overcome some of the drawbacks that were evident in ANN: (1) finding global solutions, (2) over-fitting unlikely, (3) generating non-linear solutions using the Kernel Function, and (4) obtaining optimized solutions using a limited training dataset. While SVM overcame some drawbacks of ANN (finding global optimized solutions and over-fitting, Lin et al. 2006), it required a long simulation time for large complex problem, and in the selection of an appropriate kernel function and associated parameters (C and ε). Fotovatikhah et al. (2018) reviewed the available AI and computational intelligence (CI) methods in the literature including ANN, fuzzy sets, wavelet models, SVM, EC and hybrid methods employed in hydrology, flood and waste flow prediction. They found that EC and SVMs showed lower error rates compared to other machine learning and soft computing techniques. Yu et al. (2004) presented a combined application of Chaos Theory and SVM where the parameters were optimized with an EA to reduce prediction error. In SVM, Gaussian Kernel function, being more suitable, was applied to hydrological time-series application (Liong and Sivapragasm, 2002). An EA engine, called Shuffled Complex Evolution (SCE), was applied to determine five parameters, i.e. time delay, embedding dimension and three SVM parameters (tradeoff between empirical error and model complexity, insensitive loss function, and width of Gaussian kernel function). EA based SVM (EC-SVM) was used to predict runoff time-series for catchments including the Tryggevælde Catchment, Denmark and the Mississippi River, USA. The results showed that EC-SVM improved the prediction accuracy compared to standard chaos technique, Naïve, ARIMA and Inverse Approach. Wang et al. (2013) applied an EA, called particle swarm optimization (PSO), to determine SVM parameters. They further proposed ensemble empirical mode decomposition (EEMD) for decomposing annual rainfall series in SVM to avoid model over-fitting or under-fitting. The proposed model (PSO-SVM-EEMD) improved the rainfall-runoff forecasting significantly compared to ordinary least-square regression model and ANN. Sivapragasam et al. (2001) enhanced the performance of SVM by pre-processing the input data using a noise-reduction algorithm, Singular Spectrum Analysis (SSA). SSA was coupled with SVM and used to predict the flows from the Tryggevælde Catchment (Denmark). It improved the prediction accuracy compared to the non-linear prediction (NLP) method.

Literature on the application of AI approaches including ANN, ANFIS, SVM and GP in hydrological time-series prediction indicates that their performances are not consistent for all applications and it is difficult to state which method is superior. Superior performance depends on appropriate parameters and network configurations. Researchers have attempted to improve the performance of these methods using hybrid approach (ANFIS) or by combining them with other algorithms (EC-SVM) to optimize the parameters. However, they still require numerous iterations and significant computational time to generate optimum solutions. To overcome this, Huang et al. (2006) proposed a learning algorithm, called "Extreme Learning Machine (ELM)". ELM determines weights related output analytically with randomly generated input weights. The performance of ELM has been compared by Huang et al. (2006) with conventional neural network (BP) and SVM on some benchmarking problems in the function approximation and classification areas. Huang et al. (2006) reported that ELM is capable of approximating any continuous function and implementing any classification. ELM learns faster (Taormina and Chau, 2015) and is stable with a wide range of number of hidden nodes. ELM was also applied by Taormina and Chau (2015) in the selection of input variables for rainfall-runoff modelling. They obtained most accurate solutions with ELM is coupled with Binary-coded discrete Fully Informed Particle Swarm Optimization (BFIPS). The performance of ELM depends on the activation function and the random assignment mechanism. With appropriately selected activation function and random mechanism, ELM does not degrade the generalization capability (Lin et al., 2014). Numerous experiments and applications have demonstrated the effectiveness and efficiency of ELM (Huang et al., 2006). Atiquzzaman and Kandasamy (2016b) demonstrated that ELM's learning speed and accuracy were comparable to Standard Chaos Technique, Inverse Approach and EC-SVM in the forecasting of hydrological time-series (refer to Chapter 4). However, the robustness of ELM's performance (improved accuracy) on different input parameters, longer lead day prediction and extrapolation capability was not investigated by Atiquzzaman and Kandasamy (2016b) (refer to Chapter 5).

The following sections present the brief description of Artificial Neural Networks (ANN), Genetic Programming and Extreme Learning Machines as this study applies these three AI techniques. ANN and GP are applied in this study for comparison against ELM.

2.3.1. Brief Description of Artificial Neural Network

A lot of works has been particularly carried out in the application of ANN in stream flow forecasting and runoff modelling due to its capability to reproduce the unknown relationship existing between a set of input and output variables. American Society of Civil Engineers (ASCE) has officially formed a committee on application of ANN in and they reported that since the early nineties, ANNs have been successfully used in R-R modelling and other hydrology related areas such as stream-flow forecasting, ground-water modelling, water quality, water management policy, precipitation forecasting, hydrologic time series, and reservoir operations.

Artificial Neural Network (ANN) is a network that connects many simple elements called neurons. Each neuron has a small amount of local memory. The neuron connections are established through communication channels which carry numeric data encoded by various means. Neurons become active when it receives data through the communication channels.

The architecture of ANN follows the model similar to human brain and nerve cells. Historically, much of the motivation to build ANN came from the desire to produce artificial systems capable of mimicking the behaviour of human brain. Neural Network model derives the statistical structures present in the input data set by using the architecture and learning paradigms. The information acquired after learning the data structure is stored at the connections between the elements of the neural architecture. At the beginning, the architecture is not structured and the learning algorithms extracts the regularities present in the data by finding a suitable set of synapses during the process of observation of the examples. Thus, ANNs solve problems by self-learning and self-organization i.e. the network recognizes the features of input data itself and displays its findings. They derive their intelligence from the collective behaviour of simple computational mechanisms at individual neurons.

In ANN, there are two types of architectures including feed-forward and recurrent architectures. The feed-forward architecture allows connections only in one direction and the neurons are arranged in layers, starting from a first input layer and ending at the final output layer with one or more hidden layers. The information passes from the input to the output side. The recurrent architecture, however, permits back-coupling and any type of connections is allowed. This is generally achieved by recycling previous network outputs as current inputs, thus allowing for feedback.

Feed-forward network is usually used in hydrological problem as the recurrent architecture based models are significantly more complex in terms of time and storage requirements. This study considers only ANN with a feed-forward architecture. A 3-layered feed-forward architecture is shown in Figure 2. 1. The 3 layers are called input, hidden output layers. Each layer consists of several neurons which are interconnected by weight functions. The input variables (observed data) are fed to input neurons directly. The variable information is passed on to hidden and output layers through the interconnections between the neurons. The neurons in input layer transform via weight functions which are estimated through this process. The transformation is performed in two stages as shown below (Sivapragasam and Muttil, 2005):

- Determining Weighted Sum.

  "Input from each neuron is multiplied with weights and a weighted sum is performed":

$$Y_j(s) = \sum_{i=0}^{n} w_{ij}(s-1).x_i(s-1) \tag{1}$$

  where "$Y_j(s)$ = weighted sum for neuron j in layer s; $w_{ij}(s\text{-}1)$ = weight in the link between neuron j in layer s and neuron i in layer (s-1); and $x_i(s\text{-}1)$ = input from neuron i in layer s-1".

- Selecting Activation Function.

  An activation function, $F(s)$, such as the sigmoid function expressed as:

$$F_j(s) = \frac{1}{1 + e^{-Y_j(s)}} \tag{2}$$

$F_j(s)$ is the output of the neuron j in layer s.

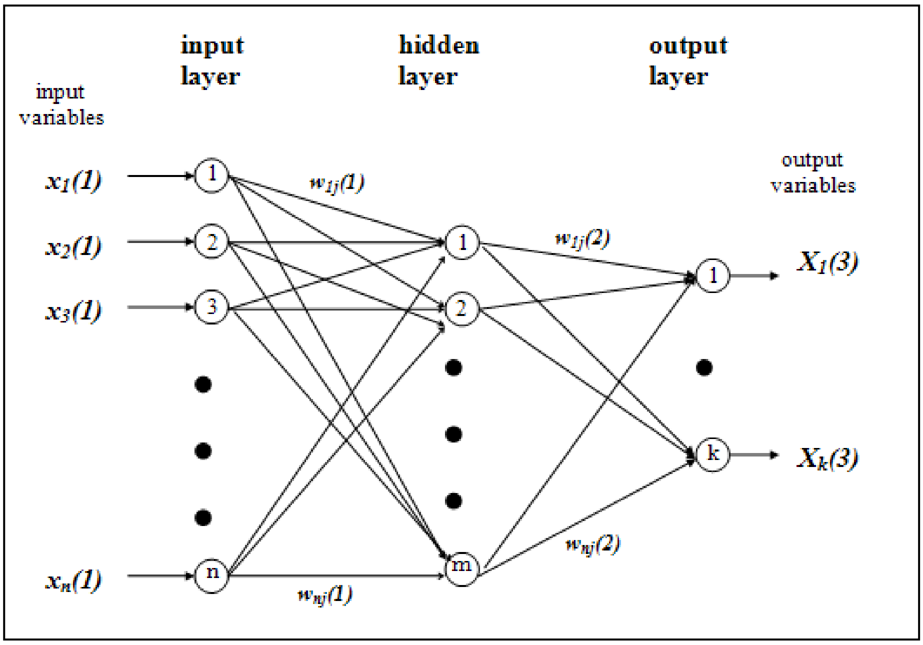


Figure 2. 1: 3-Layered Feed Forward Neural Network Architecture

Initially, ANN generates the weights related to the interconnections randomly. In this process, a learning rate (α) and a momentum rate (β) are defined. The learning rate plays an important role and controls the variation (incremental change) of interconnecting weights. During the iterative training process, the variation in the weight functions is controlled by the learning rate based on the percentage of the difference between the observed and model output. If the high learning rate is selected, larger weight change is observed, and the model learns the input dataset quickly. The momentum rate ensures the model from being trapped to local optima and increase the rate of learning at the same time. The change in the previous interconnection weights is multiplied by the momentum rate. The relationship between the learning rate and momentum rate is described as:

$$\Delta w_{ij}(s) \quad = \quad \alpha\delta_j(s)x_i(s) \quad + \quad \beta\Delta w_{ij}(s-1) \tag{3}$$

where $\Delta w_{ij}(s)$ = "weight adjustment between node j in layer s and node i in layer (s-1)";

$\delta_j(s)$ = "local or instantaneous gradient"; and

$x_i(s)$ = "input of neuron j from previous layer's neuron i".

Equation 3 demonstrates that the momentum rate (β) increases the rate of variation of weight when the local gradient component is in the same direction as that of the learning component. Alternatively, the learning rate becomes faster when the error back- propagation is downward and vice versa.

ANN model is trained with a list of input data. The model adjusts the interconnection weights and computes the desired output until some termination criteria are met. The trained ANN model with the optimized interconnection weights, can be readily used to produce outputs for a set of known inputs.

2.3.2. Brief Description of Genetic Programming

"*GP is a domain-independent automatic programming for evolving computer programs to solve, or approximately solve problems*" (Koza, 1992, 1997; Liong et al., 2002). GP which is a member of EA family, is actually a generalization of genetic algorithm (Aytek and Kisi, 2008). Poli et al. (2008) defined *"Genetic programming (GP) is an evolutionary computation technique that automatically solves problems without requiring the user to know or specify the form or structure of the solution in advance".*

GP provides a transparent and structured system compared to other AI approach such as ANN, as ANN produces their knowledge in terms weight matrix that is sometime not accessible to human understanding (Savic et al., 1999). Scientists, researchers and water manager usually focus on the agreement of predicted and observed behaviour of a complex hydrological process using some kind of fixed relationship. If the comparison is accepted, the model is considered to be correct within that context (Babovic and Keijzer, 2002). Hence, GP can mimic this complex relationship and derive the governing equations directly from measurement. Genetic Programming has the advantage of providing inherent functional relationship explicitly over ANN. So, GP induced rainfall-runoff relationships can be an alternative to commonly used rainfall-runoff models.

GP uses optimization mechanism to evolve simple program where Darwin's natural selection theory of evolution is applied to progressively generate the offspring from better parents. In GP, trial parent programs are repeatedly modified in the search for better or fitter solutions (Langdon, 1998). In this process, the quality criteria are defined to improve the accuracy of EAs. These criteria are then used to measure and compares solution candidates in a stepwise refinement of a set of data structures and return an optimal or near optimal solution after a number of generations (Jayawardena et al., 2005). The accuracy of solution depends on the level of noise in the data set. If the data is noise free, GP generates a function in symbolic form which is defined by Liong et al. (2002) as symbolic regression. The symbolic regression is error driven evolution and may be linear, quadratic or higher order polynomial. GP has been extremely popular due to the success at searching complex non-linear spaces and the robustness in practical application.

2.3.2.1. Generation of Offspring from Parent Population

Population in GP consists of functional relationship or computer program. In order to create new relationship from parent relationship, the parent relationships are represented by parse tree structures composed of function set and terminal set (see Figure 2. 2). The functions are mathematical or logical operators and terminals are constants and variables. These trees are dynamically modified by genetic operators which are called selection, crossover and mutation to optimize its fitness value in the evolution process. The genetic operator is applied to select individuals. Selection process involves some probabilistic approach to copy individuals from previous generation to the next generation based on fitness value. After selection, crossover and mutation are applied. Crossover operator interchanges randomly selected subtrees of each chosen parent pair to generate syntactically correct offspring. Figure 2. 3 shows the crossover of two parent population. After the crossover, the program probabilistically selects a single parental solution program from the population based on objective function value and performs mutation operation. There are several types of mutations possible in the process. For example, two of them are: (1) the child population can be mutated by replacing a function or a terminal with another function or a terminal; and (2) the whole subtree of a child population can be interchanged by another subtree. The subtree in the process can be generated using the same approach applied at the beginning to generate the initial population of points. The final solution is shown in Figure 2. 4.

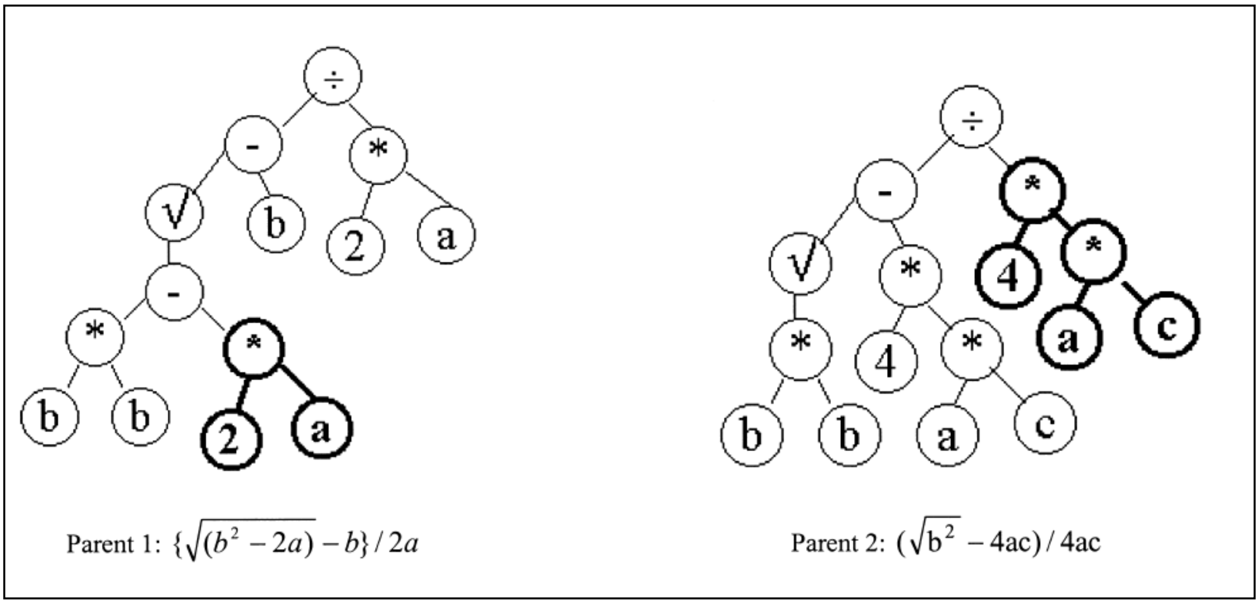


Figure 2. 2: Parent Population in GP (Source: Liong et al., 2002)

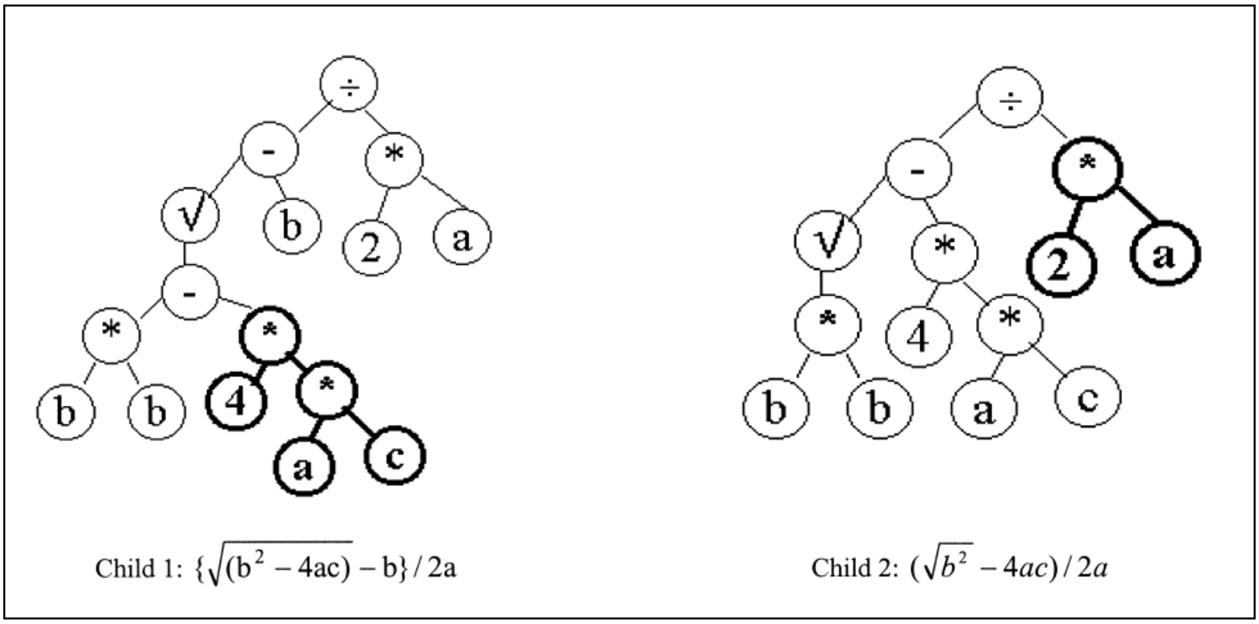


Figure 2. 3: Child Population in GP (Source: Liong et al., 2002)

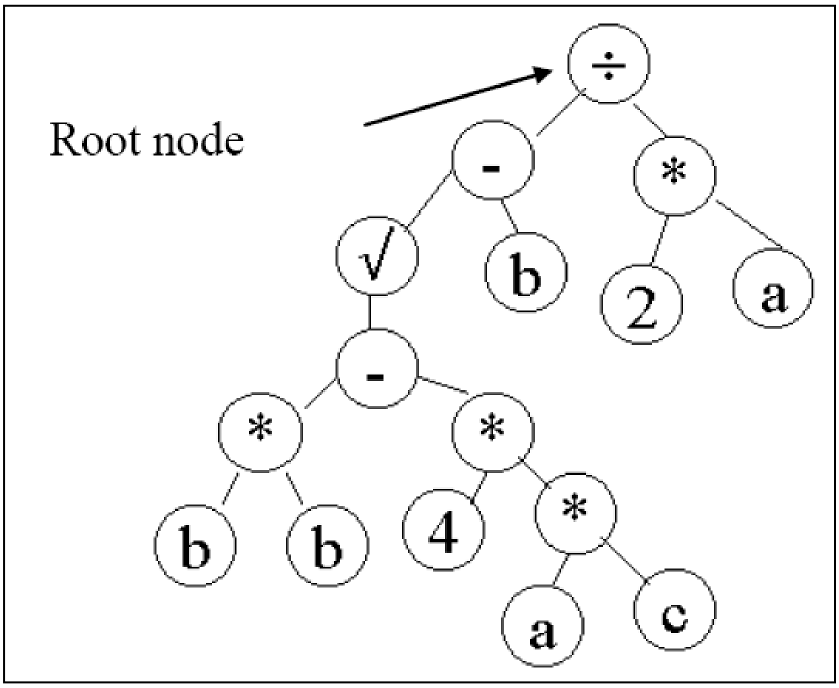


Figure 2. 4: GP Parse Tree Representing {sqrt(b2-4ac)-b}/2a (Source: Liong et al., 2002)

2.3.2.2. Working Mechanism

The basic steps of GP (Figure 2. 5) are described as follows:

1. Create a set of initial population of points/solutions.

2. Evaluate each solution (parse tree) and assign the fitness.

3. Generate a subset of population of points according to their objective function values (fitness). Solutions with higher fitness values will be selected to produce offspring (children).

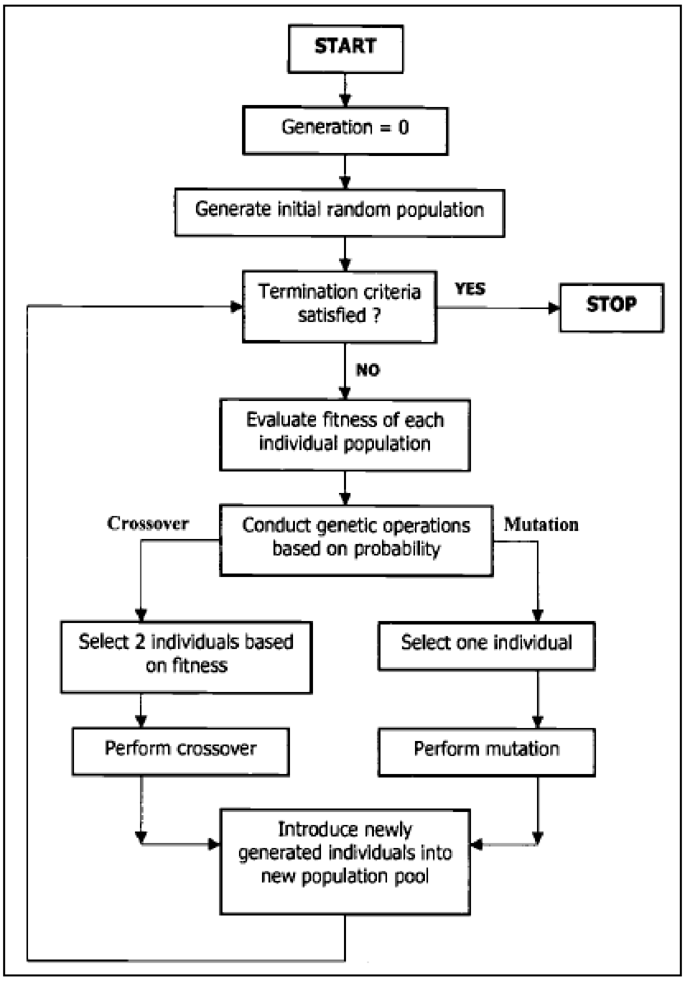


Figure 2. 5: Flow Chart of Genetic Programming (Source: Liong et al., 2002)

4. Selects pairs of solutions randomly from the subset of population of points for mating and apply crossover operation. Crossover will interchange the genetic components between two selected points;
5. Choose a crossover location where the genetic materials of the parent population will be interchanged (binary bit) to produce child population.

6. Apply mutation operation which randomly select a genetic information (0 or 1) of the solution and change it from 0 to 1 or vice versa.
7. Copy the resulting mutated child chromosomes into the new population.
8. Evaluate the fitness value (performance) of the new population.
9. Repeat steps 3-8 until some termination criteria are met.

2.3.3. Brief Description of Extreme Learning Machine (ELM)

Extreme Learning Machine (ELM) is a relatively new AI techniques developed by Huang et al. (2006). ELM is a single-hidden layer feed-forward neural network (SLFN) that provides efficient unified solutions where the input weights and hidden layer biases are chosen randomly (Huang et al., 2006). ELM's hidden node parameters are independent between the hidden layer and the training data which means that it generates the hidden node parameters without depending on training data. However, ELM's connections with output neurons are adjustable. ELM determines weights related to output analytically with randomly generated input weights. ELM transforms the training of Feed-Forward Neural Network into a linear problem in which only connections with output neurons are adjusted. Thus, the well-known generalized inverse technique is directly applied for the solutions.

ELM's learning algorithm is much simpler, and the learning speed is extremely fast as it avoids iterative tuning to determine the weights. The advantages of ELM are: (1) faster learning speed than conventional method; (2) learns with single iteration; (3) better generalization performance; (3) automatically determines all the network parameters analytically; (4) suitable for many nonlinear activation function and kernel functions; (5) straightforward in reaching solutions without facing issues like local minimum, improper learning rate and overfitting; (6) suitable for online and real-time applications; and (7) a viable alternative technique for large-scale computing and machine learning.

The mathematical equation for ELM can be formularized as (Figure 2. 6):

$$f_L(x) = \sum_{i=1}^{L} \beta_i G(a_i, b_i, x_j) = \sum_{i=1}^{L} \beta_i g(a_i . x_j + b_i) \quad (4)$$

where, a_i is the weight vector connecting the i^{th} hidden node and the input variables and b_i is the bias of the i^{th} hidden node, L is random hidden nodes; β_i is the weight connecting the hidden node and the output node and $g(x)$ is activation function (example, sigmoidal function: $g(x) = 1/(1 + \exp(-x))$; $x \in R^n$ and $a_i \in R^n$).

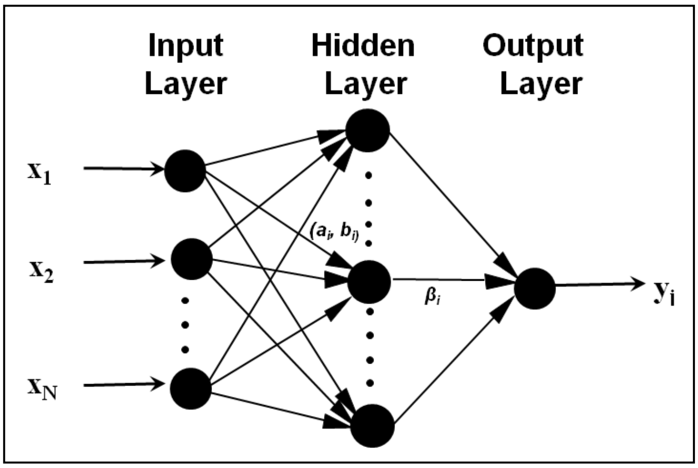


Figure 2. 6: Structure of Neural Network

When the difference between the target (t_j) and the model $\{f_L(x) = y_j\}$ is zero for a time series of N samples,

$$\sum_{j=1}^{L} ||y_j - t_j|| = 0 \quad (5)$$

where, $J = 1, \ldots N$.

This means:

$$\sum_{i=1}^{L} \beta_i g(a_i . x_j + b_i) = t_j \quad (6)$$

Equation (6) can be written as:

$$H\beta = T \quad (7)$$

where H is called hidden layer output matrix of SLFN.

For a fixed input weight and input biases, training of SLFN finds a least squares solution $\hat{\beta}$ of above equation.

$$||H(\tilde{a},\tilde{b},\tilde{x})\hat{\beta} - T|| = {}^{min}_{\beta}||H(\tilde{a},\tilde{b},\tilde{x})\beta - T|| \tag{8}$$

where, $\tilde{a} = a_1, \dots a_L$; $\tilde{b} = b_1, \dots b_L$; $\tilde{x} = x_1, \dots x_N$

$$H(\tilde{a},\tilde{b},\tilde{x}) = \begin{bmatrix} g(a_1.x_1 + b_1) & \dots & g(a_L.x_1 + b_L) \\ \vdots & \dots & \vdots \\ g(a_1.x_N + b_1) & \dots & g(a_L.x_N + b_L) \end{bmatrix}_{NxL}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{Lxk} \text{ and } T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{Nxk}$$

where, *k* is the number of targets.

Equations (7) or (8) is solved using the smallest norm least-squares solution method, where

$$\hat{\beta} = H'T \tag{9}$$

H' is called Moore-Penrose generalized inverse of matrix *H* (hidden layer output) and *T* is target matrix. If the number of hidden neurons and the number of samples are equal, SLFN can approximate the training of samples with zero error (Huang et al., 2012). H' can be calculated using several methods including orthogonal projection method, orthogonalization method, iterative method, singular value decomposition (SVD), etc. In ELM, the SVD method is used to calculate H'. Huang et al. (2012) represented $H' = (H^TH)^{-1}H^T$ if H^TH is nonsingular or $H' = H^T(HH^T)^{-1}$ if HH^T is nonsingular according to orthogonal projection. Based on ridge regression theory, a value of $1/C$ is added to the diagonal of H^TH or HH^T in the calculation of the output weights β to get stable and better generalization performance. Thus equation (9) can be written as,

$$\boldsymbol{\beta} = \boldsymbol{H}^T(\frac{1}{C} + \boldsymbol{HH}^T)^{-1}\boldsymbol{T} \text{ or } \boldsymbol{\beta} = (\frac{1}{C} + \boldsymbol{H}^T\boldsymbol{H})^{-1}\boldsymbol{H}^T\boldsymbol{T} \tag{10}$$

The corresponding output function becomes:

$$f_L(\boldsymbol{x}) = \boldsymbol{h}(\boldsymbol{x})(\frac{1}{C} + \boldsymbol{H}^T\boldsymbol{H})^{-1}\boldsymbol{H}^T\boldsymbol{T} \tag{11}$$

where $\boldsymbol{h}(\boldsymbol{x})$ is called hidden-layer output matrix or feature mapping matrix. Huang et al. (2011, 2012) reported that the generalization performance of ELM is less sensitive to the dimensionality of the feature space (L). ELM's performance is good when L is large enough (e.g. >1000). For better results the regularization coefficient (C) can be optimized.

If the feature mapping matrix is unknown, Huang et al. (2012) described how the Kernel Matrix of ELM can be used:

$$\Omega_{ELM} = \boldsymbol{H}\boldsymbol{H}^T; \Omega_{ELMi,j} = \boldsymbol{h}(\boldsymbol{x}_i).\boldsymbol{h}(\boldsymbol{x}_j) = K(x_i, x_j)$$

$$f_L(\boldsymbol{x}) = \boldsymbol{h}(\boldsymbol{x})\, \boldsymbol{H}^T(\frac{1}{C} + \boldsymbol{H}\boldsymbol{H}^T)^{-1}\boldsymbol{T} \tag{12}$$

$$f_L(\boldsymbol{x}) = \begin{bmatrix} K(x, x_1) \\ \cdot \\ \cdot \\ K(x, x_N) \end{bmatrix}^T (\frac{1}{C} + \Omega_{ELM})^{-1}\boldsymbol{T} \tag{13}$$

In the above equation the Kernel $K(\boldsymbol{x}, \boldsymbol{x}')$ can be represented using Gaussian Kernel function:

$$K(\boldsymbol{x}, \boldsymbol{x}') = \exp\,(-\gamma\|\boldsymbol{x} - \boldsymbol{x}'\|^2) \tag{14}$$

where γ is the Kernel parameter. In order to achieve good outcome from KELM (Li et al., 2014), appropriate values of C and γ need to be chosen. Huang et al. (2012) tested KELM using several values of C and γ in a range between 2^{-24} and 2^{25}. In this large range, optimization method could be used to select values of these two parameters (C and γ).

2.4. Evolutionary Algorithms

Evolutionary Algorithms (EAs) are optimization techniques that mimic the evolutionary processes. EAs have been applied widely to solve complex engineering problems. They apply the principle of survival of the fittest from a population of potential solutions and explore the search space to produce better approximations to a solution. The population of points is generated randomly at the beginning. Each point is then evaluated against the objective function in the first generation. At the end of first generation, the stopping criteria is checked. If the stopping criteria is not satisfied, a new set of points (offspring) is created. The offspring created with this process is better suited to their environment than the parents. The performance of the children is then evaluated and move to second generation**.** This process is continued until the termination criteria is satisfied or a predetermined number of generations (epoch) is reached.

EAs share the information and keep the best solution from current generation for the next generation. Keeping the best solution (survival of the fittest) ensures the search engine from being trapped to local optima. The EAs process is presented in Figure 2. 7.

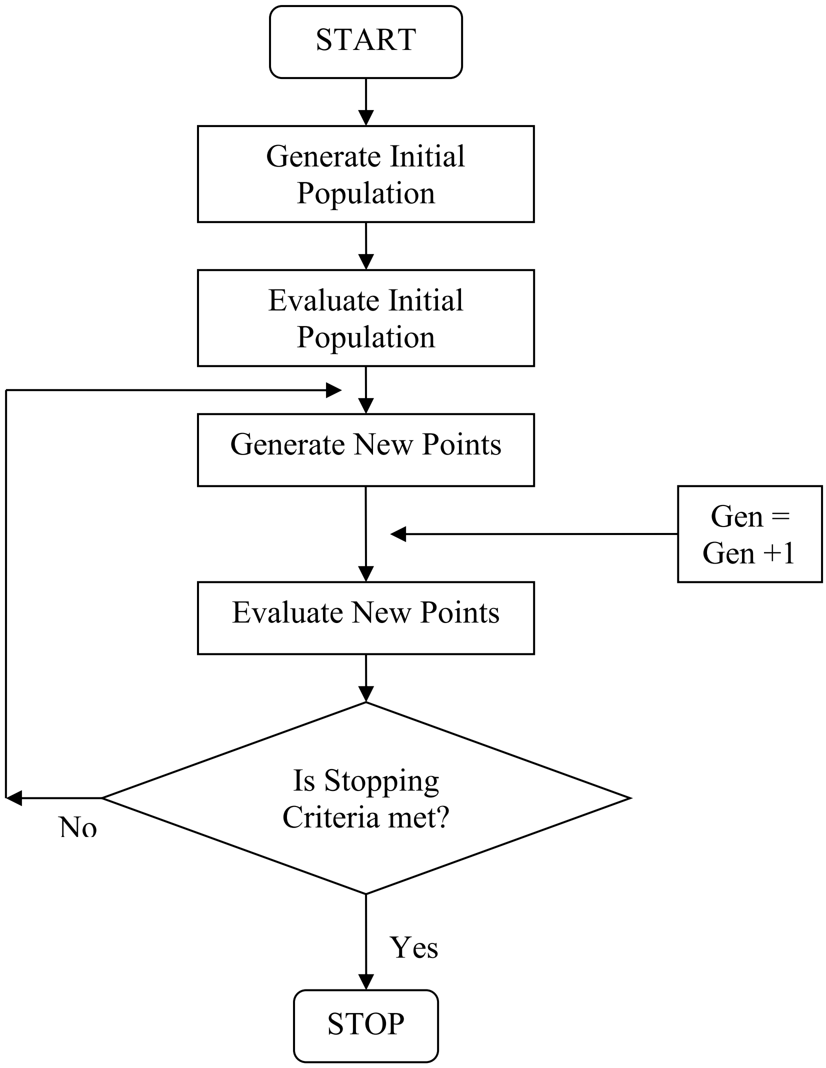


Figure 2. 7: Flow Chart of Evolutionary Algorithm (Source: Atiquzzaman, 2004)

The family of EAs includes techniques such as Evolutionary Algorithms (e.g. Genetic Algorithm), Evolutionary Programming (EP) (Fogel et al., 1966), Evolutionary Strategy (ES) (Schwefel, 1981) and Genetic Programming (GP) (Koza, 1992).

Various Evolutionary Algorithm (EA) based techniques have recently been successfully used in the field of rainfall-runoff modelling, both for the calibration of conceptual rainfall-runoff models and also as black box tools. Amongst these techniques, GAs have been widely applied to different problems in water resources (Babovic and

Keijzer., 2000; Cieniawski et al., 1995; Dandy et al., 1996; Franchini, 1996; Liong et al., 1995b; and Wang, 1991) since the technique is robust and can be understood and implemented easily. Besides GA, there are other types of algorithms available such as Ant Colony Optimization Algorithms (ACOAs) (Dorigo et al., 1996), Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995), Shuffled Complex Evolution (Duan et al., 1992, Liong and Atiquzzaman, 2004), Shuffled Frog Leaping Algorithm (SFLA) (Eusuff and Lansey, 2003) and Non-Dominated Sorting Genetic Algorithm (Atiquzzaman et al., 2006).

2.4.1. Genetic Algorithm (GA)

Genetic Algorithm (GA) (Holland, 1975; Goldberg, 1989) is an example of EAs that mimics Darwinian survival-of-the-fittest philosophy. GA has been applied to many engineering problems including calibration of conceptual rainfall-runoff model, water supply system design and optimization of water distribution network.

GA's natural selection of the solution in the searching process guides the evolution in the right direction to optimal solution. In the searching process, the historical information is exploited to direct the search process towards the optimum by sharing the knowledge.

GA performs well and provide promising solutions for those problems where solution search space is non-convex and lots of local optimum solutions exist within the search space. It explores the search space in the most promising areas and improves the quality of the population of points (approximations of the solutions) over the generations.

Generally like EAs, GA starts the solutions process with a population of points (initial decision vectors) generated randomly. Each solution vector (population of point) consists of a set of parameters (decision variables) of the problem that need to be optimized. With regard to rainfall-runoff calibration problem, the decision vector comprises many variables including runoff coefficient. GA converts the decision vector (decision variables) to a binary number (e.g. 0 and 1) of finite lengths.

The string of the solution of the problem in GA is described as chain consists of series links by Perez and Joaquin (1995). The performance of the chain is evaluated (represented) by the objective function of the model. The solution variables of a rainfall-runoff calibration problem contain a set of links which carries a certain characteristic of the solution.

There are three fundamental operations undertaken in GA method. These include selection, crossover and mutation. These three operations modify the selected decision variables to most appropriate children (offspring) before passing on to next generation.

2.4.1.1. Selection in GA

In GA, good individuals are selected naturally according to the value of objective function (fitness). In any generation, good solution may be selected multiple times whereas the worst solution may be discarded.

Consider the following two variables in a two-dimensional problem that are represented by binary numbers of five digits each:

X1 = 01010

X2 = 10111

The binary representation for X1 and X2 can be placed head-to-tail to produce a ten digit number. Several of such ten-digits numbers generate a population points of the problem. From the population of points, a subset of solution vectors is selected according to the value of objective function. After the selection of the subset, a new group of solution vectors is generated by applying crossover and mutation processes. Generally, two solution strings of the decision vectors are selected for carrying out the crossover operation and generate new strings.

2.4.1.2. Crossover in GA

The purpose of crossover is to transfers the genes of the parents to children. A single location along the strings of the points is identified randomly and the binary numbers are exchanged at that location. Two head and tail segments are produced by cutting the two parent strings. The individual segments (e.g. tail) are interchanged to generate child binary numbers (offspring population). Figure 2.8 illustrates the crossover process.

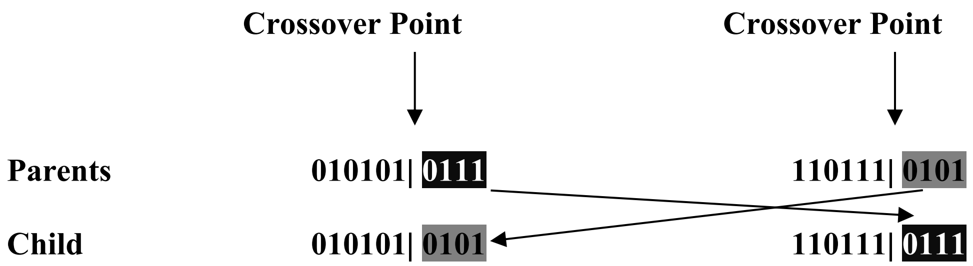


Figure 2.8: Illustration of Crossover Operation (Source: Atiquzzaman, 2004)

2.4.1.3. Mutation in GA

A mutation process is applied to child population. After crossover, the resulting binary numbers (offspring population) are mutated. In this process, a random binary number (gene) is selected and altered. The value of binary bit is changed from 0 to 1 or vice versa. The valuable genetic information obtained from crossover process is safeguarded.

Mutation process is important in the optimization as value of child's objective function may not be changed after the first two processes (i.e. selection and crossover). As a result, the search engine will lose the diversity and confine the solution space to a local optima. Mutation operation will assist keeping the search process towards global optima. However, the probability of mutation to a particular string is very small. The operation of mutation is shown

Figure **2.9**.

Location for Mutation

Offspring	**0101010101**
Binary string after mutation	**0101000101**

Figure 2.9: Illustration of Mutation Operation (Source: Atiquzzaman, 2004)

2.4.2. Nondominated Sorting Genetic Algorithm (NSGA-II)

Deb et al. (2000) developed a multiobjective optimization algorithm, called "Nondominated Sorting Genetic Algorithm (NSGA-II)". NSGA-II can provide a trade-off between several objectives which are considered in the solution scheme. The trade-off information generated by NSGA-II assists water manager in making a sound decision for alternative solutions. NAGA-II initially generates a set of population P with N solutions randomly. It generates child population (Q_t) from the parent population (P_t) of size N. These parent and child populations are mixed up together to form the population of P_t+Q_t. The entire population is then sorted and classify using a fast nondominated sorting algorithm. This process generates different nondominated fronts (F1, F2, etc). The new parent population (P_t+1) is generated using the solutions from first front (F1). The process is repeated until the solution size becomes N. One set of solutions from all fronts is accepted. The approved solutions are rearranged based on the "crowded comparison criterion". The purpose of applying "crowded comparison criterion" is to keep the diversity in the process without being trapped in a local optima. The process ensures the diversity by selecting a point in a less crowded region of population. The new children (offspring) population is recreated, and the procedure is continued in the subsequent generations. The advantage of NSGA-II is that it can handle any number of objectives. The disadvantage is that it is computationally less efficient than other types of multiobjective genetic algorithm. More details can be found in (Deb et al., 2000). The schematic diagram of NSGA-II is shown in Figure 2. 10. NSGA-II has been successfully applied in different types of problems including optimization of reservoir operation (Sivapragasam, 2002), optimization of water distribution modelling (Atiquzzaman e. al., 2006) and so forth.

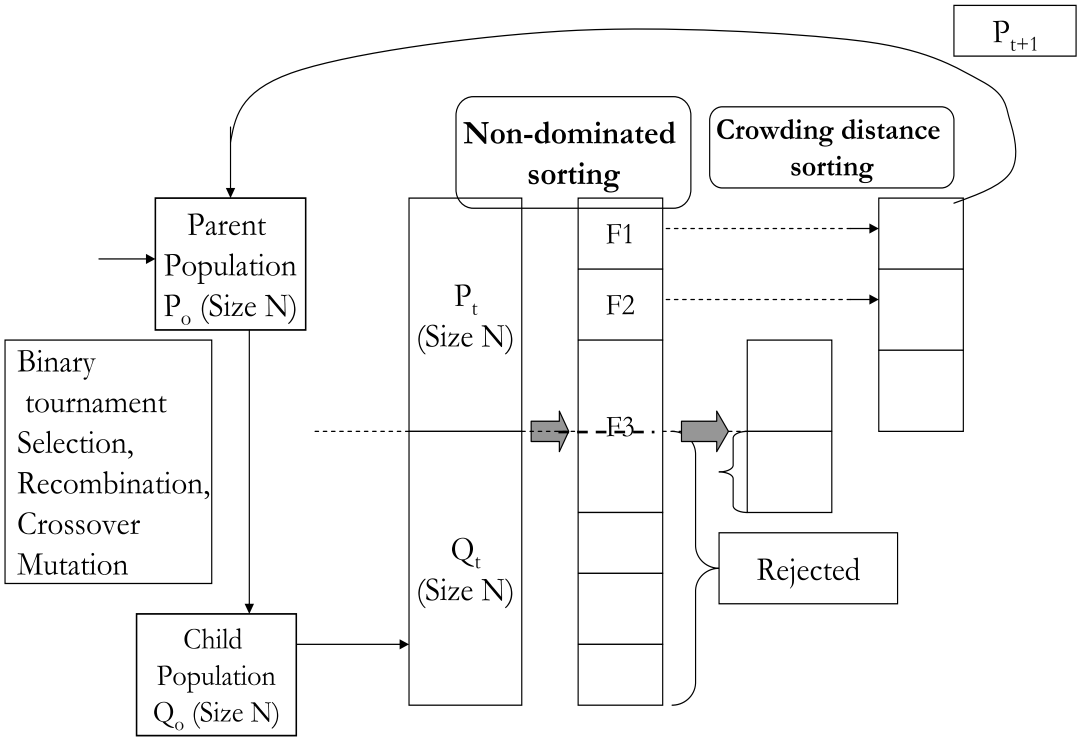


Figure 2. 10: Schematic Diagram of NSGA-II Procedure (Source: Al-Fayyaz, 2004)

2.4.3. Simulated Annealing (SA)

Metrpolis et al. (1953) and Kirkpatrick et al. (1983) applied Simulated Annealing (SA) efficiently in solving combinatorial problems (Atiquzzaman, 2004). The basic concept of SA is driven by the thermal processes. For example, the thermal process involves the way of cooling and annealing of solids. If the solid material is heated up to a maximum value, it melts and gets mobility. At this stage, the atoms in the solid molecules arrange themselves with the high energies. When the temperature of solid molecules is decreased, the melted solids form a crystalline structure. However, the crystal structure becomes irregular if the cooling is undertaken very rapidly. Suppose, "*the current energy state i of the solid with energy E_i is changed to the state j with energy E_j applying a perturbation mechanism. The later state j will be the new current state if the energy difference (E_j – E_i) is less than or equal to zero. Otherwise, if the energy difference is greater than zero, the state j will be accepted with a probability of [exp (E_i – E_j)/K_B*T]; where, K_B is Boltzmann constant; T denotes temperature*" (Atiquzzaman, 2004).

Pham and Karaboga (2000) described that the SA algorithms search based on four principals which are: *"(1) representation of solutions; (2) definition of cost function; (3) definition of the generation mechanism for the neighbours; and (4) designing a cooling schedule*". In the solution process of SA, feasible solutions represent the states of the solid and the objective function values (cost) are the energies of the state. The new solution is generated by randomly changing the current feasible solution according to the Metropolis's criterion. The objective functions values of the two solutions are determined. If the difference in objective functions values of the two solutions is negative, the new solution will replace the current solution. Otherwise, it is accepted based on Boltzman's probability (see above). This generation of new solution and the acceptance of that solution are repeated until the search engine finds the global optima (satisfies the stopping criteria or reaches the maximum number of evaluation).

2.4.4. Shuffled Complex Evolution (SCE)

Duan et al. (1992) developed a global optimization tool at the University of Arizona, called "Shuffled Complex Evolution (SCE)". SCE has been applied to a variety of engineering problems and proven to be an effective and efficient algorithm by many researches (Duan et al., 1993; Liong and Atiquzzaman, 2004; Atiquzzaman and Liong, 2004).

Thyer et al. (1999) has described that "*SCE works on the basis of four concepts: (1) combination of deterministic and probabilistic approaches; (2) systematic evolution of a complex of points; (2) competitive evolution; and (4) complex shuffling*". The algorithm starts the solution process with the random generation of a population of points within the feasible space. The sample of points has the parameters values which are restricted by the lower and upper bounds. As the initial population of points are generated randomly and the searching is not biased to pre-defined points, this algorithm provides the potential to reach global optimum solutions. Each generated point is evaluated against the pre-specified objective functions and constraints. After the evaluation, the points are sorted in ascending order based on the objective function values. The population of points is then partitioned into several complexes. Each complex will have $2N + 1$ points, where N is the dimension of the problem. SCE uses this complex of points and search in different direction within the feasible domain. With this process, each point in a complex may get the opportunity to reproduce a new point. A sub-complex is then created from each complex with $N + 1$ points where "Nelder and Mead Simplex Method (NMSM) (Nelder and Mead, 1965)" is applied for global improvement. The best point with higher fitness value is selected to generate child. Two main steps in the NMSM, namely reflection and contraction are performed to get a better point (offspring). The worst parent point in the sum-complex is replaced with this new child point. Once the evolution process is complete, the complexes are combined into the new population of points. The new sample population is evaluated and sorted again based on objective function. The points are shuffled for information sharing and reassigned into new complexes. This process is continued until stopping criteria are met.

2.4.5. Other Optimization Algorithms

There are other optimization algorithms available including "Ant Colony Optimization Algorithms (ACOAs), Shuffled Frog Leaping Algorithm (SFLA) and Particle Swarm Optimization (PSO)".

The basic search process in ACOAs (Dorigo et al., 1996) is similar to Genetic Algorithm (GA) or Simulated Annealing (SA). The general behaviour of real ant is incorporated in ACOAs. Ants find the food sources following the shortest paths from the nest without the strength of vision. The individual ant communicates with other ant using pheromone trails. During this searching process, the pheromone trails are dissipated on the shortest paths. This indicates the distance and quality of the food source. When other ants find the pheromone trail, they get attracted to follow it. The path is reinforced and attracted by more ants to follow the trail. The pheromone level in most attractive path is increased over time whereas this reduces to nil in poor paths. Dorigo et al. (1996) developed ACOAs based on this behaviour of the real ants. They use the following analogies: *"(1) artificial ants scan the solution space while real ants search their natural environment for food; (2) the objective function values represent a mapping of the food sources quality and an adaptive memory is equivalent to the pheromone trails*" (Atiquzzaman, 2004). Instead of real ant, artificial ants are equipped in ACOAs which find the feasible solutions within the search space using a heuristic function.

Kennedy and Eberhart (1995) proposed a similar approach, called "Particle Swarm Optimization (PSO)". PSO is a population-based search technique similar to EAs. In PSO, the behaviour of bird flock is incorporated. The algorithm simulates the behaviour of a bird flock where social information is shared. When the bird flock searches for food, individuals learn the experience and discoveries from others. The behaviour of one individual is guided by the best local or global companions in the search space. In addition, individuals also adjust their flying speed and direction based on their previous experiences. All the individuals observe the behaviour and memorise the flying histories and eventually converge to global optimal solution. Eusuff and Lansey (2003) developed “Shuffled Frog Leaping Algorithms (SFLA)” based on the concept of PSO and SCE.

2.5. Summary

The application of conceptual rainfall-runoff modelling techniques, their calibration using traditional algorithms and more powerful evolutionary algorithms have been discussed. It has been found that the traditional algorithms have failed to converge to optimal solution as the search space of a conceptual rainfall-runoff model is complex. Hence, evolutionary algorithms have attracted the attention of the researches due to their robust capability to produce optimal result.

The literature of AI techniques has been discussed. These techniques including ANN, ANFIS, SVM and GP have been very popular to predict the hydrological flows. Aapplication of AI approaches in hydrological time-series prediction indicates that their performances are not consistent for all applications and it is difficult to state which method is superior. Superior performance depends on appropriate parameters and network configurations. Researchers have attempted to improve the performance of these methods using hybrid approach (ANFIS) or by combining them with other algorithms (EC-SVM) to optimize the parameters. However, they require significant computational time and numerous iterations for reasonable prediction of runoff from rainfall. In order to overcome the long computational time and to produce generalized solution, a learning algorithm called Extreme Learning Machine (ELM), developed by Huang et al. (2006) was used in this study.

This thesis discusses the application of this relatively new Artificial Intelligence (AI) technique (both node band Kernel based ELM). ELM’s performance is compared against other widely used techniques including ANN, SVM, GP and EC based SVM.

CHAPTER 3

PREDICTION OF INFLOWS FROM DAM CATCHMENT UISNG GENETIC PROGRAMMING

This chapter includes the major part of

- Atiquzzaman, M. and Kandasamy, J. (2016). "Prediction of Inflows from Dam Catchment using Genetic Programming", International Journal of Hydrology Science and Technology, vol 6, No. 2, pp103-117, http://dx.doi.org/10.1504/IJHST.2016.075560.

3. Prediction of inflows from dam catchment using genetic programming

3.1. Introduction

Conceptual rainfall-runoff modelling is essential for flow estimation from the catchment. In principal, both conceptual and physically based distributed models require a large number of parameters such as catchment characteristics, losses, flow paths, meteorological and flow data. The values of some of these parameters are evaluated through calibration. Accurate calibration can be performed manually or using available computer based hydroinformatics tools such as evolutionary algorithms (GA, SCE and PSO). The calibration process of complex models may be cumbersome and requires considerable effort and experience for large topographically varying catchment where catchment characteristics change significantly. Even though the model is calibrated, the parameters from one catchment may not be representative for the other catchment. In this case, hydroinformatics tools like GP and ANN can be used where no parameters associated with catchment and soil characteristic are necessary. The driving factor behind the application of hydroinformatics tools was to ease the complex numerical modelling process.

The study aims to introduce a scheme for establishing a rainfall-runoff relationship or hydrological flow forecasting tool for the analysis of yield from a dam catchment. The model uses Artificial Intelligence (AI) based data driven modelling methods with all the necessary catchment data to establish an efficient flood forecasting tool. Hence, AI techniques, namely, Genetic programming (GP), Artificial Neural Network (ANN) with MIKE11-NAM (DHI, 2013) are proposed for long term runoff prediction from a dam catchment. These tools are chosen in this study because it gets trained with the input data and also does not need all the catchment characteristic data which are difficult to measure in the field. A catchment located in New South Wales, Australia was selected. The calibration shows excellent agreement between the observed and simulated flows recorded over thirty years. The model was also applied for assessment of future one hundred years flows using rainfall input generated from two different assumed climate change scenarios.

3.2. Proposed Scheme

In the present study, the hydroinformatics tools (GP, ANN) are proposed to estimate the long term catchment runoff using the past and current information of weather data and past catchment flow as input data. However, the long term historical catchment runoff measurement is not normally available for many catchments. Hence, a traditional lumped conceptual rainfall-runoff model, for example MIKE11-NAM is suggested. The MIKE11-NAM requires the same input as precipitation, potential evapotranspiration and observed flow. It operates by continuously accounting for the moisture content in the surface, subsurface and groundwater storages.

The schematic diagram of the proposed methodology is shown in Figure 3.1. The step-by-step procedure is also described below:

1. Meteorological data (rainfall and evaporation) and available observed flow for the catchment was collected.
2. A MIKE11-NAM model was built and calibrated using these data for the period of available data. It was built with the same rainfall used in the previous analysis (GP) and the evaporation data from 1954 to 1981.
3. The simulated runoff from MIKE11-NAM was generated.
4. GP was trained and validated using NAM predicted flow, rainfall and evaporation data as input and observed flow as output for the period of available data.
5. The GP model was applied to real-time prediction of flows.

The model's performance is reported through comparisons of simulated and observed flows using goodness-of-fit measures.

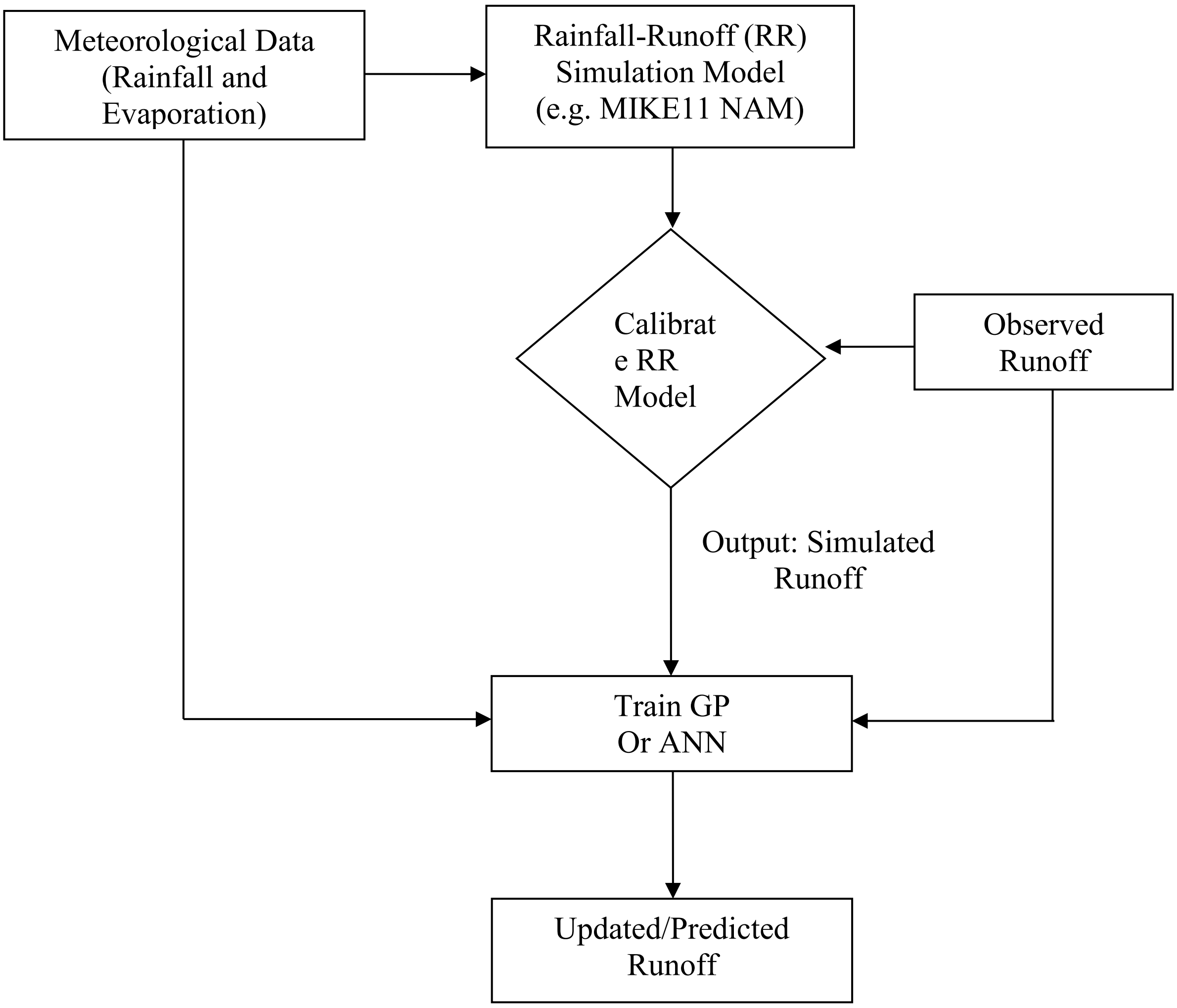


Figure 3.1: Schematic Diagram of the Proposed Method

The trained GP can also be applied to predict long-term catchment runoff using future predicted or forecast rainfall. The proposed procedure is shown in Figure 3.2.

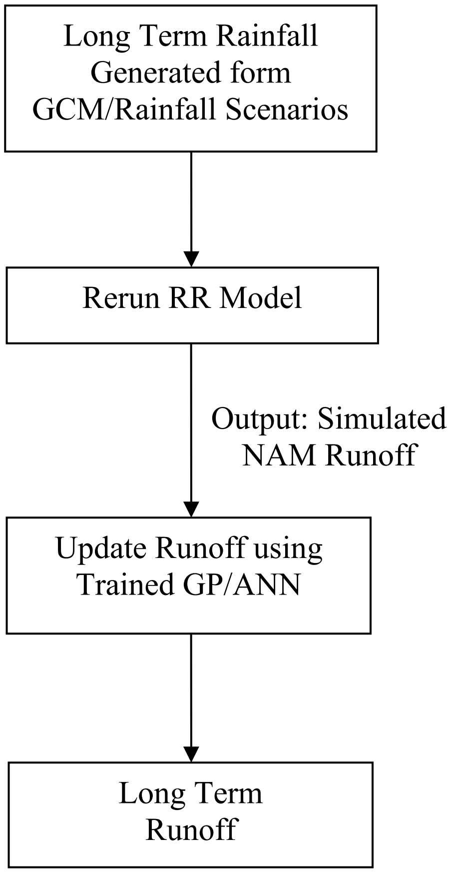


Figure 3.2: Long term Runoff Prediction

3.3. Application

GP and ANN are applied for forecasting of Duckmaloi Weir Inflows. Duckmaloi Weir is located on Duckmaloi River (see Figure 3.3), adjacent to the eastern side of Oberon Dam catchment, Australia. The catchment area at the weir is approximately 112 km^2 and storage capacity 20 ML (DNR, 2007). A Sacramento model was built and calibrated by DNR. The results from proposed method will be compared against Sacramento results.

Firstly, the aim of this study is to develop relationship between the future inflow at the Duckmaloi catchment outlet using rainfall and runoff data available up to the current time t. Mathematically, the relationship can be expressed:

$$Q_{t+n\Delta t} = f(R_t, R_{t-\Delta t}, \ldots R_{t-m\Delta t}, Q_t, Q_{t-\Delta t}, \ldots Q_{t-m\Delta t}) \qquad (1)$$

Where, Q is the inflow (m^3/s), R is the rainfall intensity (mm/day), n refers to how far into the future the inflow prediction is desired, m represents how far back the recorded data in the time series are affecting the inflow prediction and Δt is time interval.

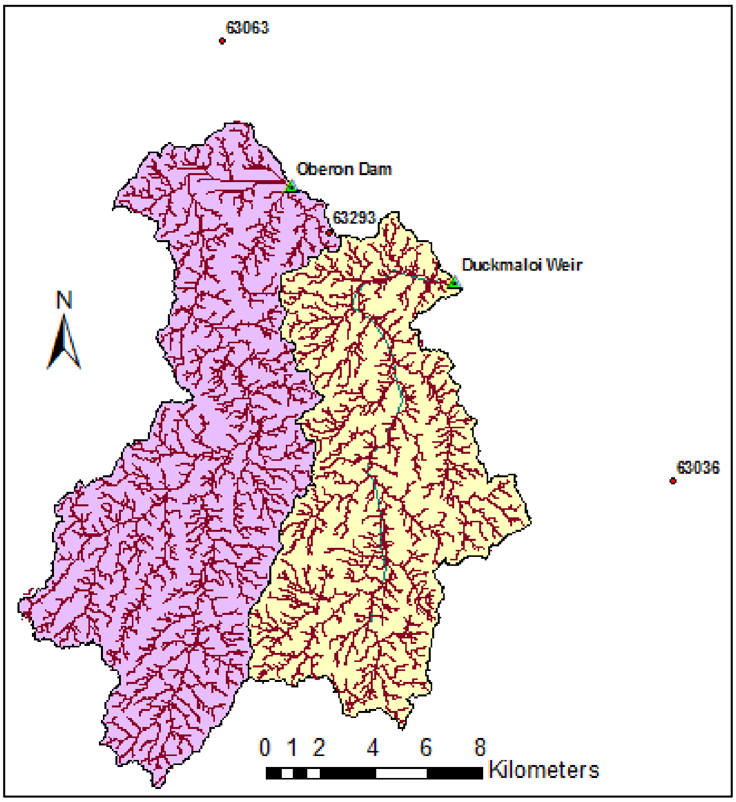


Figure 3.3: Oberon Dam and Duckmaloi Weir Catchments

The performance of the model results is reported through the comparisons of simulated and observed flows using two goodness-of-fit measures. They are coefficient of determination and coefficient of efficiency.

Coefficient of Determination: Coefficient of determination (R^2) is defined as the squared value of the coefficient of correlation which is calculated as:

$$R^2 = \left(\frac{\sum_{i=1}^{n} (O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2} \sqrt{\sum_{i=1}^{n} (P_i - \overline{P})^2}} \right)^2 \qquad (2)$$

Where, O observed, and P predicted values.

R^2 estimates the combined dispersion against the single dispersion of the observed and predicted series. The range of R^2 lies between 0 and 1 which describes how much of the observed dispersion is explained by the prediction. A value of 0 means no correlation at all whereas a value of 1 means that the dispersion of prediction is equal to that of the observation.

Coefficient of Efficiency: Coefficient of Efficiency (E) proposed by Nash and Sutcliffe (1970) is defined as one minus the sum of the absolute squared differences between the predicted and observed values normalized by the variance of the observed values during the period under investigation (Krause, et al., 2005). It is calculated as:

$$E = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \qquad (3)$$

The range of E lies between 1 (perfect fit) and $-\infty$.

3.3.1. Case Study I

Firstly, an example event is demonstrated with the rainfall and flow data in year 1990. The inflow forecasting for the Duckmaloi catchment is conducted for 1-day lead-time prediction. The GP and ANN are trained with the input data set containing variables of rainfall and inflow at current time and the value of n is set to 1 (see eq. 1). In these models, fifty percent of the data was used for training and fifty percent for validation. The GP and ANN results are presented in Figure 3.4 and Figure 3.5 respectively. Both models produce very good prediction of Duckmaloi Weir inflows. The goodness-of-fit measure is presented in Table 3. 1. Visually, GP produces better prediction than ANN especially during recession. Figure 3.5 shows some noise in the prediction at the tail of the hydrograph. GP usually derives physical relationship between the variables. A series of relationships are produced by GP. However, only one is shown below.

$$Q_{t+\Delta t} = R_{t+\Delta t} + Q_t - 0.0776213 * Q_{t-\Delta t} \tag{4}$$

Where, $Q_t$is discharge at current time, $Q_{t+\Delta t}$ is discharge at future time, R_t is rainfall at current time and Δt is time interval.

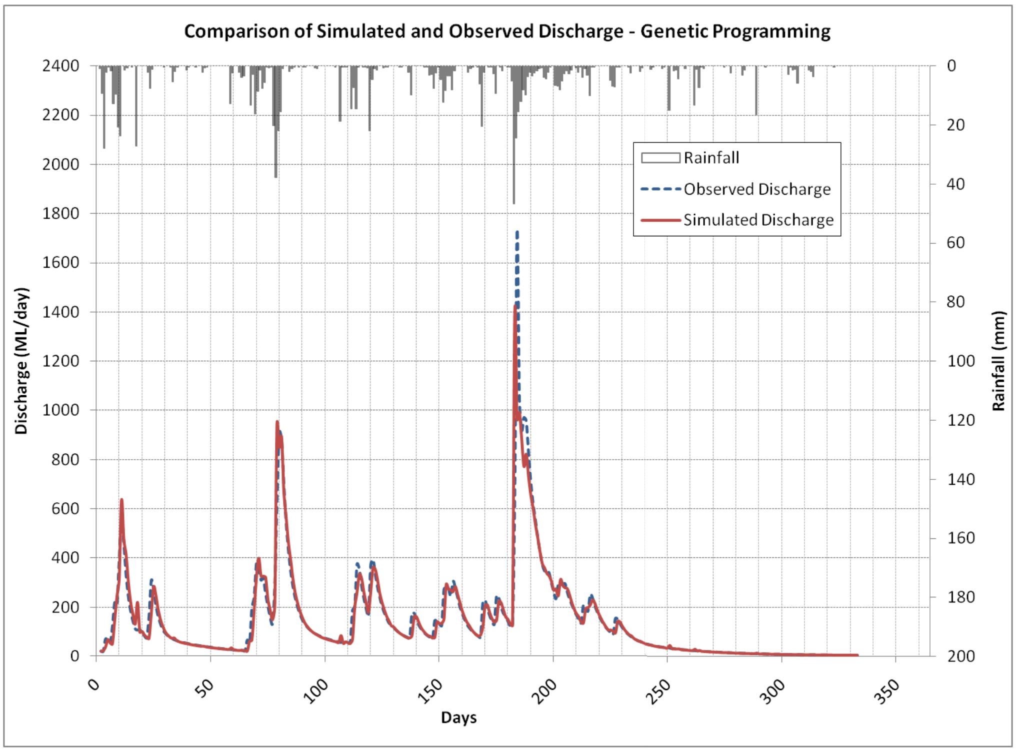


Figure 3.4: Comparison of Hydrograph between Observed and GP Runoff – Year 1990

Table 3. 1 Goodness-of-fit measures - 1990

Parameter	Genetic Programming	ANN
Coefficient of Determination (R^2)	0.88	0.87
Coefficient of Efficiency (E)	0.88	0.87

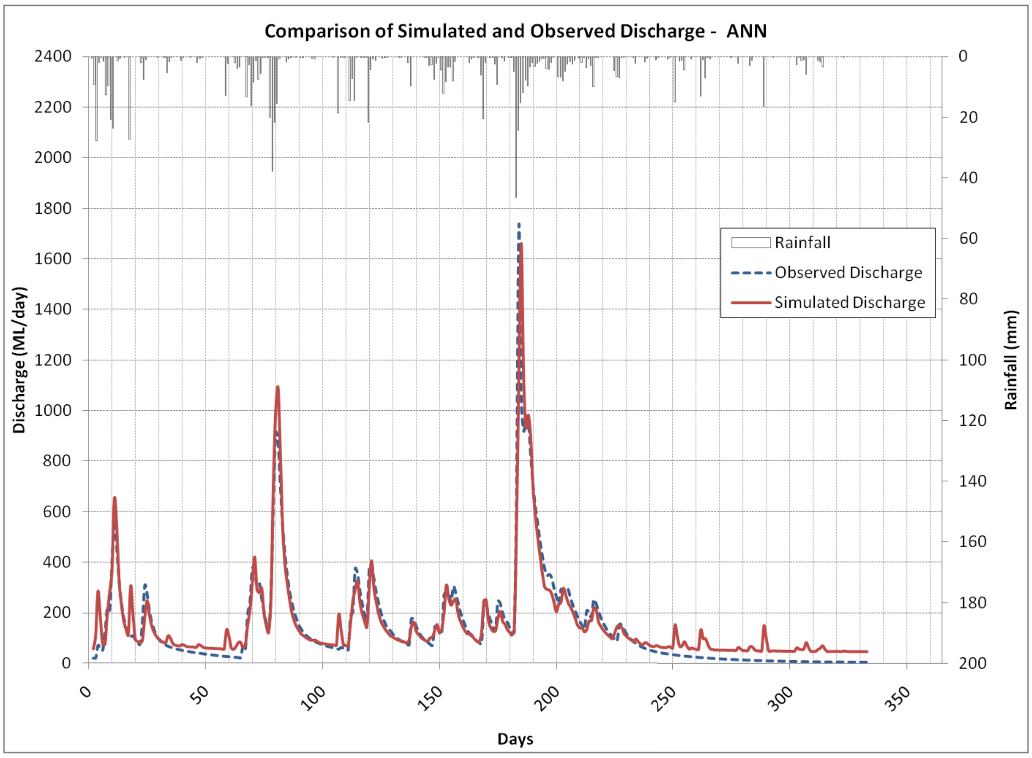


Figure 3.5: Comparison of Hydrograph between Observed and ANN Runoff – Year 1990

3.3.2. Case Study II

In this example, GP and ANN are trained again with whole series of rainfall and runoff data as used in fish river water supply scheme IQQM modelling report (DNR, 2007). The data contain time series from 11/10/1954 to 19/02/1981. The comparison of measured and simulation Duckmaloi Weir inflows are presented in Figure 3.6 and Figure 3.7 respectively. GP performs slightly better than ANN and the coefficient of determination is found to be 0.73 (see Table 3. 2) which implies very good prediction for long term time series.

Table 3. 2 Goodness-of-fit measures – 1954 to 1981

Parameter	Genetic Programming	ANN
Coefficient of Determination (R^2)	0.73	0.71
Coefficient of Efficiency (E)	0.73	0.71

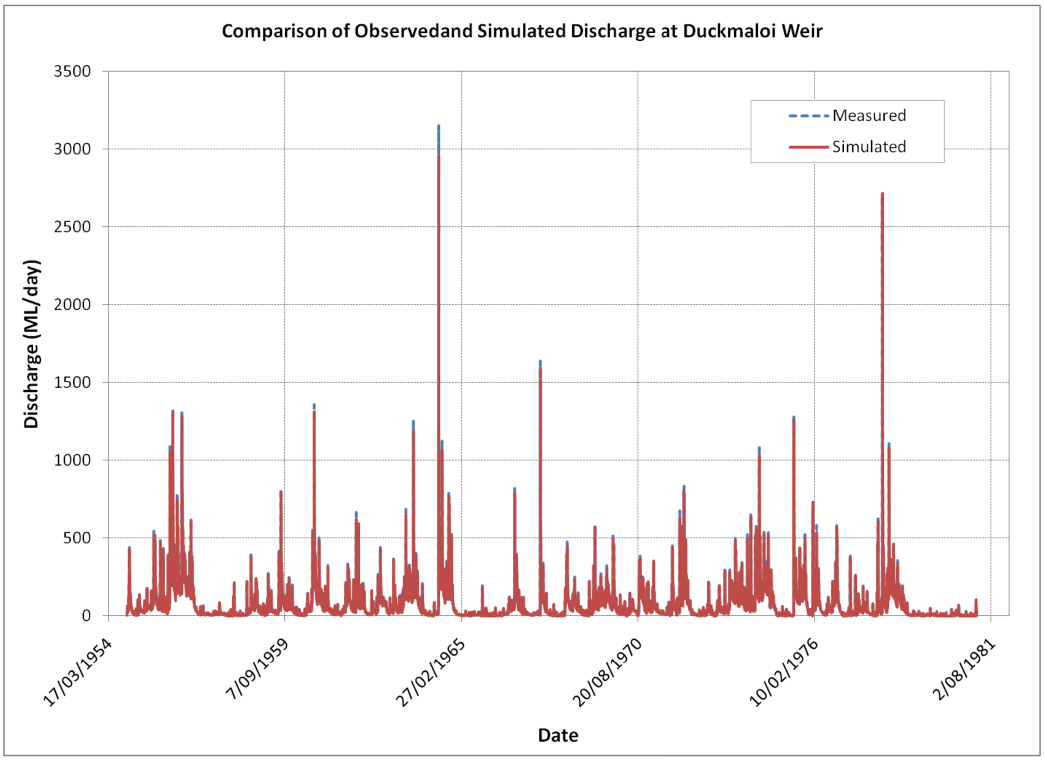


Figure 3.6: Comparison of Measured and Simulated Inflows at Duckmaloi Weir - GP

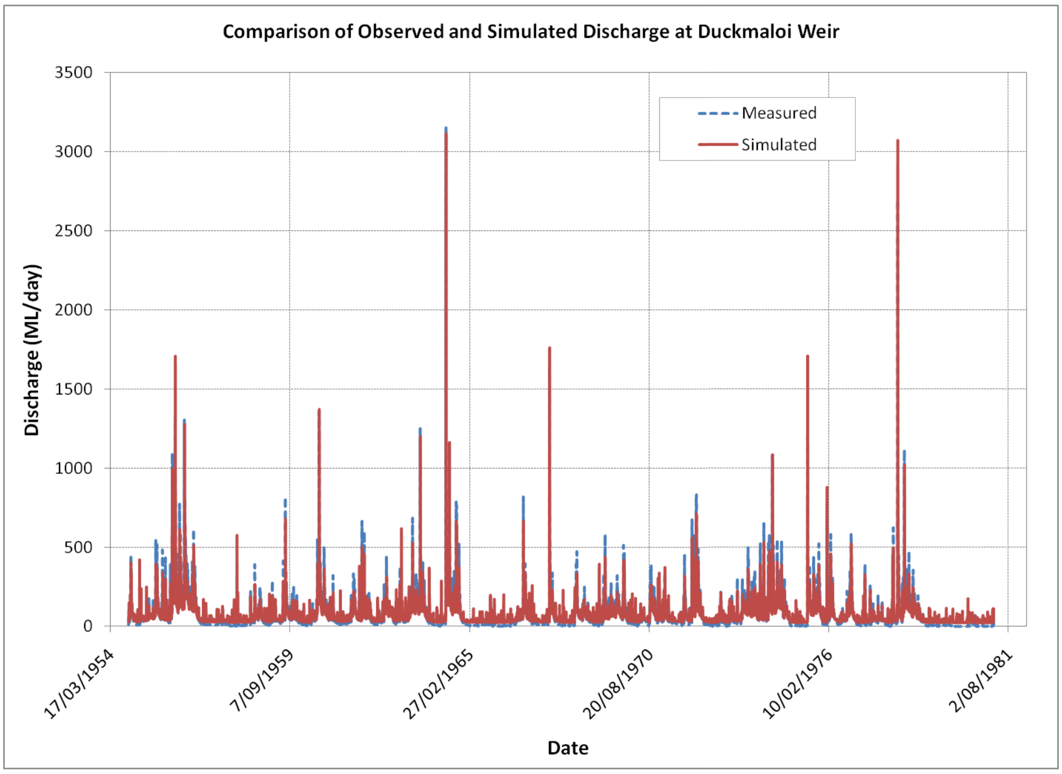


Figure 3.7: Comparison of Measured and Simulated Inflows at Duckmaloi Weir – ANN

3.3.3. Comparison of GP and Sacramento Model Results

Comparison of observed and simulated discharges from Genetic Programming and Sacramento models are presented in Figure 3.8 to Figure 3.15. Almost all the figures show that Sacrament model either over-predicted or under-predicted at and around the peak discharge. Figure 3.16 shows a comparison for an event from June 1960 to October 1960. It has been found that GP is following the observed discharges especially during the recession part reasonably well compared to Sacramento model. Yearly volumes of inflows to Duckmaloi Weir are calculated and plotted in Figure 3.17. Figure 3.17 presents that Sacramento model under-predicted in 1960, 1971 and 1972 and over-predicted in 1963, 1967, 1968 and 1980.

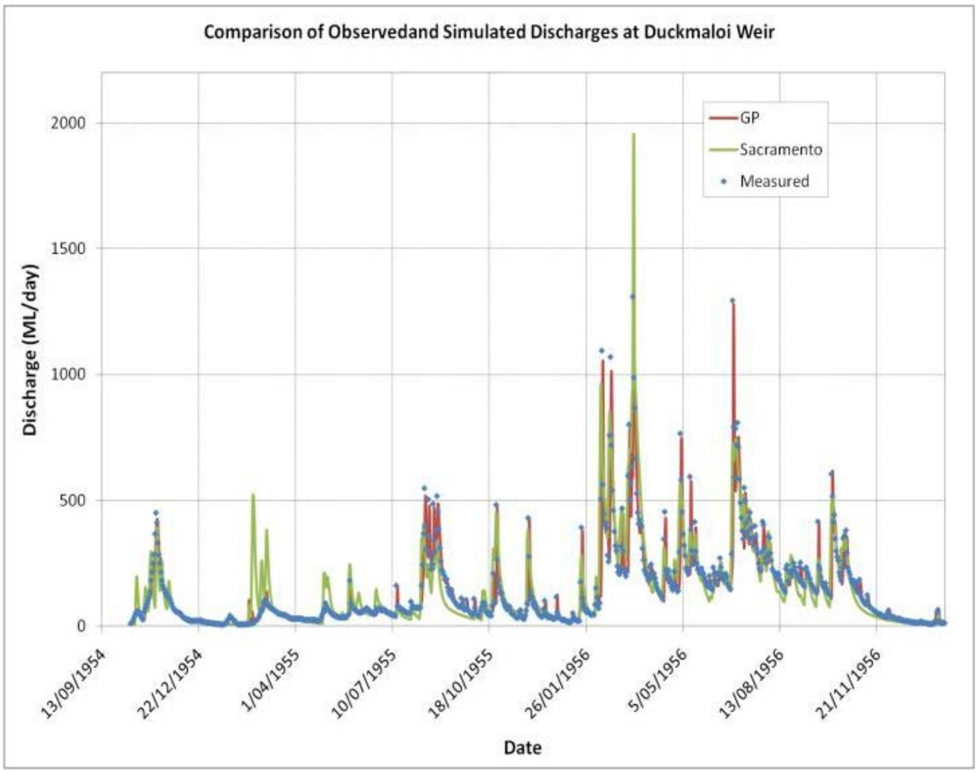


Figure 3.8: Comparison of Observed and Simulated Discharges from GP and Sacramento Models – 1954 to 1956

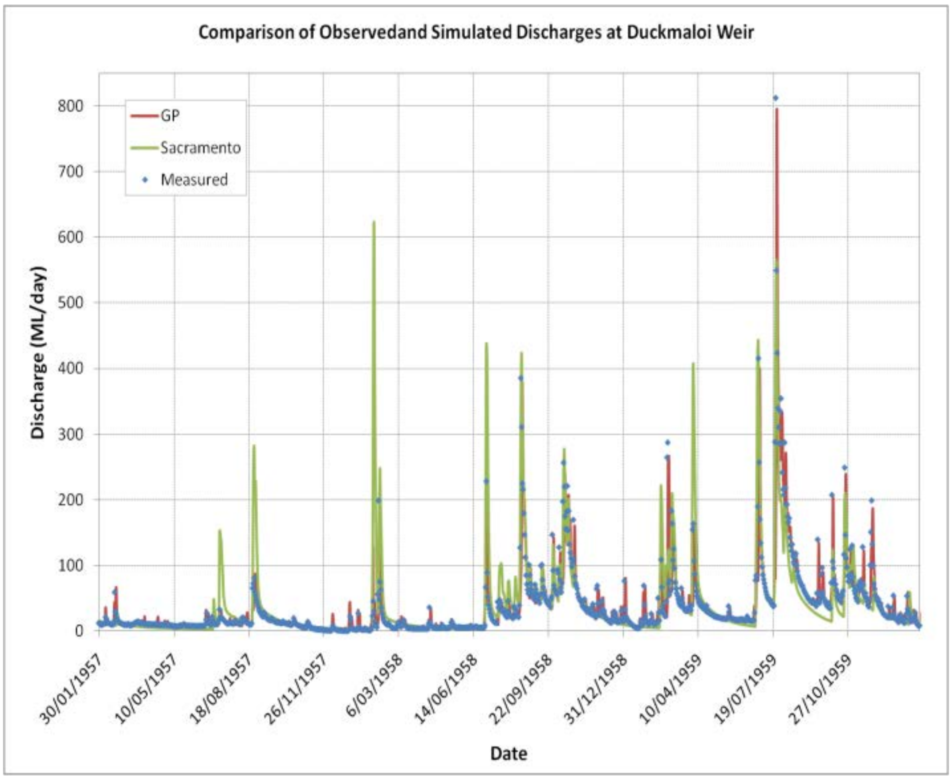


Figure 3.9: Comparison of Observed and Simulated Discharges from GP and Sacramento Models – 1957 to 1959

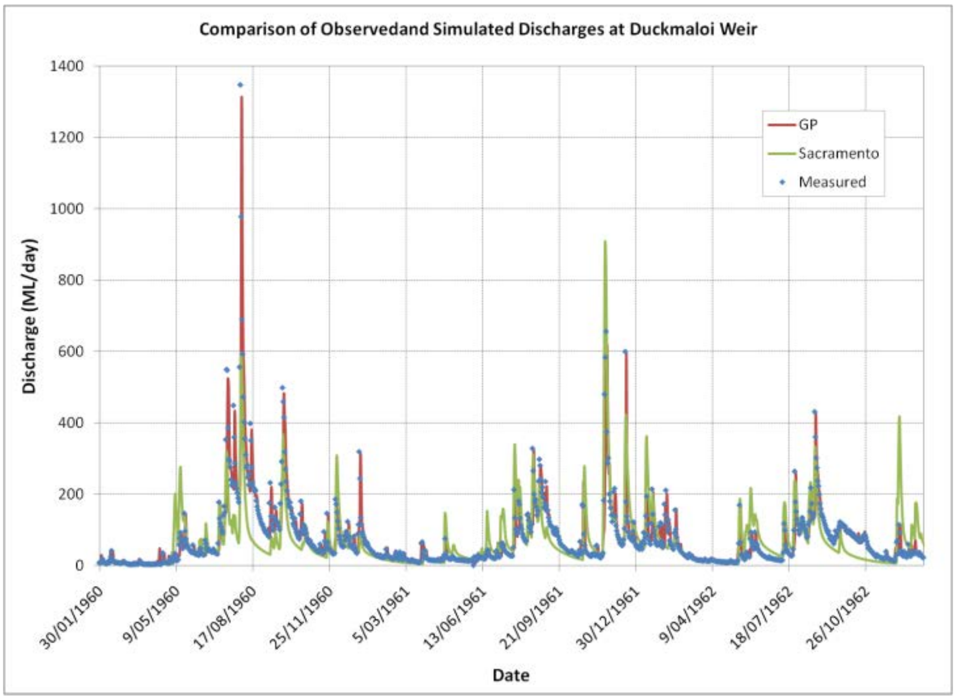


Figure 3.10: Comparison of Observed and Simulated Discharges from GP and Sacramento Models – 1960 to 1962

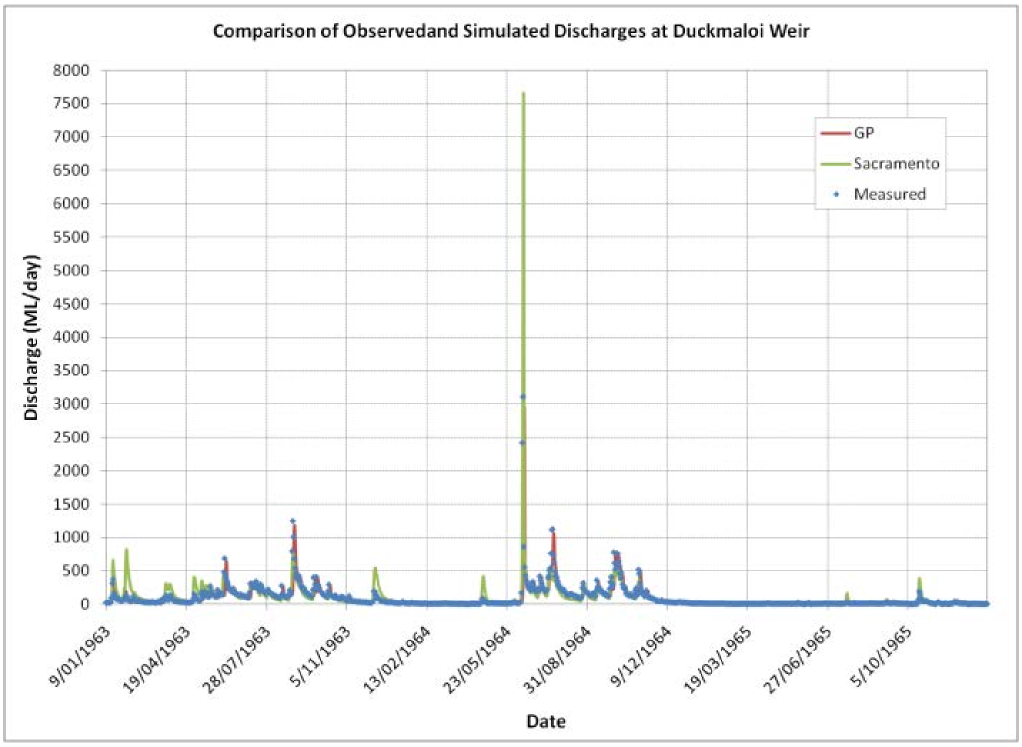


Figure 3.11: Comparison of Observed and Simulated Discharges from GP and Sacramento Models – 1963 to 1965

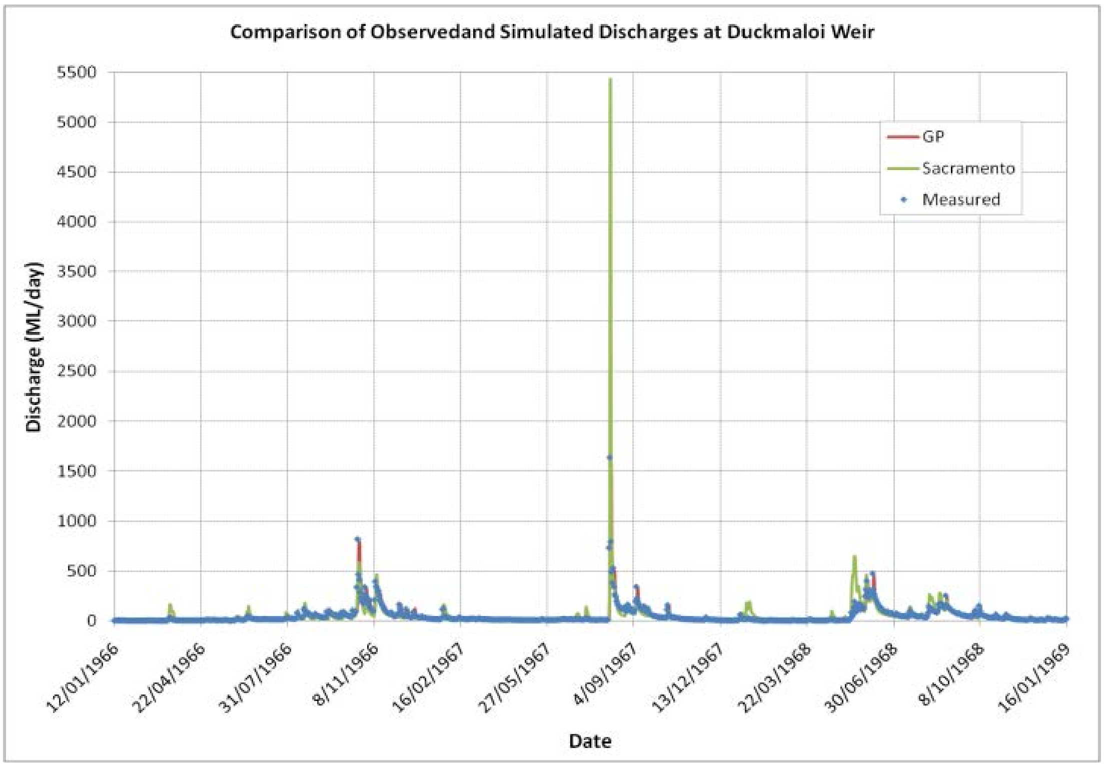


Figure 3.12: Comparison of Observed and Simulated Discharges from GP and Sacramento Models – 1966 to 1969

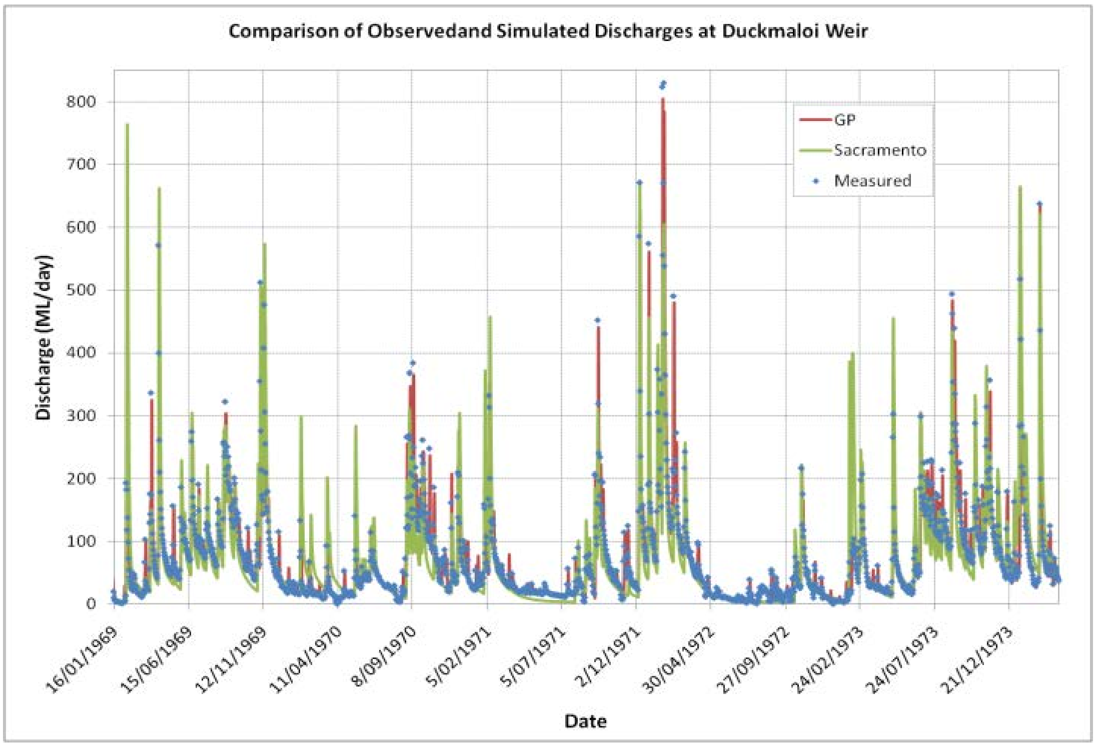


Figure 3.13: Comparison of Observed and Simulated Discharges from GP and Sacramento Models – 1969 to 1973

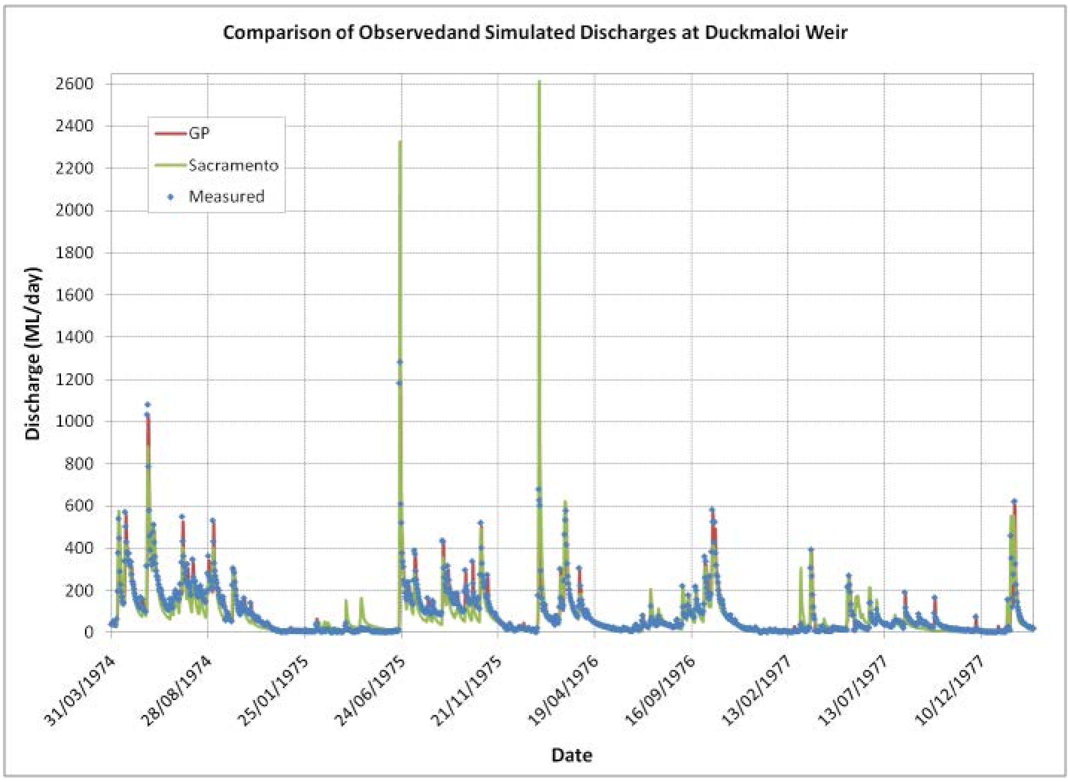


Figure 3.14: Comparison of Observed and Simulated Discharges from GP and Sacramento Models – 1974 to 1977

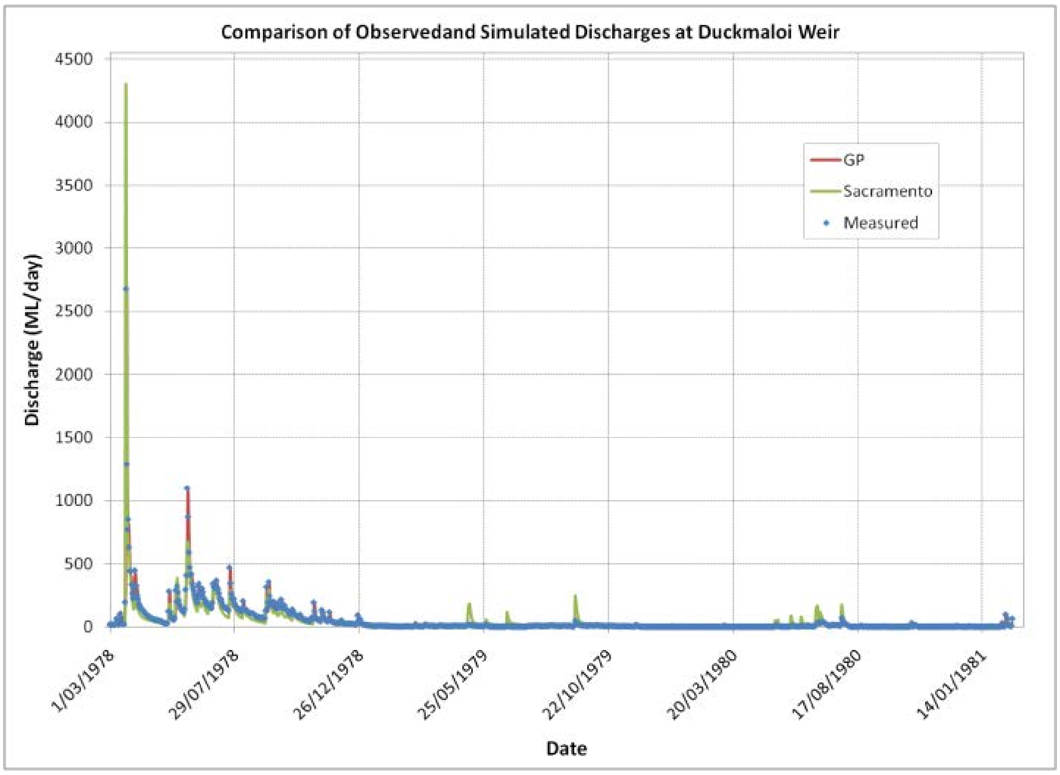


Figure 3.15: Comparison of Observed and Simulated Discharges from GP and Sacramento Models – 1978 to 1981

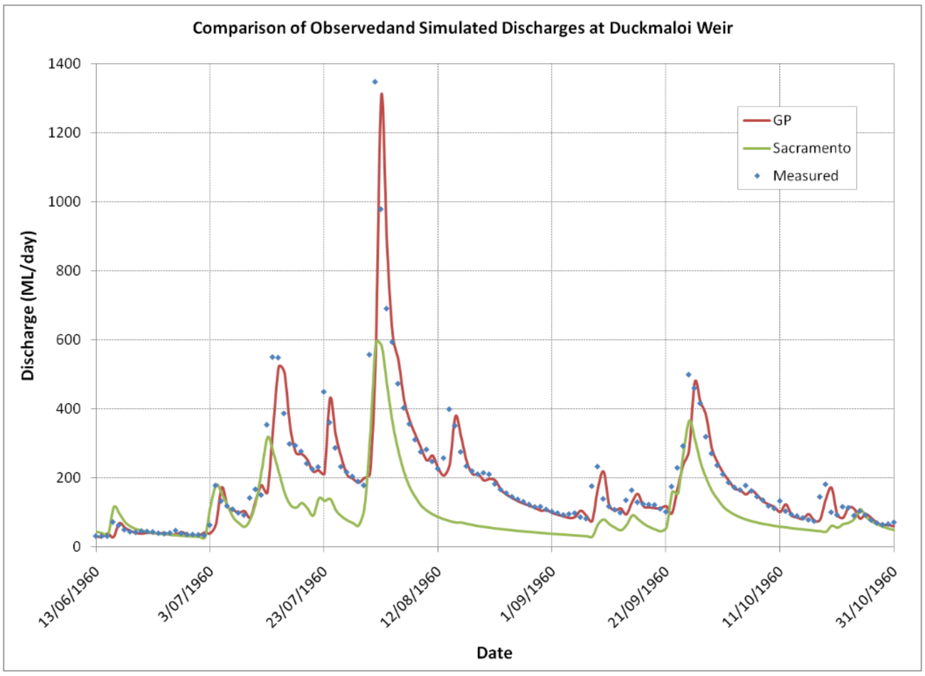


Figure 3.16: Comparison of Observed and Simulated Discharges from GP and Sacramento Models – June to October 1960

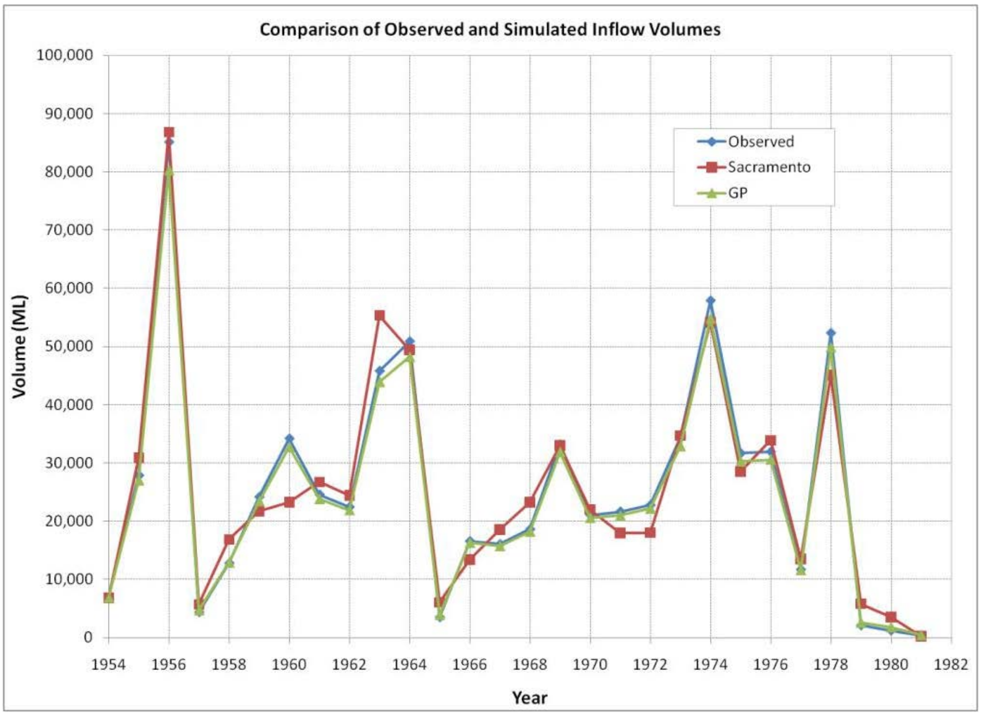


Figure 3.17: Comparison of Observed and Simulated Yearly Volumes of Inflows at Duckmaloi Weir

To measure the model performance, a low flow event is selected. Figure 3.17 shows the total volume of inflows to the Duckmaloi Weir were very low in 1965. The corresponding inflow series is depicted in Figure 3.18. The goodness-of-fit measures for the GP and Sacramento models are estimated for this particular low flow series and presented in Table 3. 3. Table 3. 3 shows that the coefficient of determination is similar from both model but the coefficient of efficiency for GP is close to 1 which means that the performance of GP is reasonable. The flow frequency curves from GP model results and observed flows is shown in Figure 3. 19. This is also reflected in scatter plot in Figure 3.20 which shows that majority of GP predicted flows lies around 45 degree line compared Sacramento flows.

Table 3. 3: Model Performance Criteria

Performance Criteria	GP	Sacramento
Coefficient of Determination (R^2)	0.80	0.83
Coefficient of Efficiency (E)	0.78	-1.18

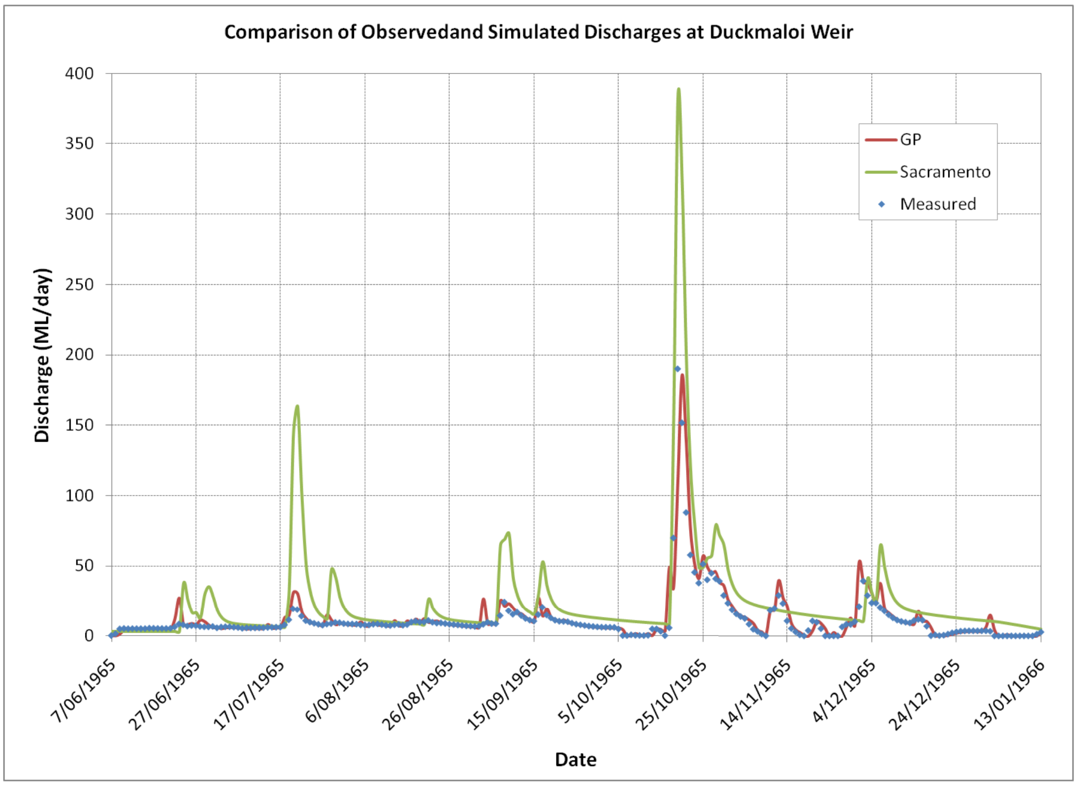


Figure 3.18: Low flow series in year 1965.

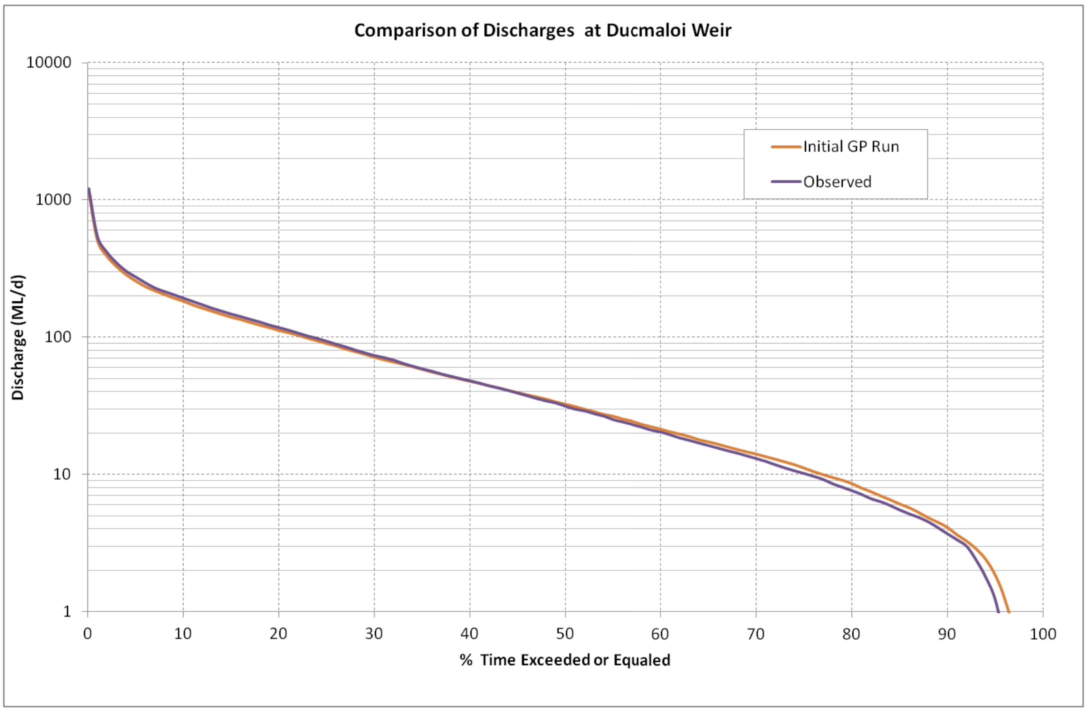


Figure 3. 19: Comparison of Duckmaloi Weir Inflows – 1954 to 1981

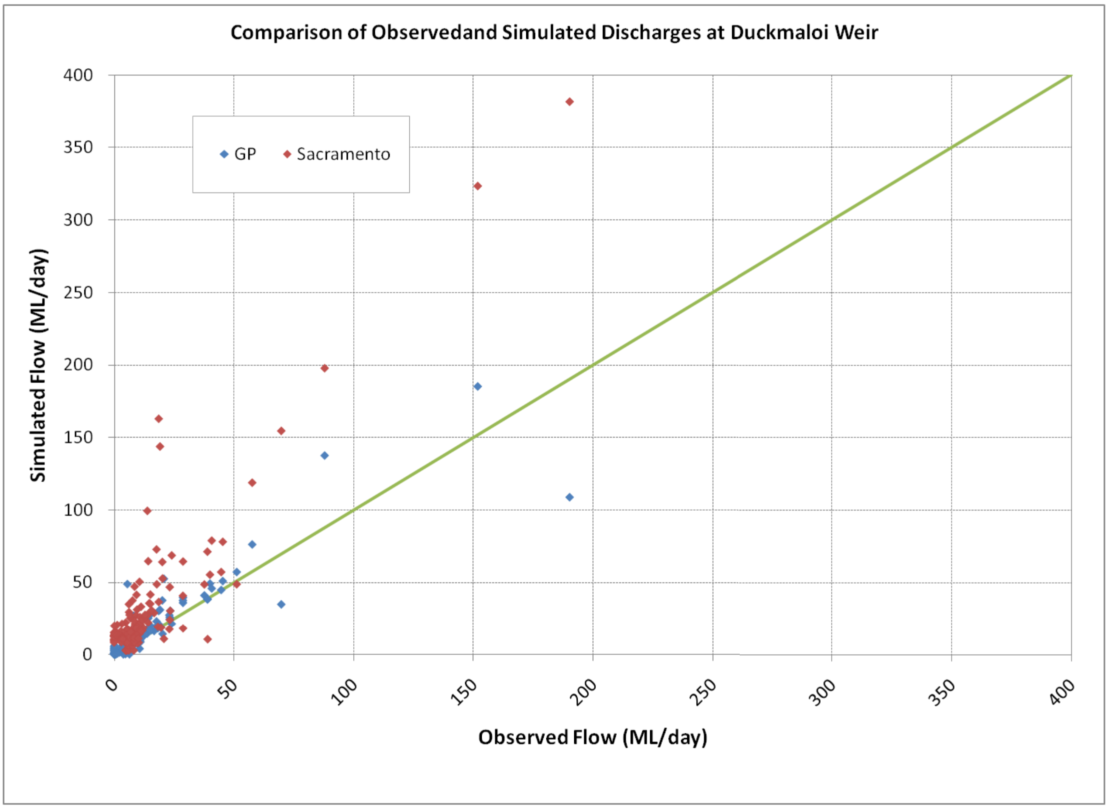


Figure 3.20: Scatter Plot of Observed and Simulated Discharges – 1965

3.4. Improvement of Model Calibration using GP

GP model was built using the lagged observed flows as an input. However, GP automatically discards input variables (lagged flows) that has less influence on the output. The lagged inflow on the previous day determined by GP has significant influence on the model prediction. The drawback of this model is that the model input is dependent on the catchment runoff observed on the previous day which may be erroneous or not available. The model also cannot be applied for long term simulation as the observed data is not available. Nonetheless, this can be overcome by using a hybrid approach where the runoff is generated by a traditional hydrological model which is subsequently used as an input to GP as a substitute for observed lagged flow. An attempt is made in this research to apply a conceptual rainfall-runoff model to generate the series of discharges from rainfall and evaporation data. In this analysis, a MIKE11-NAM model (DHI, 2013) is considered.

NAM model was built with the same rainfall as used in section 3.3.2 and the evaporation data as shown in Figure 3.21. The model was developed with the NAM parameters as given in Table 3. 4. In this hybrid approach, the MIKE11-NAM parameters were initially fine-tuned. The model was calibrated with NAM's "autocalibration" functionality between the period of 11/10/1954 and 19/02/1981. The initial and updated NAM parameters are shown in Table 3. 4. The performance of NAM is shown graphically in Figure 3. 22 in terms of ranked plot. The coefficient of determination from this model was found to be 0.78.

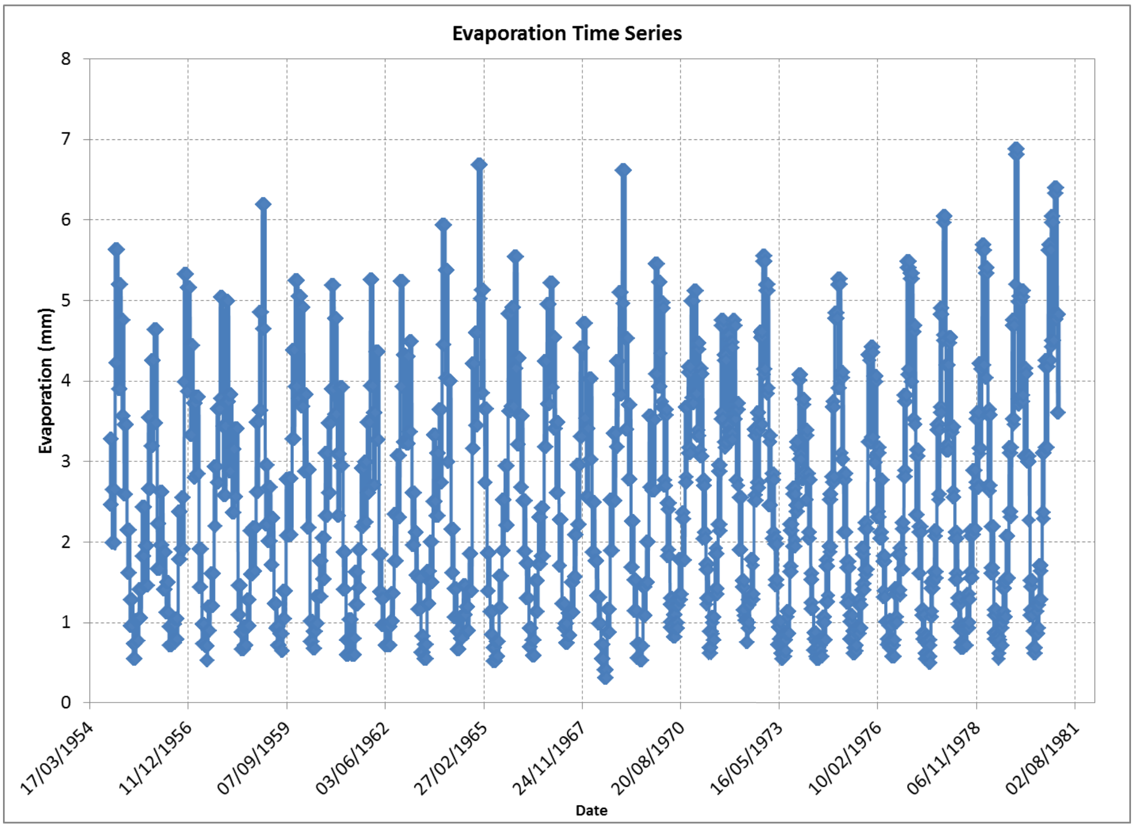


Figure 3.21: Evaporation Time Series

NAM predicted flow was then used as inflow to improve the calibration using GP. The initial GP model was developed using the input of rainfall and the NAM predicted flow to predict the observed flow. The GP model is shown below (see equation 5). The flow duration curve is shown in Figure 3.23. Figure 3.23 demonstrates that GP has significantly improved model calibration especially flow under 40 ML/day. The performance of GP is also improved further by including the base flow (see Figure 3.23). The corresponding derived relationship from GP is shown equation 6. The model accuracies in terms of R^2 are shown in Table 3. 5. GP with model base flow component performed better (Figure 3.23) than and NAM and GP without the base flow.

$$Qgp = 0.6534*Qnam + 0.00526*R*Qnam - 0.4636*SIN(0.6534*Qnam) \quad (5)$$

$$Qgp = 0.7155*BF + 0.4908*Qnam*BF + 0.007869*R*Qnam \quad (6)$$

Where, Qgp = Predicted flow by GP; $Qnam$ = Predicted flow by NAM; R = Rainfall; BF = Base Flow

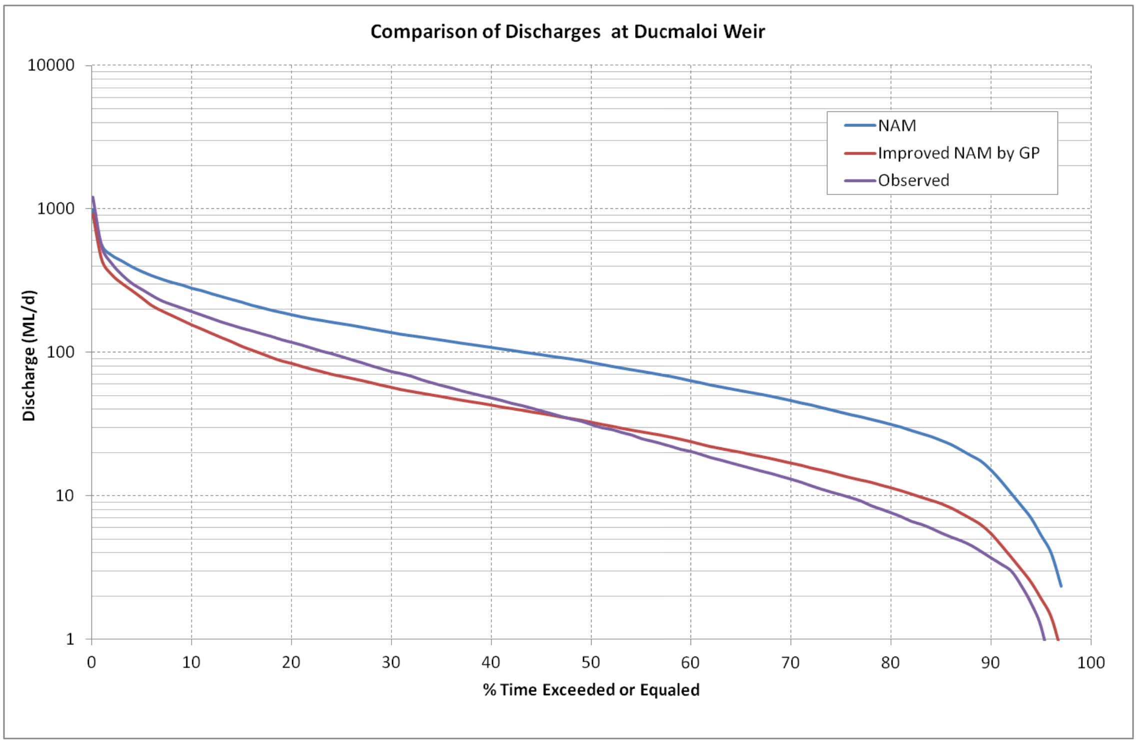


Figure 3. 22: Ranked Plot - Comparison of Duckmaloi Weir Inflows

Table 3. 4: NAM Model Parameters

Parameter	Initial Value	Calibrated Value	Unit
Maximum Water Content in Surface Storage (Umax)	19.6	19.38	mm
Maximum Water Content in Root Zone Storage (Lmax)	300	297.25	mm
Overland Flow Runoff Coefficient (CQOF)	0.124	0.12	-
Time Constant for Routing Interflow (CKIF)	778.1	805.61	hour
Time Constant for Routing Overland Flow (CK1)	22.9	25.68	hour
Root Zone Threshold Value for Overland Flow (TOF)	0.64	0.61	-
Root Zone Threshold Value for Interflow (TIF)	0.935	0.86	-
Root Zone Threshold Value for GW Recharge (TG)	0.925	0.96	-
Time Constant for Routing Baseflow (CKBF)	3833	3718.64	hour

Table 3. 5: Mode Performance – GP vs. NAM

Model	Coefficient of Determination (R^2)
NAM	0.78
GP Without BF	0.81
GP with BF	0.82

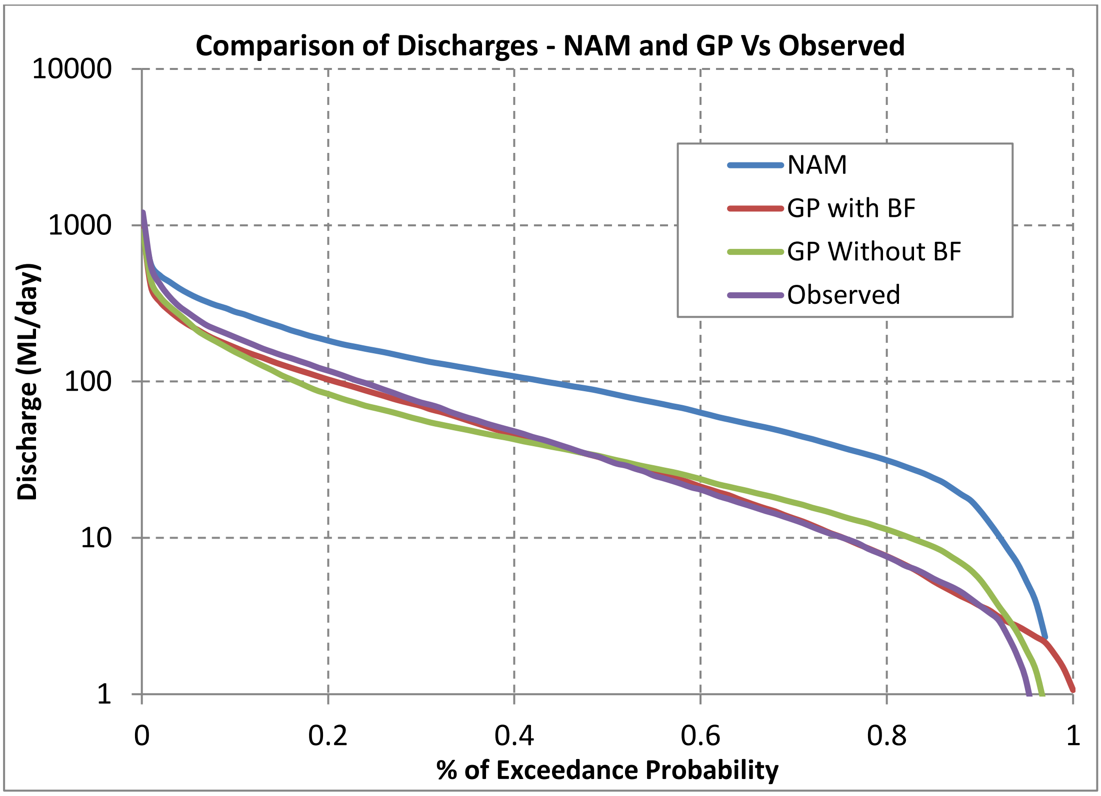


Figure 3.23: Ranked Plot of Daily Recorded and Modelled Inflow to Duckmaloi Weir Improvement by Base Flow

3.5. Long Term Rainfall Scenario Analysis

This analysis required long term (100 year) inflow and rainfall time series (1890-2006) which were collected from NSW State Water Corporation (DNR, 2007). From this long term rainfall series, two future climatic scenarios (assumed two hypothetical rainfall time series) were generated using the following procedures before feeding the data to GP model as described in the previous section. These two rainfall scenarios have been developed to analyse the affect rainfall variation on the catchment flow. These analyses will provide some likely scenarios and useful information to water manager for planning and management of the catchment.

3.5.1. Scenario 1: Stretching the Minimum Rainfall Duration in Sequence (Stretched rainfall)

In this scenario, the dry period is extended by assuming the low rainfall over the five years in last 100 years will continue for next 10 years. The step-by-step procedures are described below:

- Yearly total rainfalls are estimated from last more than 100 year rainfall series starting from 1901 to 2006, (Figure 3. 24). It can be seen in Figure 3. 24 that a five year spell of minimum total rainfall occurred from 1936 to 1940.
- In the next step, five years total rainfall series were calculated. The five year total rainfall values were sorted in ascending order which shows that the first three minimum five yearly rainfalls occurred in 1936-1940, 1906-1910 and 1901-1905. These three five year periods are considered the worst drought sequence in last 100 years.
- A future time series was generated assuming the drought could be worse than what

had happened historically. With this assumption, these drought sequences are placed one after another.

- The rainfall in 1936-40 remained unchanged but the rainfall in 1941-1945 was replaced by that in 1906-1910 and 1946-1950 by 1901-1905. The other five yearly total rainfalls were reshuffled randomly. The original and future stretched five yearly rainfall (drought) series are presented in Figure 3. 25.
- The new five yearly total rainfalls series were distributed back to daily rainfall using the same temporal pattern as in the original time series.
- The initial estimates of flows were generated using MIKE11-NAM.
- The GP was run to update the flows.

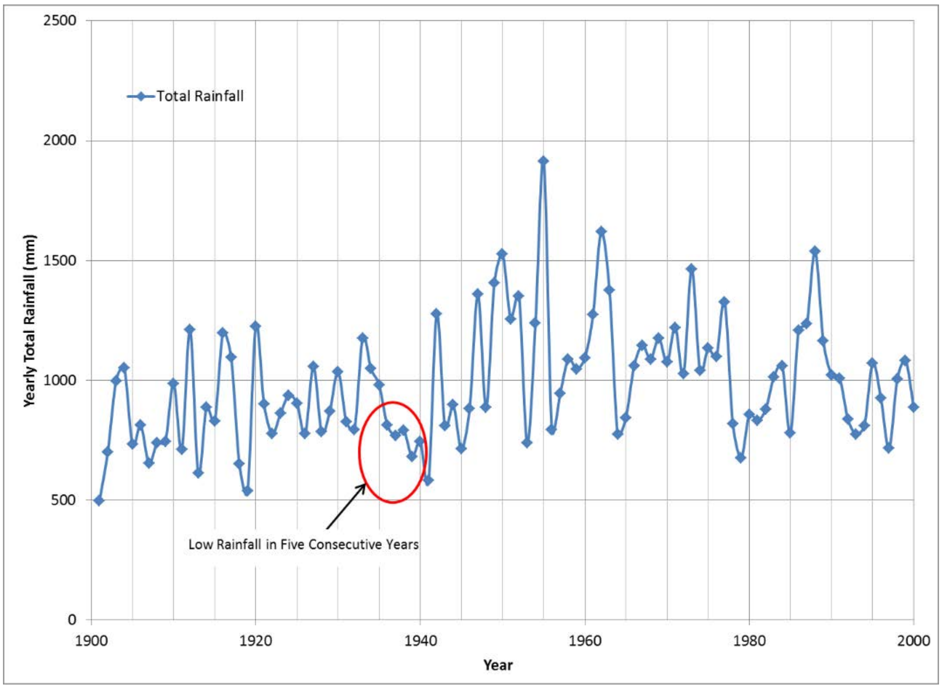


Figure 3. 24: Yearly Total Rainfall in the Past 100 Years

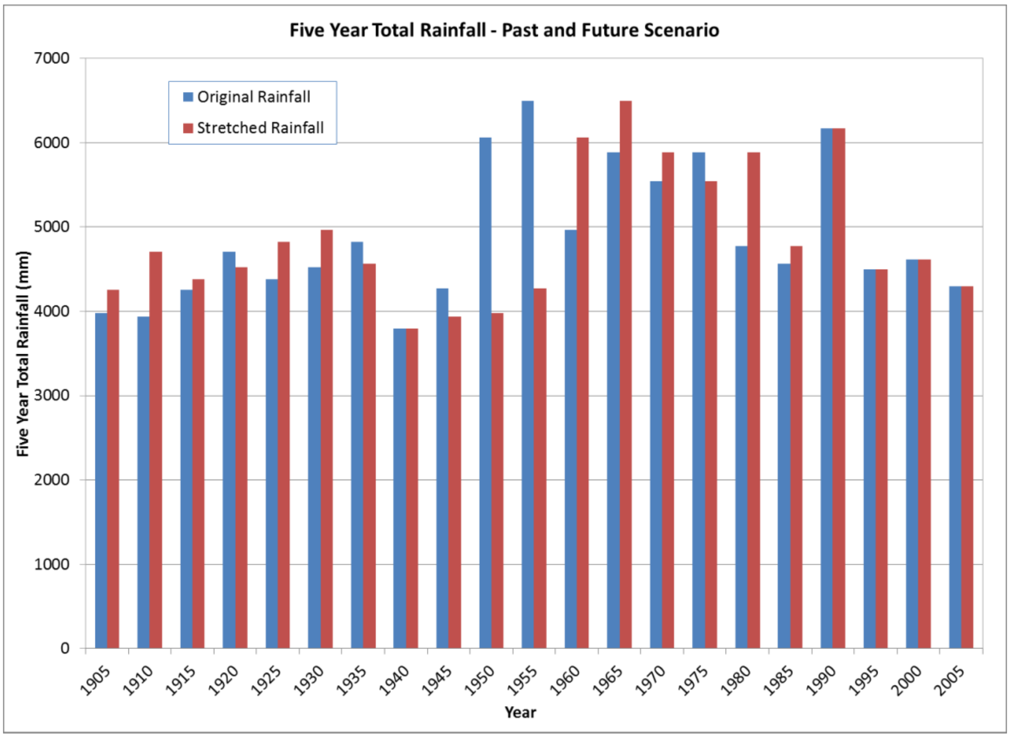


Figure 3. 25: Original and stretched rainfalls - Scenario 1. The x axis label is the year ending of the 5 year period.

3.5.2. Scenario 2: Rainfall Variation

In this scenario, instead of extending the dry period, the rainfall during dry period is decreased and the rainfall in wet period is increased by a certain percentage. The step-by-step procedure is described below:

1. The total rainfall over five consecutive years was calculated in a manner similar to steps 1 and 2 of Scenario 1.
2. Rainfall totals above the average were increased by 20% and rainfall totals below average declined by 20%. The present and adapted five year total rainfalls are presented in Figure 3. 26.
3. The new five yearly total rainfalls series were distributed back to daily rainfall using the same temporal pattern as in the original time series.
4. The initial estimates of flows were generated using MIKE11-NAM.
5. The GP was run to update the flows.

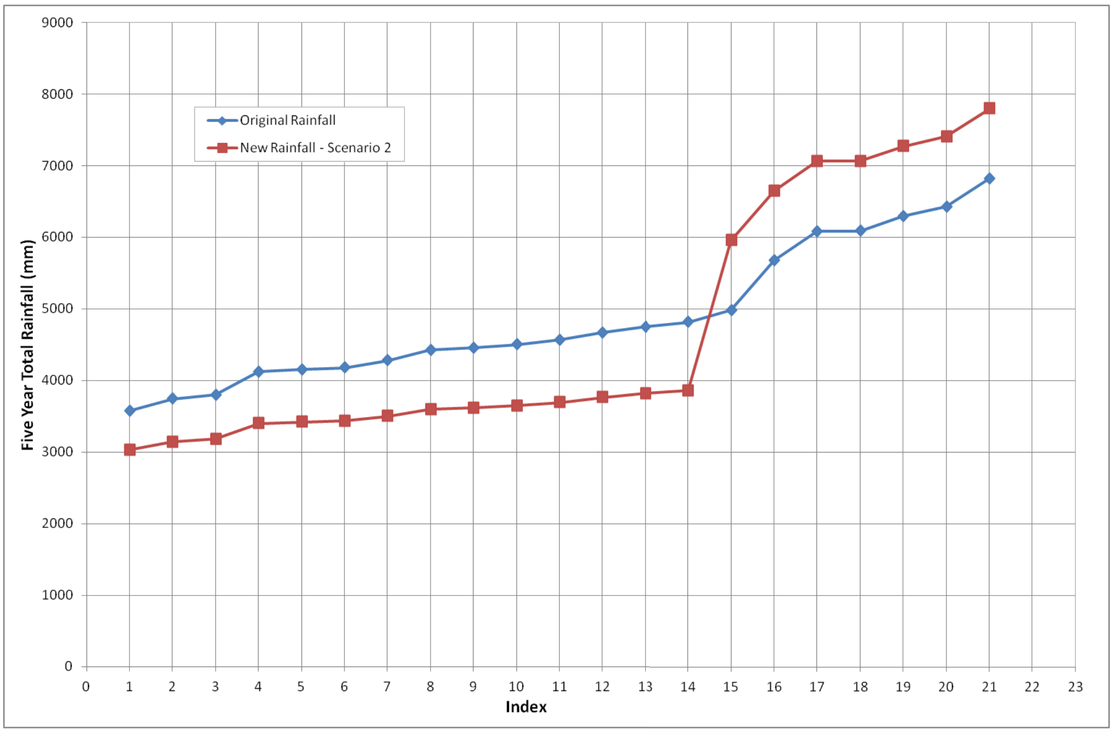


Figure 3. 26: Original and Varied Rainfalls – Scenario 2

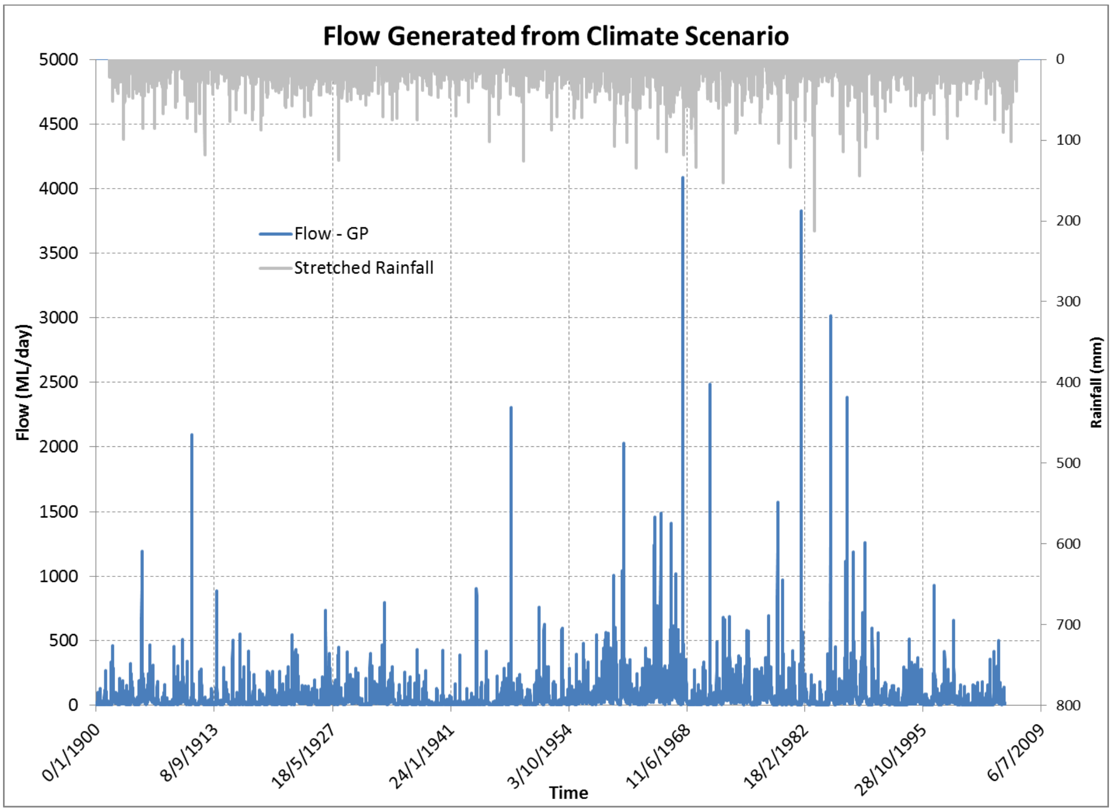


Figure 3. 27: GP Flow from Stretched Rainfall (Scenario 1)

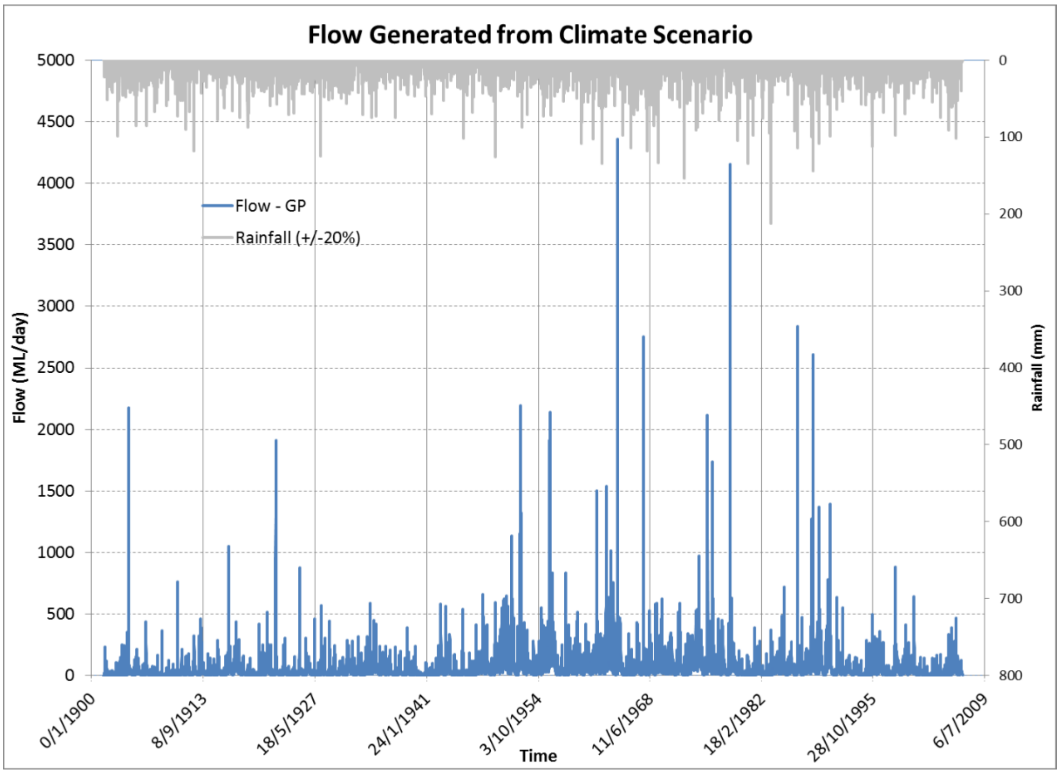


Figure 3. 28: GP Flow from Rainfall Changes (Scenario 2)

3.5.3. Rainfall Scenario Results

The calibrated NAM model was applied to determine initial estimates of 100 year inflows at the Duckmaloi Weir for both rainfall scenarios. The 100 year flows generated are shown in Figure 3. 27 and Figure 3. 28 respectively. The inflows were updated using the GP model as described in equation 5. The results (estimated flow) in terms of ranked plots are shown in Figure 3. 29. Figure 3. 30 illustrates the corresponding yearly volume. Figure 3. 29 shows that how both scenarios decrease yields at the Duckmaloi Weir if the drought condition persists. The catchment flows yield below 135 ML/d (86 ML/d for Scenario 1 and 132 ML/d for Scenario 2) for 90% of the time (see Table 3. 6). Table 3. 6 describes how catchment yields will change if the future climatic scenarios (Scenario 1 and Scenario 2) vary compared to last 100 year rainfall condition. Scenario 1 and 2 intersects at discharge of 30 ML/d (Figure 3. 29) for the percentage of time exceeded or equalled of 30% (seeTable 3. 6). After this point, the discharge to the Duckmaloi Weir decreases sharply compared to scenario 1 due to the impact of 20% decrease in rainfall. Scenario 2 results also show that 30% of the time there would be no flow to the dam catchment. If the future climatic condition follows Scenario 2, alternative source of water supply needs to be identified.

The scenario testing demonstrates how this method could be used for making future water resources management plans under different climate scenarios and contribute to decisions concerning water supply from alternative sources.

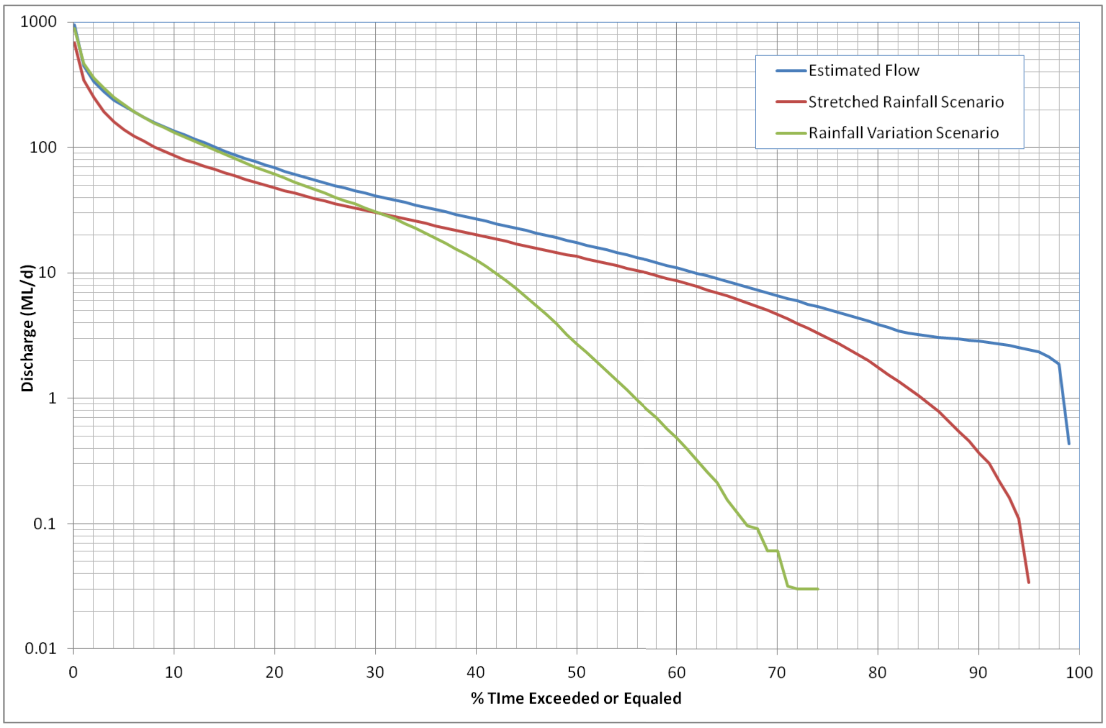


Figure 3. 29: Ranked Plot of 100 years Daily Inflows to Duckmaloi Weir for Scenarios 1 (Stretched Rainfall) and 2 (Rainfall Variation)

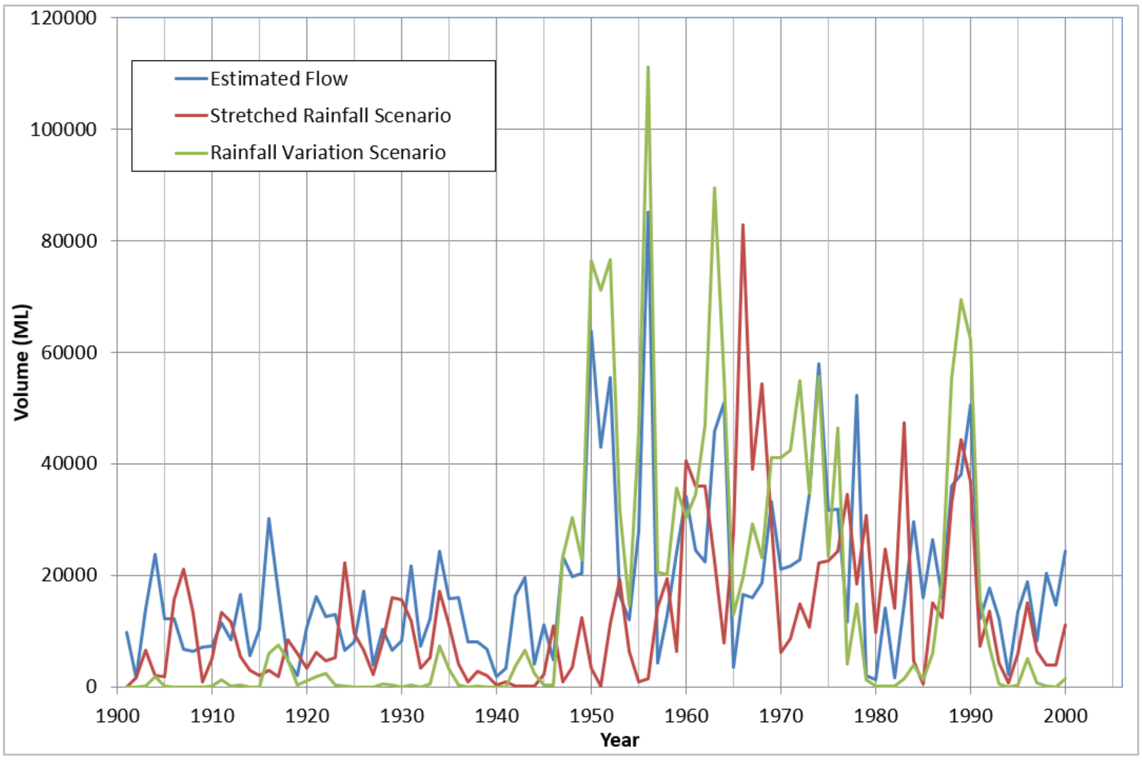


Figure 3. 30: Yearly Volume of 100 Year Inflows to Duckmaloi Weir for Different Scenarios 1 (Stretched Rainfall) and 2 (Rainfall Variation).

Table 3. 6: Discharge against % of Time Exceeded or Equaled

% Time Exceeded or Equalled	**Discharge (ML/d)**		
	Estimated Flow	Scenario 1	Scenario 2
1	449	343	465
5	213	139	219
10	135	86	132
30	41	30	31
50	17	13	3
70	7	5	0

3.6. Discussion

This study demonstrates the application of GP for predicting real-time inflows to a dam catchment, named Duckmaloi Weir. In the first example, the GP model performed well when one day lagged flow was used for training and validation. In the second example, the lagged observed flows were replaced with the runoff generated from a traditional calibrated hydrological model (MIKE11-NAM). The output from NAM was improved by training GP together with the rainfall data. The final calibrated results from GP indicated excellent agreement between the observed and simulated flows (e.g. R^2>0.8). This methodology of using hybrid model is more versatile and is better suited for the following reasons:

- historical observed flow may be erroneous, and parts of the time series may be missing;
- more suitable for long-term forecasting (e.g. 100 year); and
- more suitable for real-time prediction as the 1-day lagged data is often not available.

Finally, two examples of long-term climatic scenarios were applied to predict the possible future 100 year water inflows to Duckmaloi Weir under extreme and extended drought conditions using flows from the NAM model (second example). The application of AI (e.g. GP) to improve runoff generated from a traditional conceptual hydrological model for a real catchment and future possible rainfall scenarios analysis, will provide an alternative solution to water manger. These example rainfall scenarios are hypothetical but can be more appropriately replaced by other more relevant scenarios. For example, downscaled rainfall from the climatic model can be used to assess the impact of climate change on catchment runoff and dam operation. The analysis demonstrates how it can be useful for planning future water resource management and decision-making in a dam catchment.

3.7. Summary

In this chapter, application of Genetic Programming (GP) and Artificial Neural Network (ANN) have been demonstrated in predicting flow using the rainfall and past historical observed lagged flow for Duckmaloi Weir catchment located in Oberon, Australia. GP performed well compared to ANN. The performance of GP was also compared against traditional Sacramento model and GP's results were superior.

Two examples showing one-day lead prediction solely using GP and another showing a hybrid approach with MIKE11-NAM and GP reveal some promising results. For 1-day prediction, the GP model demonstrated a closer agreement between observed and modelled flows with current rainfall and lagged flows. The hybrid model was applied to update flow prediction from MIKE11-NAM. This approach is useful when measured or gauged flows are not complete or missing and it is also suitable for long-term prediction. The 100 year flows were predicted assuming two hypothetical rainfall time series. The results from this hypothetical rainfall analysis show how the flow conditions vary in the dam catchment in drought conditions. The analysis provides some information to water manager about the potential application of hydroinformatics tools (GP, MIKE11-NAM and GP hybrid models) in the operation and management of water resources.

CHAPTER 4

PREDICTION OF HYDROLOGICAL TIME-SERIES USING EXTREME LEARNING MACHINE (ELM)

This chapter includes the major part of

- Atiquzzaman, M. and Kandasamy, J. (2016). "Prediction of Hydrological Time-Series using Extreme Learning Machine", Journal of Hydroinformatics. 18.2, pp. 345-353, http://dx.doi.org/10.2166/hydro.2015.020.

4. Prediction of Hydrological Time-Series Using Extreme Learning Machine (ELM)

4.1. Introduction

The application of data-driven modelling approaches including Artificial Neural Network (ANN) and Support Vector Machine (SVM) has been widespread in the water resource engineering field, especially for predicting hydrological time-series. This is because they can establish complex non-linear relationships between input and output variables (Tokar and Johnson., 1999). The main advantage of these techniques is that they do not require the information about the complex nature of the underlying hydrological process. When data-driven modeling is applied, input variables including precipitation, lagged precipitation, and lagged discharges are normally employed to forecast the discharges (Akhtar et al., 2009). Many of these data-driven modelling methods including ANN, ANFIS and SVM are slow requiring numerous iterations to generate optimal solutions (Ding et al., 2015 and Zhang et al., 2007), and may not be suitable for real-time prediction where quick response is vital. Huang et al. (2006) reported that applying typical feed-forward neural network has been limited due to the use of conventional gradient-based slow learning algorithms in training and iterative determination of network parameters. To overcome the long computational time and to produce generalized solution, a learning algorithm called Extreme Learning Machine (ELM), developed by Huang et al. (2006) was used in this study. The performance of ELM was compared with conventional NN and SVM on benchmarking problems in the function approximation and classification areas. Huang et al. (2006) found that ELM approximates any continuous function and implements any classification. ELM may need more hidden nodes but learns faster than SVM. The generalization performance of ELM is stable with a wide range of number of hidden nodes.

Ding et al. (2015) stated that ELM, which requires a single iteration, overcomes the slow training speed and over-fitting problems unlike other conventional ANN learning algorithm. ELM's robustness and fast learning rate was proved in different fields including real dataset classification and regression (Huang et al., 2012). Zhang et al. (2007) applied ELM to multi-category classification problems in cancer diagnosis and found that ELM did not have problems like falling in local minima and over-fitting which are commonly experienced by iteration based learning methods.

This study demonstrates that the method partly overcomes the slow learning issue by using Extreme Learning Machine (ELM) which predicts the hydrological time-series very quickly. ELM, which is also called single-hidden layer feed-forward neural networks (SLFNs), is able to well generalize the performance for extremely complex problems. ELM randomly chooses a single hidden layer and analytically determines the weights to predict the output (Huang et al., 2006).

The application of ELM uses a MATLAB program developed for predicting hydrological flow time-series. The ELM method was applied to predict hydrological flow series for the Tryggevælde Catchment, Denmark and for the Mississippi River at Vicksburg, USA. The results confirmed that ELM's performance was similar or better in terms of Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE) compared to ANN and other previously published techniques, namely Evolutionary Computation based Support Vector Machine (EC-SVM), Standard Chaotic Approach and Inverse Approach (Yu et al., 2004).

4.2. Application

ELM is applied to estimate the catchment runoff. ELM is an AI technique where the input weights and hidden layer biases are randomly chosen and the output weights are determined analytically (Huang et al., 2006). ELM generates the parameters associated with hidden nodes without depending on training data. However, ELM transforms the training of Feed-Forward Neural Network into a linear problem where only connections with output neurons are adjusted to generate the solutions. Unlike ANN, ELM does not require complex network architecture to obtain good results. ELM uses three fixed layers i.e. input, hidden and output layers. In these layers, the number of input variables (flows), the number of nodes in hidden layers and the activation function (sigmoid function) in output layer need to be defined beforehand. ELM's learning speed is extremely fast compared to other machine learning techniques (e.g. SVM) as it avoids iterative tuning to determine the weights (Huang et al., 2006 and Huang et al., 2012). Other advantages of ELM can be found in Huang et al. (2006).

In this study, ELM was applied to predict runoff (one-step-ahead prediction) using the past and current information of hydrological flows as input data. Mathematically, the relationship can be expressed as:

$$Q_{t+\Delta t} = f(Q_t, Q_{t-\Delta t}, \ldots Q_{t-m\Delta t}) \tag{1}$$

if past historical flow series is considered.

Or, $$Q_{t+\Delta t} = f(Q_t, Q_{t-\Delta t}, \ldots Q_{t-m\Delta t} . dQ_t, dQ_{t-\Delta t}, \ldots dQ_{t-m\Delta t}) \tag{2}$$

if past historical flow and flow difference data series are considered.

Or, $$dQ_{t+\Delta t} = f(dQ_t, dQ_{t-\Delta t}, \ldots dQ_{t-m\Delta t}) \tag{3}$$

if past historical flow difference series is considered.

where, Q is the flow (m^3/s), $dQ_{t+\Delta t}$ is error predictor, $dQ_t = Q_{t+\Delta t} - Q_t$, m represents how far back the recorded data of the time-series affects the flow prediction and Δt is time interval.

Once the error predictor is determined from the model in equation (3), the predicted flow is estimated as:

$$Q_{t+\Delta t} = Q_t + dQ_t \quad (4)$$

The performance of trained ELM was evaluated with standard goodness-of-fit measures such as Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE).

The RMSE and NRMSE are defined as:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}[(Q_m)_t - (Q_o)_t]^2} \quad (5)$$

$$\text{NRMSE} = \sqrt{\sum_{t=1}^{N}[(Q_m)_t - (Q_o)_t]^2 / \sum_{t=1}^{N}[(Q_o)_t - \bar{Q}_o]^2} \quad (6)$$

where $(Q_m)_t$ and (Q_o)t are the predicted and observed values at time t; N is the number of observations and $\bar{Q}_o$ is the mean observed flow.

RMSE represents the forecasting error and estimates the sample standard deviation of the differences between predicted values and observed values. It is a good measure when large model errors are not desirable. The NRMSE normalizes the RMSE and facilitates comparison between datasets. NRMSE close to zero indicates a perfect match between the observed and predicted values and greater than one means predictions are inferior to the constant mean value (Liong et al., 2002).

ELM was used to estimate the one-lead-day prediction of flows for Tryggevælde Catchment (Denmark) and Mississippi River at Vicksburg. The ELM was trained with the same data as used in Liong et al. (2002) and Yu et al. (2004) and the results were compared with Standard Chaos Technique, Inverse Approach, ANN and EC-SVM. In Yu et al. (2004), data in the period 1975-1991 was used for training and 1992-1993 for validation in Standard Chaos Technique. Phoon et al. (2002) used 1975-1989 for training, 1990-1991 for testing and 1992-1993 for validation in their application of the Inverse Approach.

In this study, data in the period 1975-1991 was used for training and data between 1992-1993 for validation similar to the Standard Chaos Technique. The number of hidden nodes in ELM was selected as the number of training samples (6204). This is because ELM can generate zero error when the number of hidden neurons learns the same number of distinct observations (Huang et al., 2006). For the output node, the widely used sigmoid activation function was chosen.

4.3. Tryggevælde Catchment

The Tryggevælde Catchment, Denmark (130.5 km^2) is located in the eastern part of Sealand, north of Karise. The catchment is predominantly characterized by clay soil. The daily measured flows are available for the period 1 January 1975 to 31 December 1993 (Figure 4. 1). The statistics of flow series are: mean flow = 0.977 m^3/s; standard deviation=1.367 m^3/s; maximum flow = 11.068 m^3/s; and minimum flow = 0.014 m^3/s. The statistics of flows represent that there are distinct wet and dry periods in the time-series.

The training and validation accuracies are presented in Table 4. 1 in terms of RMSE and NRMSE for ELMI (lagged flow, *Q*), ELMII (lagged flow difference, *dQ*) and ELMIII (*Q, dQ)*. The validation accuracies from all three ELM models were between 0.491-0.504 (RMSE) and 0.337-0.347 (NRMSE) respectively. The ELMIII performed the best amongst the three models. The time required to train ELM models was about 100sec on a Windows-based machine (Intel i7 CPU at 2.67GHz). The corresponding validations times were between 0.47-0.49sec. An ANN model, which estimates the default number of hidden nodes (81) based on number of input variables, output variables and training samples, was trained with the same dataset as ELM (hidden nodes = 6204) for approximately 100sec (training time of ELM) for comparison with ELM. The prediction accuracies of ANN obtained from 633 iterations were 0.588 (RMSE) and 0.403 (NRMSE) (Table 4. 2).

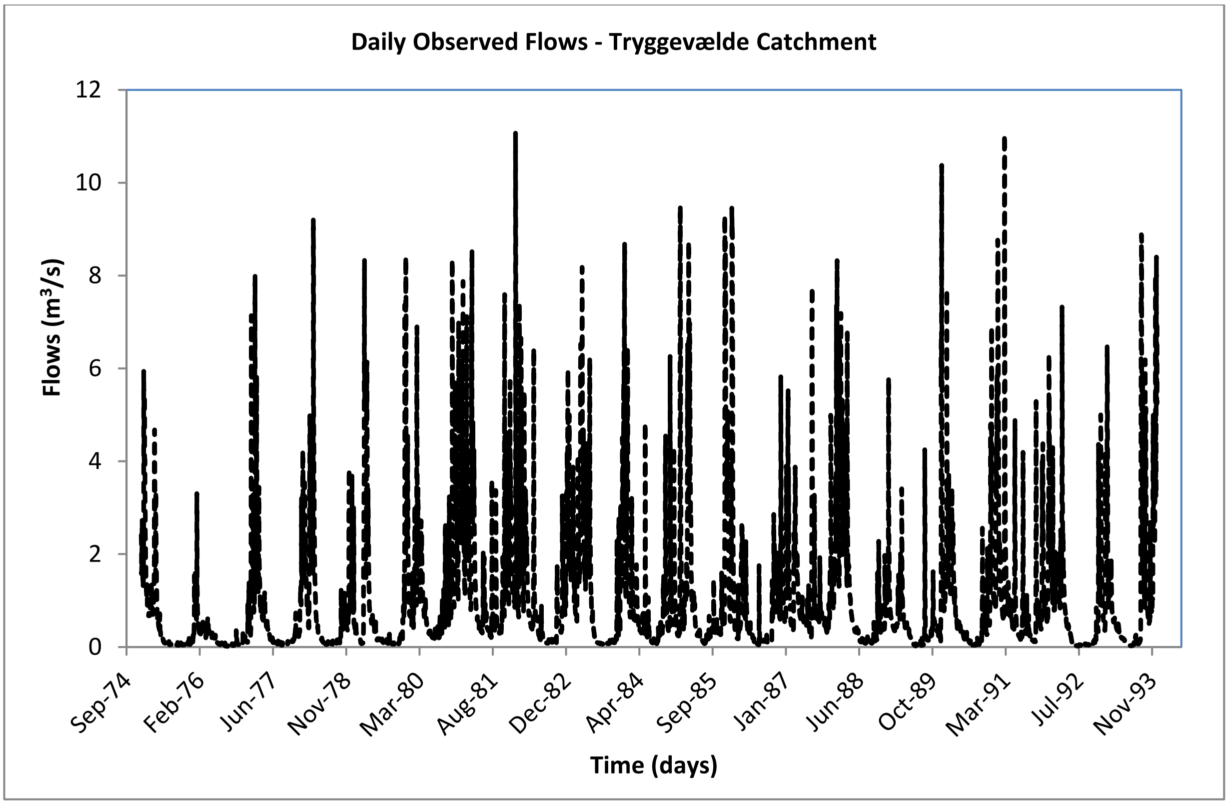


Figure 4. 1: Daily Observed Flows at Tryggevælde Catchment (Source: Yu et al., 2004)

Table 4. 1: ELM Prediction Accuracy for both Training and Validation Dataset for Tryggevælde Catchment

Model	No. of Iterations	Training			Validation		
		RMSE	NRMSE	Time (s)	RMSE	NRMSE	Time (s)
ELMI(*Q*)	Single	0.495	0.362	99.28	0.497	0.341	0.49
ELMII(*dQ*)	Single	0.508	0.372	108.09	0.504	0.347	0.47
ELMIII(*Q*, *dQ*)	Single	0.488	0.357	100.88	0.491	0.337	0.48

Table 4. 2 compares the ELM results with other available techniques (Liong et al., 2002; Yu et al., 2004). Yu et al. (2004) used two types of input time-series, namely daily flow series (*Q*) and flow difference series (*dQ*) separately in EC-SVM. The use of *dQ*-series in EC-SVM provided better results than the *Q*-series. The number of iterations required was 151,668 for EC-SVM(*Q*) and 11,800 for EC-SVM(*dQ*). All ELM techniques were faster as no additional iteration was required and produced better results (Table 4. 2). The ELMIII model improved the prediction accuracy in terms of RMSE by 24% over the standard chaotic

approach, 7% over the Inverse Approach and 4% over the EC-SVM(Q). ELMI performed similarly.

Table 4. 2: Prediction Accuracy for Validation Dataset, the Number of Iterations and Training Time from Various Techniques for Tryggevælde Catchment

Model	RMSE	NRMSE	No. of Iterations (Training)	Training Time (sec)
Standard Chaos Technique*	0.647	0.444	-	-
Inverse Approach*	0.527	0.361	-	-
EC-SVM(Q)*	0.514	0.352	151,668	-
EC-SVM(dQ) *	0.504	0.347	11,800	-
ANN	0.588	0.403	633	100**
ELMI(Q)	**0.497**	**0.341**	**Single**	99.28**
ELMII(dQ)	**0.504**	**0.347**	**Single**	108.09**
ELMIII(Q, dQ)	**0.491**	**0.337**	**Single**	100.88**

*Liong et al. (2002) and Yu et al. (2004); **Windows Intel i7 at 2.67 GHz

4.4. Mississippi River at Vicksburg Flow

A similar approach, as applied in Section 4.3, was also applied to predict flows in the Mississippi River at Vicksburg, USA and used the same daily flows documented in Yu et al. (2004). The Mississippi River basin covers more than 3,220,000 km^2 including tributaries from central USA and two Canadian provinces. The daily measured flows cover the period 1 January 1975 to 31 December 1993 (Figure 4. 2). The statistics of flow series are: mean flow = 18,457 m^3/s; standard deviation=9,727.27 m^3/s; maximum flow = 52,103 m^3/s; and minimum flow = 3,908 m^3/s.

Table 4. 3 shows that the results of training and validation obtained from ELMI(Q), ELMII(dQ) and ELMIII(Q, dQ). The time required to train ELM models was about 97sec on the same computer (Windows Intel i7 CPU at 2.67 GHz). The corresponding validation times were between 0.45-0.47sec.

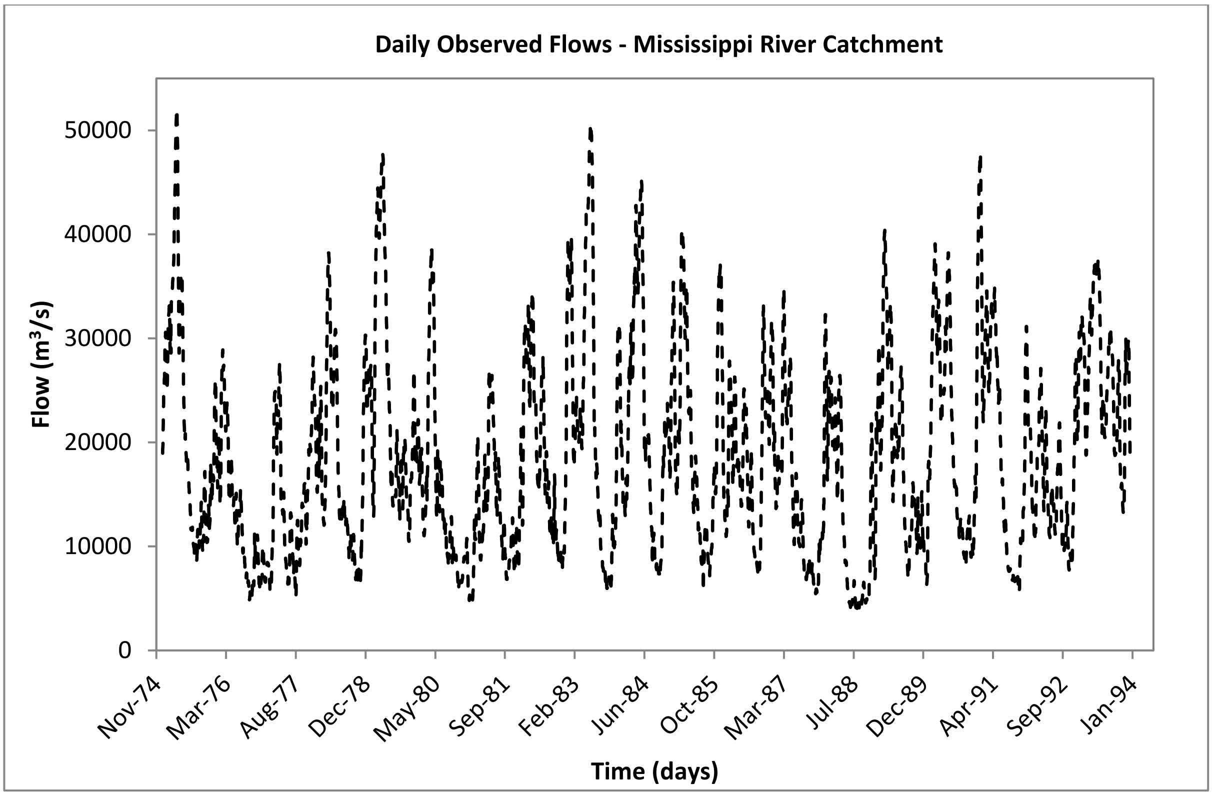


Figure 4. 2: Daily Observed Flows at Mississippi River Catchment (Source: Yu et al., 2004)

Table 4. 3: ELM Prediction Accuracy for both Training and Validation Dataset for Mississippi River Flow, Vicksburg

Model	No. of Iterations	Training			Validation		
		RMSE	NRMSE	Time (s)	RMSE	NRMSE	Time (s)
ELMI(*Q*)	Single	396.58	0.040	97.92	320.00	0.040	0.47
ELMII(*dQ*)	Single	389.37	0.0394	96.85	312.8	0.0397	0.47
ELMIII(*Q*, *dQ*)	Single	382.49	0.0387	96.84	308.66	0.0391	0.45

The results (Table 4. 3) showed that ELMIII performed best with RMSE and NRMSE of 308.66 and 0.0391 respectively. The RMSE and NRMSE values were slightly higher for the other two ELM models (ELMI and ELMII). ELMIII predicted better results (Table 4. 4) than the Standard Chaos Technique (RMSE = 1738.95 and NRMSE= 0.2064) and Inverse Approach (RMSE = 356.89 and NRMSE= 0.0452). An ANN model (default hidden nodes = 81) trained with the same dataset as ELM (hidden nodes = 6204) was run for approximately 97sec (training time of ELM) for comparison with ELM. ANN prediction accuracies obtained from 794 iterations were 549.70 (RMSE) and 0.0696 (NRMSE) (Table 4. 4).

Table 4. 4: Prediction Accuracy for Validation Dataset, the Number of Iterations and Training Time from Various Techniques for Mississippi River Flow, Vicksburg

Model	RMSE	NRMSE	No. of Iterations (Training)	Training Time (sec)
Standard Chaos Technique*	1738.95	0.2064	-	-
Inverse Approach*	356.89	0.0452	-	-
EC-SVM(*Q*)*	306.58	0.0387	1,732.579	-
EC-SVM(*dQ*) *	304.26	0.0385	47, 590	-
ANN	549.70	0.0696	794	97**
ELMI(*Q*)	**320.00**	**0.04**	**Single**	97.92**
ELMII(*dQ*)	**312.8**	**0.0397**	**Single**	96.85**
ELMIII(*Q*, *dQ*)	**308.66**	**0.0391**	**Single**	96.84**

* Liong et al. (2002) and Yu et al. (2004); **Windows Intel i7 at 2.67 GHz

Table 4. 4 shows that the RMSE and NRMSE of ELM models were slightly higher compared to EC-SVM(*Q*) and EC-SVM(*Q, dQ*) models. However, ELM predicted these solutions quickly (single run) compared to EC-SVM(*Q*) and EC-SVM(*Q*, *dQ*), where 1,732,579 and 57,590 iterations, respectively were required. This demonstrates that ELM can be efficient for online and real-time applications.

4.5. Discussion

This study demonstrates the application of a new AI technique, called ELM for the prediction hydrological flow time-series from Tryggevælde and Mississippi River Catchment. The data obtained from a relatively small (Tryggevælde Catchment, Denmark) and large catchment (the Mississippi River Catchment at Vicksburg) covered both dry and wet periods. ELM was not applied to the field of catchment hydrology before and these two catchments were selected from the literature for comparison purpose. Three different ELM models considering observed lagged flow (ELM1), flow difference (ELMII) and combination of these two variables (ELMIII) were built. The results for Tryggevælde Catchment show that ELMIII (RMSE of 0.491) performed better than ELMI (RMSE of 0.497) and ELMII (RMSE of 0.504) models. Similarly, for Mississippi River Catchment, ELMIII (RMSE of 308.66) improved the accuracy compared to ELMI (RMSE of 320.00) and ELMII (RMSE of 312.8) models. The prediction accuracies of ELMIII were also similar or better than ANN and other previously published techniques including EC-SVM, Standard Chaotic Approach and Inverse Approach. More specifically, ELMIII improved the flow prediction accuracy in terms of RMSE by 24% over Standard Chaos Technique, 7% over the Inverse Approach and 4% over the EC-SVM for the Tryggevælde Catchment. ELM provided solutions of similar accuracy to EC-SVM when predicting Mississippi River flows.

ELM's reached the solutions quickly compared to other techniques including EC-SVM. This is because no additional iteration is required in ELM whereas other techniques require thousands of iterations to predict the same flow time-series although most do so with less accuracy. Such runs typically have a much longer processing time. Importantly, this processing time will significantly increase for more complex scenarios where many more iterations are required to obtain an optimal solution. This longer processing time may be a limiting factor for real-time application. ELM learns the training dataset very quickly which means that this method is suitable for flood forecasting, the prediction of inflows for reservoir operations, supply of water to meet irrigation demand, real time control of water systems and sewer systems, etc. Furthermore, by having improved or at least comparable prediction accuracy to other available methods, ELM is no less capable for use in water resource management and decision-making.

4.6. Summary

ELM was applied to predict hydrological flow time-series for the Tryggevælde Catchment (Denmark) and Mississippi River at Vicksburg (USA). The results show that ELM's performance is reasonable for 1-day lead prediction compared to ANN and other previously published techniques. The real strength of ELM is the short computational run-time to reach solutions comparable with other techniques including EC-SVM. ELM's fast learning capability from a training dataset means that it would be more suitable for on-line and real-time applications where quick processing is important or vital. However, the robustness of ELM's performance (improved accuracy) on different input parameters, longer lead day prediction and extrapolation capability was not investigated. The sensitivity of ELM's performance on input parameters is thoroughly investigated and reported in Chapter 5 including application to a local catchment.

CHAPTER 5

ROBUSTNESS OF EXTREME LEARNING MACHINE (ELM) IN THE PREDICTION OF HYDROLOGICAL FLOW SERIES

This chapter includes the major part of

- Atiquzzaman, M. and Kandasamy, J. (2018). "Robustness of Extreme Learning Machine in the prediction of hydrological flow series.", Computers & Geosciences Journal, 120, pp. 105-114, http://dx.doi.org/10.1016/j.cageo.2018.08.003.

5. Robustness of Extreme Learning Machine (ELM) in the Prediction of Hydrological Flow Series

5.1 Introduction

Predicting hydrological flow series generated from a catchment is an important aspect of water resources management and decision making. The underlying process of prediction of flows from a catchment is complex and depends on many parameters.

Application of Artificial Intelligence (AI) based machine learning techniques including Artificial Neural Network, Genetic Programming (GP) and Support Vector Machine (SVM) replaced the complex modelling process and at the same time improved the prediction accuracy of hydrological time-series. However, they still require numerous iterations and computational time to generate optimum solutions.

This study applies the Extreme Learning Machine (ELM) to hydrological flow series modeling and compares its performance with two most superior techniques GP and Evolutionary Computation based SVM (EC-SVM) to demonstrate its fast learning capability. Atiquzzaman and Kandasamy (2016b) demonstrated that ELM's learning speed and accuracy were comparable to Standard Chaos Technique, Inverse Approach and EC-SVM in the forecasting of hydrological time-series. However, the robustness of ELM's performance on different input parameters, longer lead day prediction and extrapolation capability was not investigated by Atiquzzaman and Kandasamy (2016b). This chapter documents the performance of ELM tested with different combinations of input variables. The robustness of ELM was evaluated by varying number of lagged input variables, the number of hidden nodes and input parameter (regularization coefficient). The number of nodes in the hidden layer was varied to check the sensitivity of ELM's result. The generalization capability of ELM was investigated for longer lead-day prediction (e.g. second and third) and for its extrapolation capability. The robustness and performance of ELM were studied using the data from three different catchments located in three different climatic conditions. ELM was applied to the Tryggevælde (Denmark), Mississippi River (USA) and Duckmaloi Weir (Australia) Catchments.

The study results described in this chapter show that (1) ELM yields reasonable results with two or higher lagged input variables (flows) for 1-day lead prediction; (2) ELM produced satisfactory results very rapidly when the number of hidden nodes was greater than or equal to 1000; (3) ELM showed improved results when regularization coefficient was fine-tuned; (4) ELM was able to extrapolate extreme values well; (5) ELM generated reasonable results for higher number of lead days (second and third) predictions; (6) ELM was computationally much faster and capable of producing better results compared to other leading AI methods for prediction of flow series from the same catchment. ELM has the potential for forecasting real-time hydrological flow series.

5.2 Data and Methods

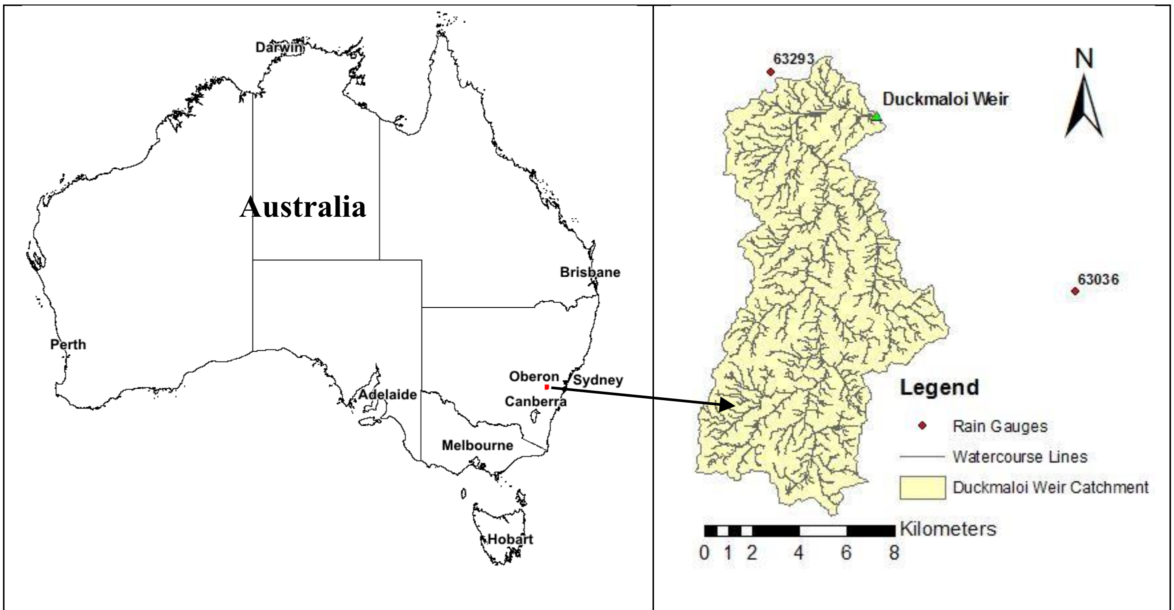
5.2.1 Catchment Data

ELM is capable of producing better flood prediction for any catchment under different climatic condition. To demonstrate the robustness ELM, data from three different catchments obtained from three different climatic conditions (Liong et al., 2002 and Yu el al., 2004) was used in this study and the results were compared with other published techniques.

The first catchment is Tryggevælde Catchment (130.5 km^2) located in Denmark in the eastern part of Sealand, north of the village Karise (Figure 4. 1). This is a small catchment characterized by clay soil which results in very flashy flow.

The second one is for the Mississippi River catchment in USA. The Mississippi River is one of the world's greatest river systems. Both catchments have the daily measured flows for the period of 1 January 1975 to 31 December 1993 (Figure 4. 1 and Figure 4. 2) (Yu et al., 2004). The Tryggevælde Catchment is small, and the maximum recorded flow is 11.068 m^3/s whereas

Mississippi River catchment is very large and the maximum flow is 52,103 m^3/s. In this study, flow data between 1975 to 1991 was used for training ELM and the data between 1992 to1993 for testing. No rainfall and evaporation data were applied as input series.



Location Map (not in Scale)　　Ducmaloi Weir Catchment

Figure 5. 1: Location of Duckmaloi Weir Catchment

The third catchment used for this analysis is the Duckmaloi Weir catchment which is located south of Oberon and approximately 180 km west of Sydney, Australia (see Figure 5. 1). The catchment covers an area of approximately 112 km^2 and is drained by Duckmaloi River and its tributaries. The weir is located on the Duckmaloi River. It provides Oberon with its water supply and cooling water for Mount Piper and Wallerawang power stations. The operational capacity of the weir is 20ML at full supply level of RL 1,057.64m AHD. A stream gauging station is located just downstream of Duckmaloi Weir and has recorded data from 18 October 1954 to 19 February 1981 (Figure 5. 2). The rainfall data recorded at the station (63036) has continuous records for more than 100 years. The statistics of flow series are: mean flow = 0.862 m3/s; standard deviation=1.417 m3/s; maximum flow = 36.014 m3/s; and minimum flow = 0.0 m3/s. The time series is shown in Figure 5. 2 which shows that there are distinct wet and dry periods in each year. In ELM, rainfall and flow data from 1954 to 1975 are used for training and from

1976 to 1981 for testing.

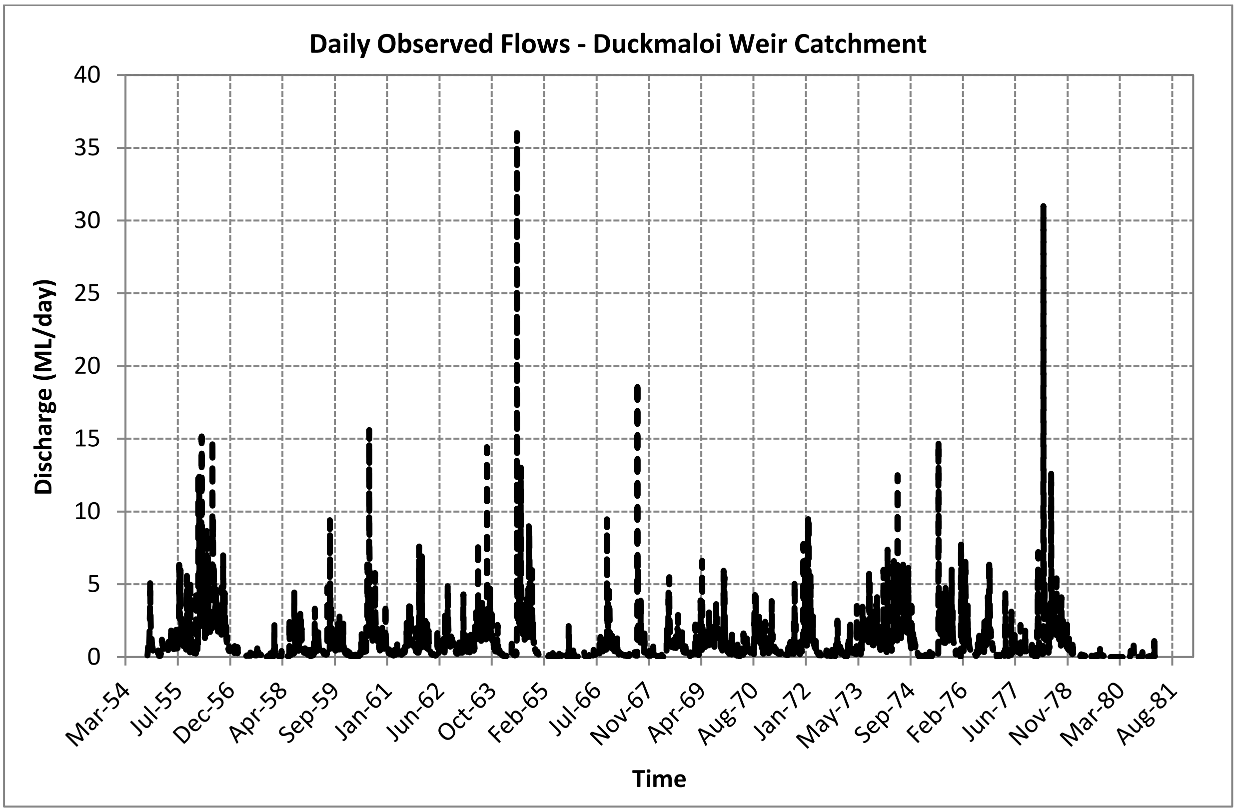


Figure 5. 2: Daily Observed Flows - Duckmaloi Weir Catchment

5.2.2 Methods

Model: The basic hidden node based ELM (Huang et al., 2006) as described in Chapter 4, has been applied in this analysis. Huang et al. (2012) stated that if the number of hidden neurons and the number of input samples are equal, ELM can, in theory, approximate the training of samples with zero error. However, in order to get stable and better generalization performance, a parameter called the regularization coefficient (*C*) (see Huang et al., 2012) was introduced in ELM. The performance of ELM also depends on the activation function. If these are appropriately selected, ELM does not degrade the generalization capability (Lin et al., 2014).

Modelling Technique: ELM and GP were used to estimate the catchment runoff using past catchment flow as input data. Mathematically, if only the past historical flow series is considered, the relationship can be expressed:

$$Q_{t+n\Delta t} = f(Q_t, Q_{t-\Delta t}, \ldots Q_{t-m\Delta t}) \tag{1}$$

if the only past historical flow series is considered.

$$Q_{t+n\Delta t} = f(R_{t+\Delta t}, R_t, R_{t-\Delta t}, \ldots R_{t-l\Delta t}, Q_t, Q_{t-\Delta t}, \ldots Q_{t-m\Delta t}) \tag{2}$$

if the past and present rainfalls and past historical flow series are considered.

where Q is the flow (m^3/s), R is the rainfall (mm), n refers to how far into the future the inflow prediction is desired; l and m represents how far back the recorded time series (rainfall and flows) affects the flow prediction. Δt is time interval.

5.2.3 Model Development

Model Architecture: In this study, the dependency of ELM on the lagged input variables, number of hidden nodes and regularization coefficient (C) were analyzed with sigmoid activation function to develop the best trained model. The authors selected sigmoid activation function as this produced best results compared to other activation functions (Atiquzzaman and Kandasamy, 2016b). The C value is optimized to improve the results.

Lagged Variables: ELM and GP's performances for one-day lead predictions (n = 1) were tested by assigning a number of lagged flows (m) as defined in equation 1. Initially, seven day lagged flows (m = 7) with the number of hidden nodes set to the number of training samples were applied.

In ELM, m was decreased one-by-one and each time the model was re-run to assess its performance. The best performing model was used for subsequent analysis.

In GP, an algorithm called Eureqa (Schmidt and Lipson, 2009) was used which automatically test a range of m in the training phase to produce a model with the m that best correlates with the output.

Number of Hidden Nodes: The number of the hidden nodes needs to be defined beforehand. The influence of the number of hidden nodes on the model prediction was analyzed with the best performing model obtained in the manner outlined in the previous section. The number of hidden nodes applied was varied from 10 to 6204 to test the model performances. The upper limit was set to 6204 as this equals the total number of training samples according to Huang et al. (2012) produces best results.

Regularization Coefficient: The performance of ELM depends on the regularization coefficient (*C*). The default value of *C* is 1. The model with an optimized number of hidden nodes found from previous analysis was chosen to undertake further test to improve the accuracy by varying the regularization coefficient. The default value was increased by a factor of ten each time in a series of runs to test the model performances. The factor ten was used to rapidly increase the *C* value to quickly access which gave a better solution.

5.2.4 Extrapolation and Higher Lead-Day Prediction

ELM's ability to extrapolate flows was tested by training it with a dataset that did not include the maximum values of the entire time-series. In this test, the input data series was split up into two groups. The portion of the time series which contained the largest discharge was used as the production dataset. The remaining of the data series was used for training. The trained model was applied to verify if it could predict the extreme values of the time-series.

The ELM model was also applied for higher lead-days (e.g. n=2, 3, 5) predictions to access and compare ELM's performance against other published AI techniques.

5.2.5 Performance Measures

The model prediction accuracies were assessed using four performance measures, namely Correlation Coefficient (CC), Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE). NSE and RMSE were found to be the two mostly used performance measures according to a review by Nourani et al. (2014).

Rathinasamy et al. (2014) proposed wavelet-based performance measures (Multiscale NSE and NRMSE) instead of traditional NSE and RMSE as they found that the proposed measures were more reliable. However, in this study NSE, RMSE and NRMSE were selected primarily to undertake a direct comparison with the results given in Yu et al. (2004) and Yu and Liong (2007). It is unlikely that other performance measure will adversely affect the assessment of ELM's performance since ELM performed well across the entire range of performance measures tested.

CC provides information on linear dependence between observed and simulated values (Kisi et al., 2013) and its values lies between 0 and 1. A value of 0 means no correlation at all whereas a value of 1 means that the dispersion of prediction is equal to that of the observation. RMSE represents the forecasting error and estimates the sample standard deviation of the differences between predicted values and observed values. A RMSE value of zero indicates perfect match whereas higher values represent no match between the observed and modelled output. It is a good measure when large model errors are not desirable. Another criterion frequently used in the context of assessing the performance of hydrological models is NSE. The NSE provides a measure of the model's ability to predict observed values. In general, high values of NSE (up to 100%) and small values for RMSE indicate good model predictions.

5.3 Results

5.3.1 Influence of Lagged Variables

The ELM model was run for Tryggevælde and Mississippi River catchments with flow data as input for different *m* values ranging from 1 to 7. The number of hidden nodes was set to the number of training samples (i.e. 6204). The CC, NSE, RMSE and NRMSE values for training and testing are presented in Table 5. 1 for Tryggevælde and Table 5. 2 for Mississippi River catchments. The time required to train ELM for the two catchments was less than 122sec. The CC and NSE are higher than 0.9 and 0.8 respectively for all training and testing results which show that ELM predicts generalized results for all lagged input variables above 1. The RMSE for Tryggevælde catchment ranged from 0.495 to 0.560 (Figure 5. 3) and NRMSE from 0.339 to 0.384 for testing results. Similarly, for Mississippi River catchment, the RMSE varied from 315.77 to 608.33 (Figure 5. 5) and NRMSE from 0.04 to 0.077 for testing results. The RMSE values for these two catchments vary as the magnitude of flows are very different (average flow for Tryggevælde is 0.977 m^3/s and 18,457 m^3/s for Mississippi River) and the deviations between observed and predicted flows differ significantly. Though, ELM produced reasonable results for all runs, the minimum error (e.g. RMSE and NRMSE) for the testing dataset was obtained when $m = 4$ (ELM4) for Tryggevælde catchment and $m = 2$ for Mississippi River catchment (see Table 5. 1). This is because smaller catchment responds quicker to changes in climatic conditions than bigger catchment. Therefore, more number of lagged variables are required to detect fast changing flows for accurate prediction. For the larger catchment (Mississippi River catchment), lagged variables above 2 produced similar results (see Table 5. 2) since catchment response is very slow. The scatter plots of observed and modelled flows for training and testing datasets are shown in Figure 5. 4 for Tryggevælde catchment and Figure 5. 6 for Mississippi River catchment. It shows good agreement between the measured and predicted daily discharge. The measured and predicted runoffs are evenly scattered around the line of agreement (best fit) especially for the Mississippi River (Figure 5. 6).

The same data was applied to GP for comparison. Table 5. 1 and Table 5. 2 show the results of GP for both catchments. GP automatically discards runs of poorer performing lagged variables and produced a solution where m = 2. The time taken was 202.8sec in 77,082 iterations for Tryggevælde catchment and 8min 20sec and 181,892 iterations for Mississippi River catchment. The GP results in terms of RMSE and NRMSE were worse than ELM. As ELM2 and ELM4 model produced comparable results, ELM4 is used in the subsequent analysis for consistency with Tryggevælde catchment.

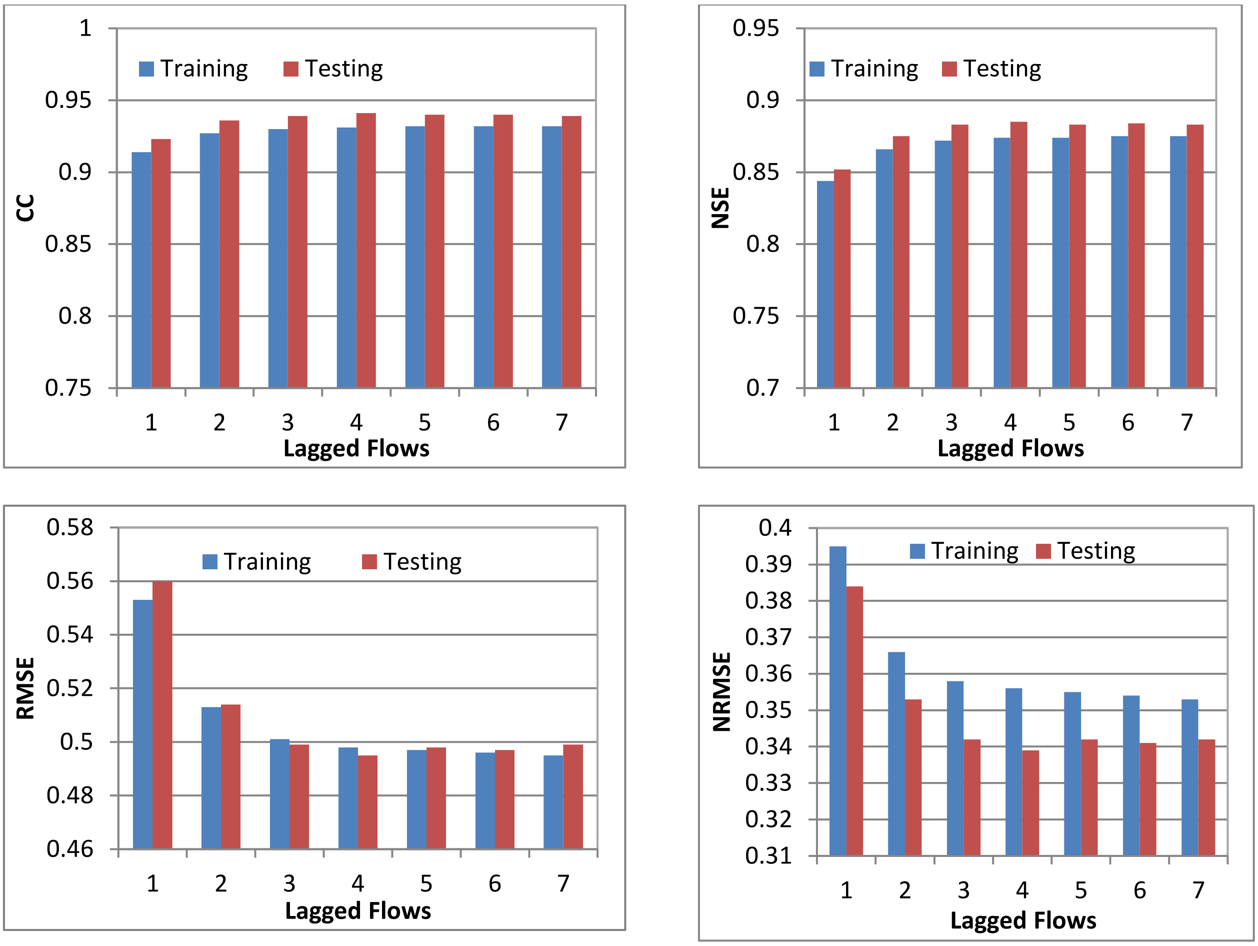
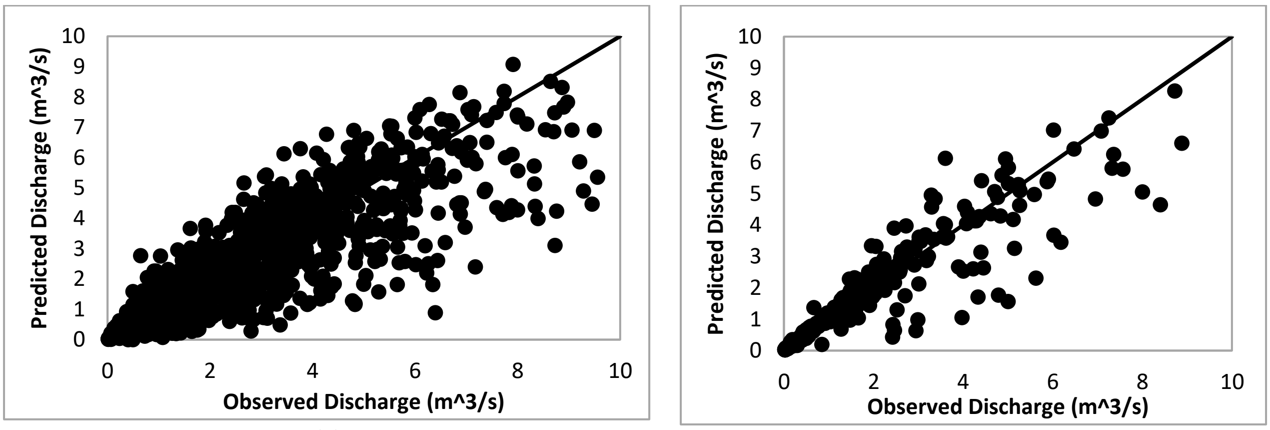


Figure 5. 3: ELM Model Prediction Accuracies for Training and Testing Dataset - Tryggevælde Catchment



(a) (b)

Figure 5. 4: Scatter Plot of Observed and Predicted Training (a) and Testing (b) Dataset for Tryggevælde Catchment

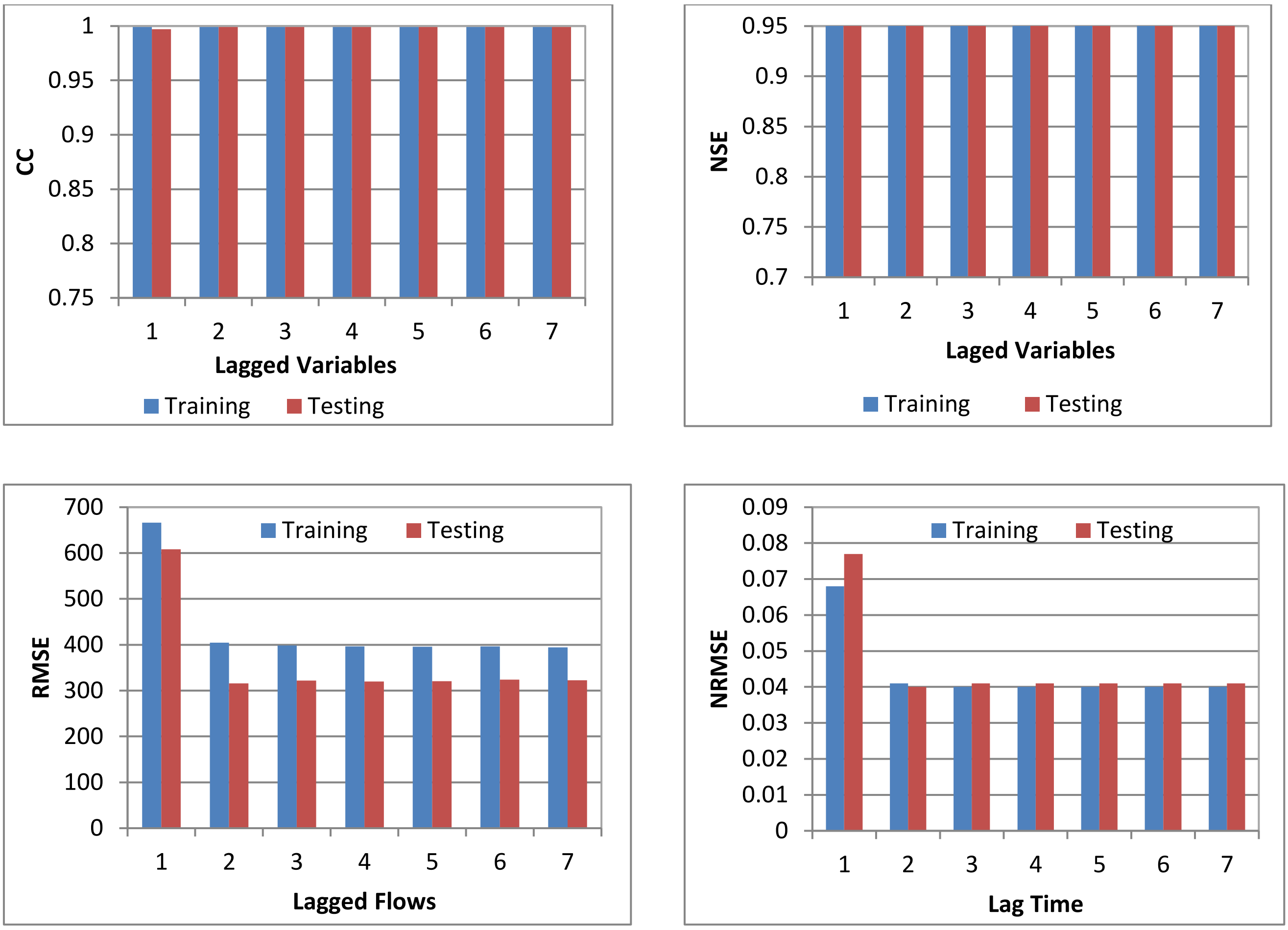


Figure 5. 5: ELM Model Prediction Accuracies for Training and Testing Dataset - Mississippi River Catchment

Table 5. 1: Comparison of Prediction Accuracies for Different Lagged Variables - Tryggevælde Catchment

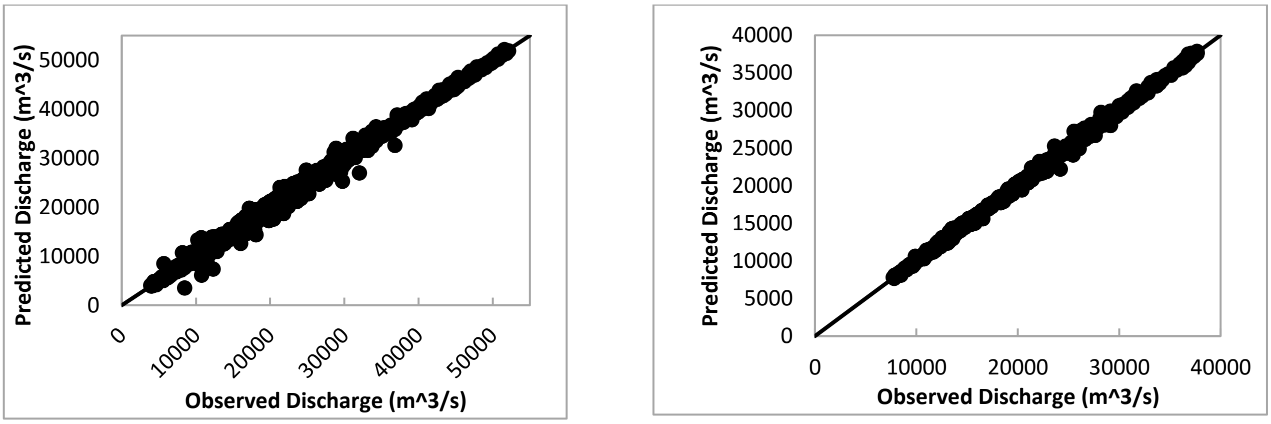
Model Run		*m**	CC	NSE	RMSE	NRMSE	Iterations	Training Time
ELM1	Training	1	0.914	0.844	0.553	0.395	Single	99.6sec
	Testing		0.923	0.852	0.56	0.384		
ELM2	Training	2	0.927	0.866	0.513	0.366	Single	106.8sec
	Testing		0.936	0.875	0.514	0.353		
ELM3	Training	3	0.930	0.872	0.501	0.358	Single	99sec
	Testing		0.939	0.883	0.499	0.342		
ELM4	Training	4	0.931	0.874	0.498	0.356	Single	99sec
	Testing		0.941	0.885	0.495	0.339		
ELM5	Training	5	0.932	0.874	0.497	0.355	Single	99.6sec
	Testing		0.94	0.883	0.498	0.342		
ELM6	Training	6	0.932	0.875	0.496	0.354	Single	100.2sec
	Testing		0.94	0.884	0.497	0.341		
ELM7	Training	7	0.932	0.875	0.495	0.353	Single	99sec
	Testing		0.939	0.883	0.499	0.342		
GP	Training	2	0.917	0.835	0.554	0.406	77,082	202.8sec
	Testing		**0.927**	**0.857**	**0.551**	**0.378**		

m* **= no of lagged flows in the input**

Table 5. 2: Comparison of Prediction Accuracies for Different Lagged Variables - Mississippi River Catchment

Model Run		*m**	CC	NSE	RMSE	NRMSE	Iterations	Training Time
ELM1	Training	1	0.999	0.995	666.16	0.068	Single	104.5sec
	Testing		0.997	0.994	608.33	0.077		
ELM2	Training	2	0.999	0.998	404.49	0.041	Single	105sec
	Testing		0.999	0.998	315.77	0.04		
ELM3	Training	3	0.999	0.998	398.7	0.040	Single	104sec
	Testing		0.999	0.998	321.88	0.041		
ELM4	Training	4	0.999	0.998	396.59	0.040	Single	104sec
	Testing		0.999	0.998	320.00	0.041		
ELM5	Training	5	0.999	0.998	395.41	0.040	Single	104.5sec
	Testing		0.999	0.998	320.58	0.041		
ELM6	Training	6	0.999	0.998	396.32	0.040	Single	121.8sec
	Testing		0.999	0.998	324.10	0.041		
ELM7	Training	7	0.999	0.998	394.66	0.040	Single	110.3sec
	Testing		0.999	0.998	322.48	0.041		
GP	Training	2	0.999	0.998	414.81	0.042	181,892	8min 20sec
	Testing		0.999	0.998	321.70	0.041		

***m** = no of lagged flows in the input**



(a) (b)

Figure 5. 6: Scatter Plot of Observed and Predicted Training (a), and Testing Dataset (b) for Mississippi River Catchment

For Duckmaloi Weir catchment, the model is run with flow and rainfall data as input for different values of *l* and *m* with number of hidden nodes of about 7745. Table 5. 3 shows the predictions accuracies for different combination of *l* and *m*. The total time required to train the ELM model ranges from 3.14min to 3.29min. The CC and NSE are found to be greater than 0.9 and 0.8 respectively for all the runs (see Figure 5. 7). Figure 5. 7 shows that the RMSE from testing results ranges from 33.099 (ELM2) to 38.235 (ELM3) and NRMSE from 0.284 (ELM2) to 0.328 (ELM3) (see Figure 5. 7). The RMSE values for this catchment are not the same compared to the previous two catchments as the difference in observed and predicted flows differs significantly. ELM produces reasonable solutions for all runs. However, the minimum error is obtained when *l* and *m* values are 2 (see model ELM2) and RMSE and NRMSE are found to be 33.099 and 0.284. The scatter plot of observed and modelled flows for training and testing datasets is shown in Figure 5. 8 for Duckmaloi Weir catchment. It shows good agreement between the measured and predicted daily discharge. The measured and predicted runoffs are evenly scattered around the line of agreement (best fit).

The comparisons of ELM and GP are presented in Table 5. 3. GP produces optimal solution based on current rainfall (l=1) and past flow (m = 1) with total number of iterations of 255,473 in 12.52min. The GP results show that CC, NSE, RMSE and NRMSE from testing results are 0.85, 0.729, 60.715 and 0.52 respectively. However, ELM produced superior results even with l =1 and m = 1 (see ELM1 in Table 5. 3) where CC, NSE, RMSE and NRMSE are 0.953, 0.907, 35.56 and 0.305 respectively. ELM2 model (Table 5. 3) improves the prediction accuracy by 45.5% in terms of RMSE and ELM1 by 41.4% compared to GP.

Table 5. 3: Prediction Accuracy for Duckmaloi Weir Catchment

Model Run		*(l, m)**	CC	NSE	RMSE	NRMSE	Iterations	Training Time (min)
ELM1	Training	**(1,1)**	**0.915**	**0.837**	**49.742**	**0.404**	Single	**3.21**
	Testing		**0.953**	**0.907**	**35.560**	**0.305**		
ELM2	Training	**(2, 2)**	**0.924**	**0.854**	**47.124**	**0.382**	Single	**3.14**
	Testing		**0.959**	**0.920**	**33.099**	**0.284**		
ELM3	Training	(3, 3)	0.939	0.881	42.535	0.345	Single	3.21
	Testing		0.947	0.893	38.235	0.328		
ELM4	Training	(4, 4)	0.935	0.874	43.783	0.355	Single	3.29
	Testing		0.949	0.897	37.502	0.321		
ELM5	Training	(5, 5)	0.937	0.877	43.169	0.350	Single	3.22
	Testing		0.952	0.902	36.566	0.313		
ELM6	Training	(6, 6)	0.938	0.880	42.776	0.347	Single	3.27
	Testing		0.952	0.904	36.173	0.309		
ELM7	Training	(7, 7)	0.939	0.881	42.535	0.345	Single	3.20
	Testing		0.950	0.900	36.883	0.316		
GP	Training	**(1, 1)**	**0.898**	**0.805**	**54.402**	**0.441**	**255,473**	**12.52**
	Testing		**0.85**	**0.729**	**60.715**	**0.520**		

****l* = no of lagged rainfall including current rainfall in the input**
****m* = no of lagged flows in the input**

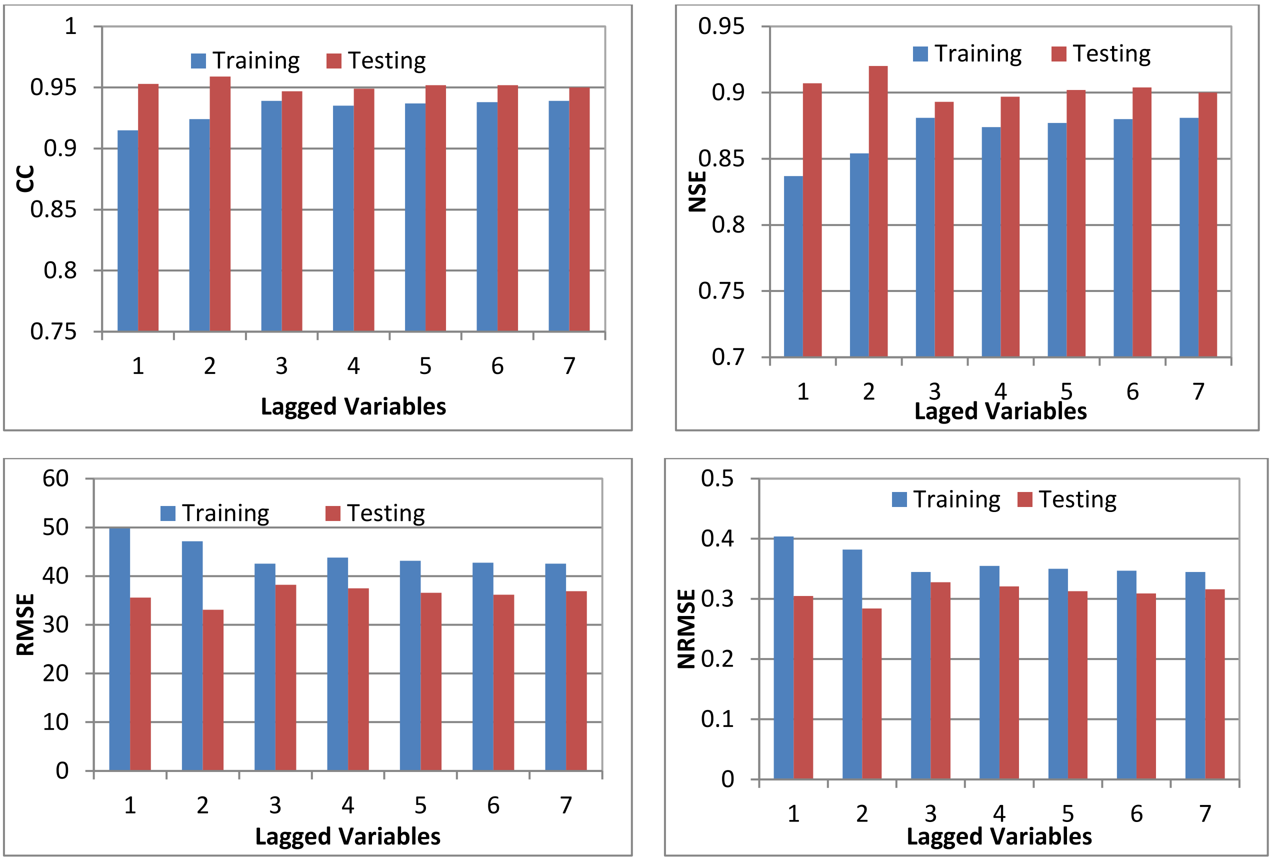
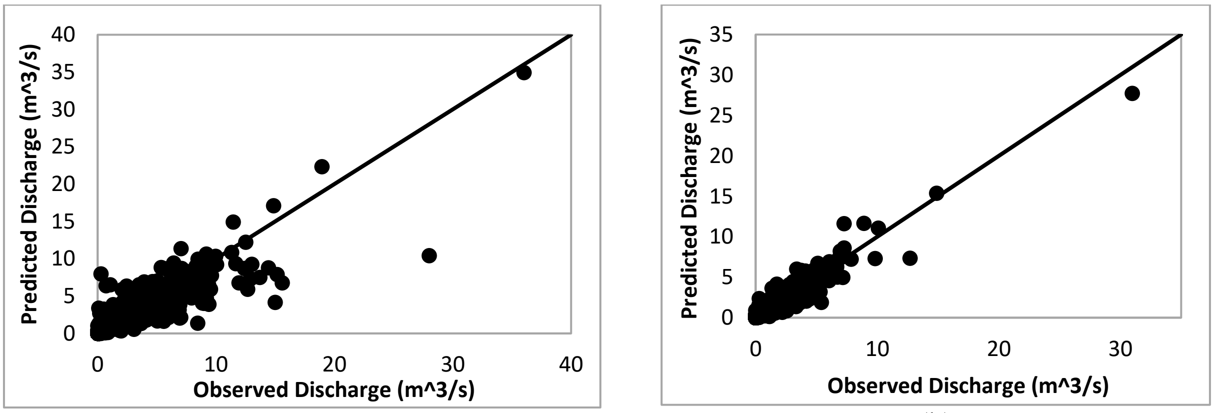


Figure 5. 7: ELM Model Prediction Accuracies for Training and Testing Dataset - Duckmaloi Weir Catchment



(a) (b)

Figure 5. 8: Scatter Plot of Observed and Predicted Training (a) and Testing (b) Dataset for Duckmaloi Weir Catchment

5.3.2 Influence of Number of Hidden Nodes

ELM4 (*m*=4) was run for Tryggevælde and Mississippi River Catchment with different number of hidden nodes to test its influence on the prediction accuracy. The number of hidden nodes tested ranged from 10 to number of training samples (6204). The results in terms of CC, NSE, RMSE and NRMSE for both training and testing are given in Table 5. 4 for Tryggevælde Catchment and Table 5. 5 for Mississippi River Catchment. The CC and NSE for both catchments are higher than 0.9 and 0.8 respectively for all runs. The prediction errors in terms of RMSE and NRMSE decrease with larger number of hidden nodes (see Table 5. 4 and Table 5. 5). The variations of RMSE with hidden nodes are presented in Figure 5. 9. For Tryggevælde Catchment, the RMSE and NRMSE values for testing dataset are 0.574 and 0.393 respectively for 10 hidden nodes (ELM4-1) and 0.495 and 0.339 respectively for 6204 hidden nodes (ELM4).

Table 5. 4: Influence of Number of Hidden Nodes on Prediction Accuracy for Tryggevælde Catchment

No.	Model Run		No of Hidden Notes	CC	NSE	RMSE	NRMSE	Training Time	% RMSE Improvement Compared to 1000 Nodes
1	ELM4-1	Training	10	0.911	0.829	0.566	0.414	<1sec	
		Testing		0.921	0.837	0.574	0.393		-
2	ELM4-2	Training	100	0.924	0.853	0.524	0.383	<1sec	
		Testing		0.933	0.860	0.526	0.361		-
3	ELM4-3	Training	200	0.925	0.855	0.520	0.380	<1sec	
		Testing		0.934	0.863	0.522	0.358		-
4	ELM4-4	Training	500	0.927	0.860	0.512	0.375	<1sec	
		Testing		0.936	0.867	0.515	0.353		-
5	ELM4-5	Training	1000	0.929	0.862	0.507	0.371	3.2sec	
		Testing		0.938	0.869	0.508	0.348		-
6	ELM4-6	Training	2000	0.930	0.865	0.503	0.368	10.9sec	
		Testing		0.939	0.871	0.502	0.343		1.2
7	ELM4-7	Training	4000	0.931	0.866	0.500	0.366	41.31sec	
		Testing		0.940	0.873	0.498	0.341		2.0
8	ELM4-8	Training	5000	0.931	0.867	0.499	0.365	63sec	
		Testing		0.941	0.873	0.496	0.340		2.4
9	ELM4-9	Training	6000	0.931	0.867	0.498	0.365	92.4sec	
		Testing		0.941	0.874	0.495	0.339		2.6
10	ELM4	Training	6204	0.931	0.867	0.498	0.364	99sec	
		Testing		0.941	0.885	0.495	0.339		2.6

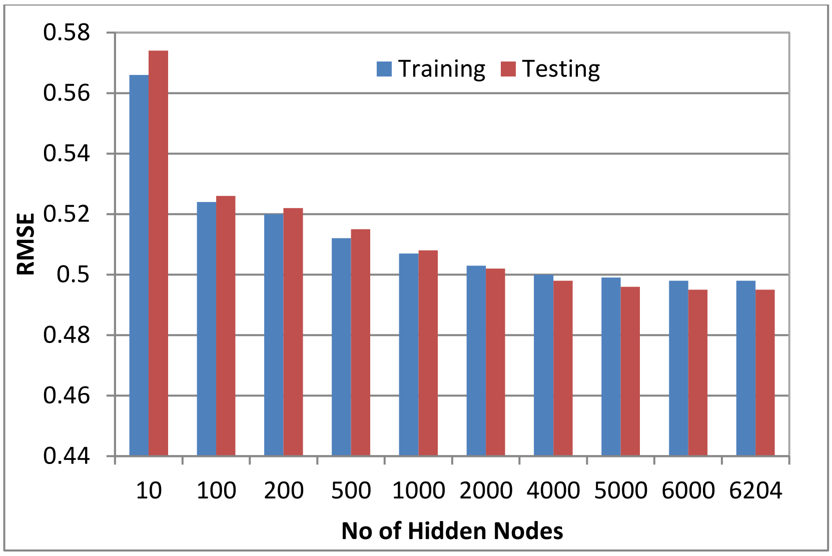


Figure 5. 9: Influence of Hidden Nodes on ELM Model Accuracy- Tryggevælde Catchment

For Mississippi River Catchment, these values range from 734.51 and 0.093 for 10 nodes to 320.15 and 0.041 for 6204 nodes respectively. The RMSE value decreased by 13.8% for Tryggevælde Catchment and 56% for the Mississippi River. The time required to train ELM increased from less than 1s for 10 nodes to less than 104sec for 6204 nodes (Table 5. 4 and Table 5. 5). The percentages of improvement of the models in comparison with 1000 nodes model (ELM4-4) are shown in last column of Table 5. 4 and Table 5. 5. The number of hidden nodes of 1000 was chosen for comparison as the accuracy does not improve significantly with nodes above this number. The maximum improvement of accuracy in terms of RMSE was only 2.6% for Tryggevælde Catchment and 1.2% for Mississippi River Catchment when the number of hidden nodes was increased from 1000 to 6204. Figure 5. 10 shows that the RMSE for a big catchment like the Mississippi River, was less sensitive to increased number of hidden nodes. Although, the accuracy of ELM did not significantly improve where the number of hidden nodes was greater than or equal to1000, the training time increased significantly. This suggests that ELM is capable of producing good solutions very fast with a modest number of hidden nodes (e.g. 1000). The model with 1000 hidden nodes (ELM4-5) was investigated for these two catchments only to further improve the accuracy by fine tuning the C parameter and compare the results with EC-SVM.

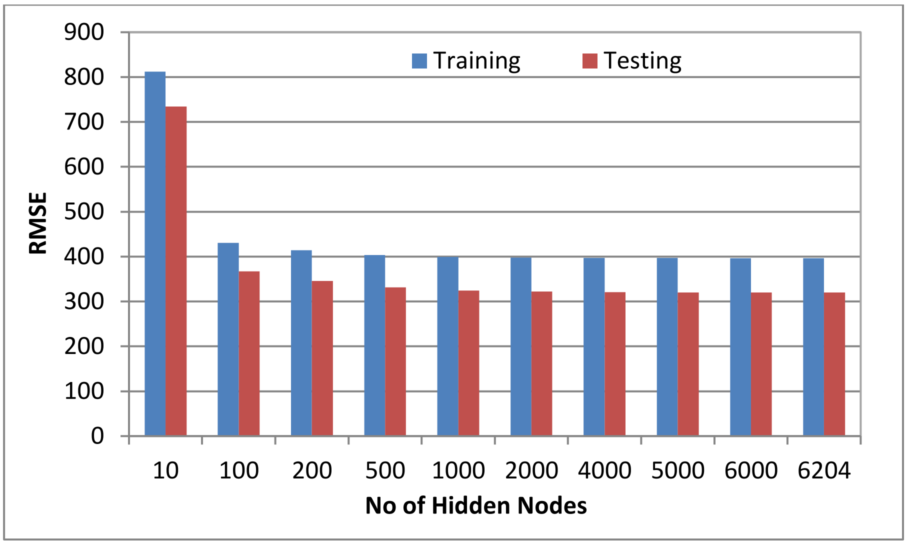


Figure 5. 10: Influence of Hidden Nodes on ELM4 Model Accuracy for Mississippi River Catchment

Table 5. 5: Influence of Number of Hidden Nodes on Prediction Accuracy for Mississippi River Flow, Vicksburg

No.	Model Run		No of Hidden Notes	CC	NSE	RMSE	NRMSE	Training Time	% RMSE Improvement Compared to 1000 Nodes
1	ELM 4-1	Training	10	0.997	0.993	812.37	0.082	<1sec	-
		Testing		0.996	0.991	734.51	0.093		
2	ELM 4-2	Training	100	0.999	0.998	430.43	0.044	<1sec	-
		Testing		0.999	0.998	367.04	0.047		
3	ELM 4-3	Training	200	0.999	0.998	414.22	0.042	<1sec	-
		Testing		0.999	0.998	345.41	0.044		
4	ELM 4-4	Training	500	0.999	0.998	403.33	0.041	<1sec	-
		Testing		0.999	0.998	331.28	0.042		
5	ELM 4-5	Training	1000	0.999	0.998	399.53	0.041	3.2sec	-
		Testing		0.999	0.998	324.07	0.041		
6	ELM 4-6	Training	2000	0.999	0.998	398.10	0.040	13.2sec	0.7
		Testing		0.999	0.998	321.89	0.041		
7	ELM 4-7	Training	4000	0.999	0.998	397.12	0.040	44.5sec	1.1
		Testing		0.999	0.998	320.59	0.041		
8	ELM 4-8	Training	5000	0.999	0.998	396.82	0.040	70.5sec	1.2
		Testing		0.999	0.998	320.32	0.041		
9	ELM 4-9	Training	6000	0.999	0.998	396.57	0.040	100.7sec	1.2
		Testing		0.999	0.998	320.15	0.041		
10	ELM 4	Training	6204	0.999	0.998	396.55	0.040	104sec	1.2
		Testing		0.999	0.998	320.00	0.041		

For Duckmaloi Weir catchment, the best model (ELM2) was run for a series of hidden nodes to understand the influence of hidden nodes on the prediction accuracy. The number of hidden nodes ranges from 10 to 7000. The results in terms of CC, NSE, RMSE and NRMSE and the ELM training times are in Table 5. 6. Table 5. 6 shows reasonable results for any number of hidden nodes with the CC and NSE values always greater than 0.9 and 0.8 respectively. ELM training time requires time less than 1s for 10 nodes to 2.63mins for 7000 nodes. The prediction accuracies in terms of RMSE decrease with the increase of hidden nodes (see Figure 5. 11). The RMSE and NRMSE are 50.381 and 0.432 for 10 hidden nodes (ELM2-1) and 33.184 and 0.284 for 7000 hidden nodes (ELM2-9). Table 5. 6 also shows that though the accuracy of ELM is not significantly improved if the number of hidden nodes is further increased above 4000, the training time is increased from 50.19s to 2.63min for 7000 nodes to get only 1.9% improvement in terms of RMSE (see Figure 5. 11 and Table 5. 6). This suggests that ELM is capable of producing similar solutions very fast with modest number of hidden nodes. However, the higher number of hidden nodes generally generates slightly less error in terms of RMSE and NRMSE.

Table 5. 6: Influence of Number of Hidden Nodes on Prediction Accuracy for Duckmaloi Weir Catchment

No.	Model Run		No of Hidden Notes	CC	NSE	RMSE	NRMSE	Training Time	% RMSE Improvement Compared to 4000 Nodes
1	ELM 2-1	Training Testing	10	0.934 0.909	0.748 0.814	61.872 50.381	0.502 0.432	<1sec	-
2	ELM 2-2	Training Testing	100	0.951 0.919	0.818 0.843	52.629 46.189	0.427 0.396	<1sec	-
3	ELM 2-3	Training Testing	200	0.954 0.923	0.827 0.851	51.301 45.033	0.416 0.386	<1sec	-
4	ELM 2-4	Training Testing	500	0.957 0.936	0.837 0.876	49.733 41.165	0.404 0.353	1.31sec	-
5	ELM 2-5	Training Testing	1000	0.959 0.944	0.844 0.892	48.659 38.412	0.395 0.329	3.95sec	-
6	ELM 2-6	Training Testing	2000	0.960 0.952	0.848 0.906	48.011 35.807	0.390 0.307	13.93sec	-
7	ELM 2-7	Training Testing	4000	0.961 0.957	0.852 0.916	47.505 33.835	0.385 0.290	50.19sec	-
8	ELM 2-8	Training Testing	5000	0.961 0.958	0.852 0.918	47.361 33.420	0.384 0.286	1.38min	1.23
9	ELM 2-9	Training Testing	7000	0.961 0.959	0.854 0.919	47.141 33.184	0.383 0.284	2.63min	1.92
10	ELM 2	Training Testing	7745	**0.924** **0.959**	**0.854** **0.920**	**47.124** **33.099**	**0.382** **0.284**	**3.14**	**2.18**

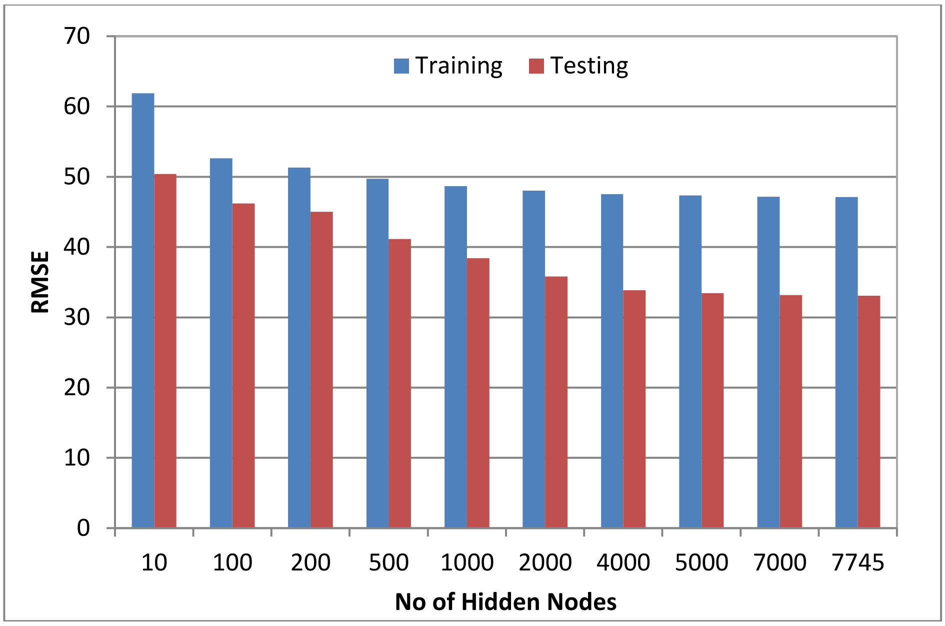


Figure 5. 11: Influence of Hidden Nodes on ELM Model Accuracy - Duckmaloi Weir Catchment

5.3.3 Improvement of Regularization Coefficient (*C*)

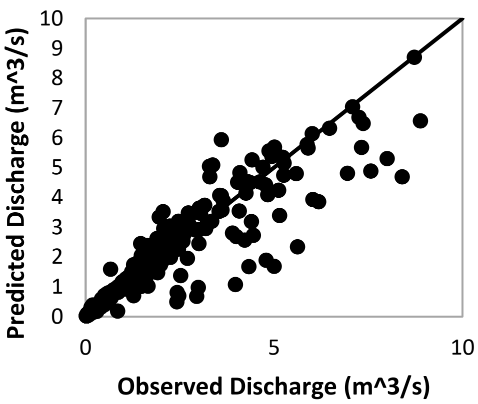
The ELM4-5 (hidden nodes = 1000, Table 5. 4 and Table 5. 5) was used to test the impact of *C* on the model performance for Tryggevælde and Mississippi River Catchments only to compare the performance of ELM with other published techniques. In all previous runs, a *C* value of 1 was used by default. Here, the value of *C* was increased in each run to improve the results. Table 5. 7 shows the improvement in the performance. The best result was obtained when the *C* value is 1E3 in 12.8sec for Tryggevælde Catchment and 1E10 in 32sec for Mississippi River Catchment. The prediction accuracy for training dataset in terms of RMSE decreased from 0.507 to 0.483 (4.7%) for Tryggevælde Catchment and from 399.53 to 347.74 (12.9%) for Mississippi River catchment. Similarly, the RMSE values for testing dataset decreased from 0.508 to 0.486 (4.3%) for Tryggevælde Catchment and from 324.07 to 296.82 (8.4%) for Mississippi River Catchment. The NRMSE behaves similarly. The comparison of observed and predicted flows using this improved ELM model is shown Figure 5. 12. The ELM4-5 model with

1000 hidden nodes and best performing value of *C* was used to investigate ELM's ability to extrapolate flows (section 5.3.5) and to give higher lead-day predictions (section 5.3.6).

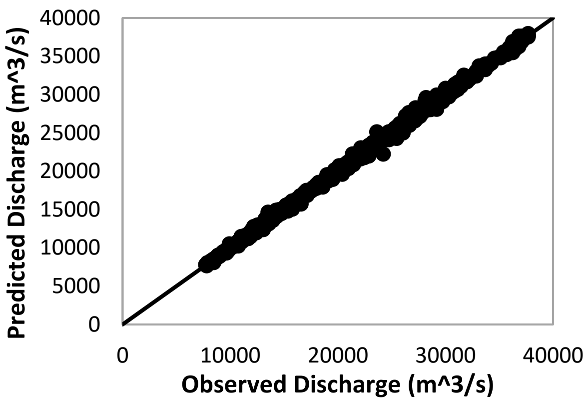
Table 5. 7: Improvement of Prediction Accuracy by Changing *C* Values

Catchment		No of Hidden Notes	C^*	CC	NSE	RMSE	NRMSE	Training Time
Tryggevælde	Training	1000	1	0.929	0.862	0.507	0.371	3.2sec
	Testing			0.938	0.869	0.508	0.348	
	Training	**1000**	**1000**	**0.935**	**0.875**	**0.483**	**0.354**	**12.8sec**
	Testing			**0.943**	**0.889**	**0.486**	**0.333**	
Mississippi River	Training	1000	1	0.999	0.998	399.53	0.041	**3.2sec**
	Testing			0.999	0.998	324.07	0.041	
	Training	**1000**	**10^{10}**	**0.999**	**0.999**	**347.74**	**0.035**	**32.0sec**
	Testing			**0.999**	**0.999**	**296.82**	**0.037**	

C* **= regularization coefficient**



(a)



(b)

Figure 5. 12: Scatter Plot of Testing Dataset for, (a) Tryggevælde Catchment and (b) Mississippi River Catchment with Improved ELM

5.3.4 Comparison with Other Techniques

The performances of different ELM models against other type of AI models (GP and EC-SVM) are summarized in Table 5. 8 for testing dataset. The EC-SVM model results used for comparison were sourced from Yu et al. (2004) and Yu and Liong (2007) as they applied their method on the same case studies. EC-SVM was selected for comparison with ELM because EC-SVM performed better than other alternative techniques such as Standard Chaos Technique, Naïve, ARIMA and Inverse Approach reported by Yu et al. (2004) and ANN, FL and wavelet models by Fotovatikhah et al. (2018).

Five ELM models (see Table 5. 8) were used for comparison. ELM, in general, showed better results compared to other methods when the number of hidden nodes is higher than 1000. However, the ELM model with 500 hidden was also included in Table 5. 8 for comparison.

The best performing GP model obtained with two lagged variables (m=2) which took 77,082 iterations and 202.8sec had prediction errors of 0.551 for RMSE and 0.378 for NRMSE for Tryggevælde Catchment. Table 5. 8 shows that ELM with two lagged variables (see ELM2 model in Table 5. 1 and Table 5. 2) outperformed GP model and improved the results in terms of RMSE. ELM2 reached this solution and in less than 105sec on a Windows Intel i7@2.67GHz machine. Better results (RMSE < 0.514 and NRMSE < 0.353) from ELM were obtained when number of lagged variables were two or above (see Table 5. 1 and Table 5. 2). The best performing ELM model (ELM4-5d) compared to GP was more accurate by 11.8% for Tryggevælde Catchment and 7.7% for Mississippi River Catchment.

Table 5. 8: Comparison of Prediction Accuracies

	Method	**(*m, C*)**	**(*d, τ*)**	**RMSE**	**NRMSE**	**Iterations**	**Training Time**
Tryggevælde	GP	(2, -)	-	0.551	0.378	77,082	202.8sec[b]
	EC-SVM (Yu et al. 2004)	-	(3,1)	0.514	0.352	151,668	207.67sec[c]
	EC-SVM (Yu and Liong, 2007)	-	(5,1)	0.501	0.344	824	5hr 25min[c]
	ELM2 (6204[a])	(2, 1)	-	0.514	0.353	Single	99sec[b]
	ELM4 (6204[a])	(4, 1)	-	0.495	0.339	Single	99sec[b]
	ELM4-5 (1000[a])	(4,1)	-	0.508	0.348	Single	3.2sec[b]
	ELM4-5d (1000[a]) (Improved ELM)	**(4, 1000)**	**-**	**0.486**	**0.333**	**4**	**12.8sec[b]**
	ELM4-4 (500[a])	(4, 1)	-	0.515	0.353	Single	<1sec[b]
Mississippi River	GP	(2, -)	-	321.70	0.041	181,892	8min 20sec[b]
	EC-SVM (Yu et al. 2004)	-	(2,1)	306.58	0.039	1,732,579	53.93min[c]
	EC-SVM (Yu and Liong, 2007)	-	(4,1)	320.44	0.041	1,214	8hr 40min[c]
	ELM2 (6204[a])	(2, 1)	-	315.77	0.04	Single	105sec[b]
	ELM4 (6204[a])	(4, 1)	-	320.00	0.041	Single	104sec[b]
	ELM4-5 (1000[a])	(4,1)	-	324.07	0.041	Single	3.2sec[b]
	ELM4-5d (1000[a]) (Improved ELM)	**(4, 10^{10})**	**-**	**296.82**	**0.037**	**10**	**32.0sec[b]**
	ELM4-4 (500[a])	(4, 1)	-	331.28	0.042	Single	<1sec[b]

[a]Number of Hidden Nodes; [b]Windows Intel i7@2.67GHz [c]Linux Pentium II@333MHz

ELM (ELM4-4) with 500 hidden nodes yielded similar results (RMSE = 0.515 and NRMSE = 0.353) compared to EC-SVM (Yu et al., 2004). However, ELM's training time was a fraction of 1sec on a Windows Intel i7@2.67GHz machine. EC-SVM (Yu et al., 2004) needed 151,668 iterations and 207.66sec on a Linux Pentium II@333mHz machine. Table 5. 8 shows how the accuracy improves when the number of hidden nodes increases. ELM4-5d model (number of hidden nodes = 1000) improved the accuracy (RMSE = 0.486 and NRMSE = 0.333) for Tryggevælde Catchment beyond the EC-SVM model (Yu et al., 2004). Similar results were obtained for the Mississippi River Catchment using the same model. The RMSE and NRMSE reduced to 296.82 and 0.037 respectively for the ELM4-5d model compared to 306.58 and 0.039 obtained by EC-SVM (Yu et al., 2004). The results demonstrate that any number of hidden nodes in ELM greater than or equal to 1000 produced better results than GP and EC-SVM (see Table 5. 4 and Table 5. 5). ELM4-5d model required 12.8sec and 32sec for two different catchments respectively on the Windows Machine and ran much faster than GP and EC-SVM. The computational time discussed is not completely comparable since two different types of machines were used. The major strength demonstrated in this analysis was ELM's ability to reach more accurate solutions faster than GP and EC-SVM. ELM requires only a single iteration and the run time, depending on the number of hidden nodes, varies between a fraction of a second to less than 2 minutes.

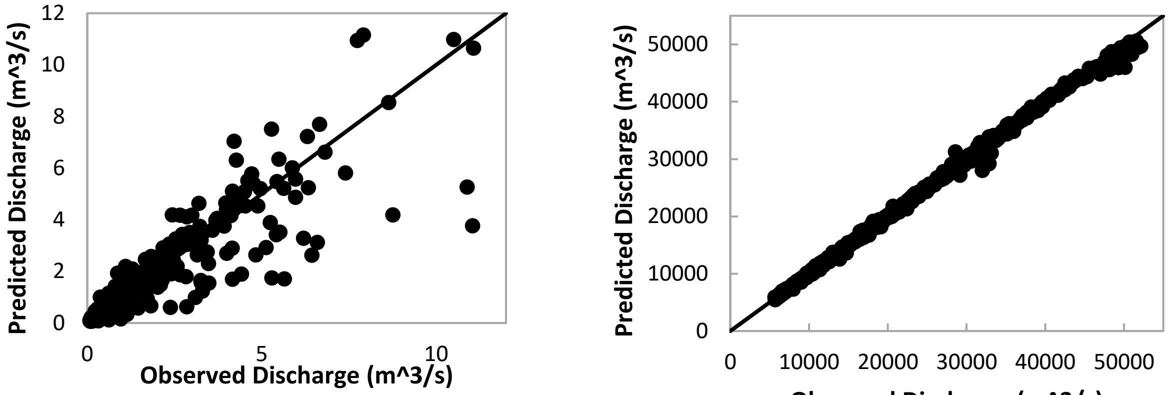
5.3.5 ELM's Ability to Extrapolate

The maximum flow in the Tryggevælde Catchment of approximately 11 m^3/s (Figure 4. 1) occurred in early 1982 and 1991; and for the Mississippi River (Figure 4. 2) a flow above 50,000 m^3/s occurred in 1975 and 1983. The portion of the dataset containing the two years with highest recorded flows were selected for testing ELM model. The other portion of the data excluding the highest peak was used for training. The results are summarized in Table 5. 9. The CC and NSE were above 0.9 and 0.8 respectively for both training and testing datasets. The errors in predicting testing data in terms of RMSE and NRMSE were 0.664 and 0.419 for Tryggevælde Catchment and 512.98 and 0.042 for Mississippi River Catchment respectively. The maximum flow extrapolated by ELM model was 10.643 m^3/s which was 97% of the observed flow for Tryggevælde Catchment. For Mississippi River Catchment, the predicted flow of 50,600 m^3/s was within 99% of the observed flow (52,109 m^3/s). The ability of ELM to extrapolate is shown in a scatter plot (Figure 5. 13). It shows reasonable results with flows around the line of agreement (1:1) for both catchments.

Similarly, for Ducmaloi Weir catchment, the maximum flow of approximately 36 m3/s occurred in the middle of 1964 (see Figure 5. 2). This year of data is excluded from training and is selected for testing purpose. Table 5. 10 shows that the CC and NSE are above 0.9 and 0.8 respectively for both training and testing dataset. The errors in terms of RMSE and NRMSE are 104.812 and 0.340 for testing data and 41.153 and 0.365 for training data respectively. This concludes that ELM performs reasonably well in the extrapolation for the prediction of flow in Ducmaloi Weir Catchment. These results show that ELM performed reasonably well in extrapolating and predicting the maximum flow values even when these were excluded from the learning process in training.

Table 5. 9: Extrapolation Capability of ELM

Catchment		CC	NSE	RMSE	NRMSE
Tryggevælde	Training	0.939	0.883	0.462	0.343
	Testing	0.908	0.824	0.664	0.419
Mississippi River	Training	0.999	0.999	345.68	0.037
	Testing	0.999	0.998	512.98	0.042



(a) (b)

Figure 5. 13: Scatter Plot of Testing Dataset for, (a) Tryggevælde Catchment and (b) Mississippi River Catchment for Extrapolation

Table 5. 10: Extrapolation Capability of ELM for Duckmaloi Weir Catchment

ELM Model Run	CC	NSE	RMSE	NRMSE
Training	0.931	0.867	41.153	0.365
Testing	0.936	0.840	104.812	0.340

5.3.6 Higher Lead Days Prediction

Table 5. 11 shows ELM's performance in terms of CC, NSE, RMSE and NRMSE for 2, 3 and 5 lead-days predictions. For the Tryggevælde Catchment, the CC values ranged from 0.83 (2 lead-days) to 0.638 (5 lead-days) and NSE values from 0.688 (2 lead-days) and 0.406 (5 lead-days). For Mississippi River Catchment, both CC and NSE values were above 0.9 and 0.8 for all three lead-days predictions. As expected, the prediction error increases for longer lead-day predictions.

Table 5. 11: Prediction Accuracy for Different Lead-Day Prediction

Catchment	Lead-Days	ELM					EC-SVM (Q)[a]	
		CC	NSE	RMSE	NRMSE	Time (sec)	NRMSE	Time (h:min)
Tryggevælde	2	0.83	0.688	0.814	0.558	3.2	0.574	1:22
	3	0.75	0.563	0.963	0.661	3.2	0.661	1:09
	5	0.638	0.406	1.123	0.771	3.0	0.768	0:55
Mississippi River	2	0.997	0.994	629.00	0.0797	2.9	0.0859	1:44
	3	0.992	0.983	1027.51	0.1302	3.2	0.1383	0:21
	5	0.972	0.944	1870.00	0.2370	3.1	0.2469	2:17

[a]Yu and Liong, 2007; PIV 2.4 GHz PC.

Compared to 1-day lead prediction the RMSE values increase to 0.814 for 2 lead days, 0.963 for 3 lead-days and 1.123 for 5 lead-days prediction for Tryggevælde Catchment. The corresponding NRMSE values change to 0.558, 0.661 and 0.771 respectively for 2, 3 and 5 lead-days predictions for this catchment. Similar behavior is observed for Mississippi River Catchment. The errors in terms of RMSE increase to 629.00, 1027.51 and 1870.00 and NRMSE to 0.0797, 0.1302 and 0.2370 for 2, 3 and 5 lead-days predictions. The last two columns of Table 5.7 also show the NRMSE and time to achieve the results from EC-SVM (Yu and Liong, 2007). Table 5.7 shows that ELM produces similar or better results than EC-SVM in a very short time (approximately 3sec) on Windows Intel i7@2.67GHz machine. For example, ELM required only 3.1sec for 5 lead-days prediction for the Mississippi River Catchment, obtaining NRMSE of 0.2370 compared to EC-SVM that needed 2 hour 17min to achieve NRMSE of 0.2469 (on PIV 2.4 GHz PC). For Duckmaloi Weir catchment, similar prediction accuracies are for higher lead-days (1, 2 and 3) prediction (Table 5. 12). The accuracies increase from RMSE of 33.99 to 45.285. The results demonstrate ELM's fast learning capability for longer lead-days predictions.

Table 5. 12: Accuracy for different lead-day prediction for Duckmaloi Weir Catchment

Model Run	Method	Lead-Day	CC	NSE	RMSE	NRMSE	Time (min)
1	**ELM2-1**	**1**	**0.959**	**0.920**	**33.099**	**0.284**	**3.14**
2	ELM2-2	2	0.931	0.876	40.961	0.351	3.14
3	ELM2-3	3	0.923	0.850	45.285	0.388	3.14

5.4 Discussion

In this study ELM, an AI Technique was presented to predict hydrological flow series. ELM's performance was demonstrated with data from three different catchment sizes i.e. a relatively smaller catchment (130.5 km^2) called the Tryggevælde Catchment (Denmark), the large Mississippi River (USA) catchment (3,220,000 km^2) and Duckmaloi Weir catchment (112 km^2). ELM proved to be fast and did not depend on complex network architectures. Firstly, ELM's performance based on different lagged flows (1 to 7 days) was tested. The best results were obtained when 2-4 lagged flows were used in the input dataset. In this analysis, the number of hidden nodes were the same as number of training samples. The results showed that all catchment models with two to four lagged flows had the better prediction accuracies (e.g. minimum RMSE values). The lagged variables indicate how far back observed flows have impact on future flow prediction. A smaller catchment (Tryggevælde Catchment) required more lagged variables (4 lagged input variables) as this responded to change in climatic condition quicker than a bigger catchment (e.g. 2 lagged variables for Mississippi River Catchment). The robustness of the models with four lagged variables was analyzed further.

The performance of ELM, in terms of run time and accuracy was improved by altering the number of hidden nodes and the value of regularization coefficient for Tryggevælde and Mississippi river catchments only for comparison purposes. A suitable value of C improves the accuracy of a model with a smaller number of hidden nodes and reduce the run time. ELM produced acceptable results very quickly (less than a second) from a modest number of hidden nodes (e.g. 1000). With higher number of hidden nodes (>1000), the accuracy improved modestly (less than 3%) though requiring a much longer time (30-100 times longer). The accuracy of ELM was improved by manually changing the value of C. Changing C improved the accuracy of ELM with hidden nodes equal to 1000 (see Table 5. 7) compared to base ELM4 (C unchanged, hidden nodes = 6404, see Table 5. 1) i.e. C more than compensated for the reduced accuracy of the model with a lower number of hidden nodes. The performance of ELM model with modified C values improved the prediction accuracies significantly from 0.508 to 0.486 for Tryggevælde Catchment and 324.07 to 296.82 for Mississippi River Catchment.

A model's ability to extrapolate is important for practical application in flood forecasting and prediction. The improved ELM model was applied to extrapolate a flow time series for all catchments. The highest flows were excluded from training dataset to investigate ELM's extrapolation capability. The model was able to predict the flows reasonably and quickly even after the exclusion of highest recorded flows from training samples. It produced reasonable results (CC > 0.9 and NSE > 0.8) for all three catchments.

ELM was computationally much faster and produced comparable or better results compared to leading AI methods (GP and EC-SVM) when predicting flow series from the same first two catchments. ELM performed better with two to four lagged variables and where the number of hidden nodes were greater than or equal to1000. ELM required a very short time (approximately 3sec) in 2, 3 and 5 lead-days prediction and produced similar or better results than EC-SVM (required computational time between 20min to 2hours). This is because ELM resolves the problem analytically in single iteration.

This chapter demonstrates ELM's potential application for real-time prediction of hydrological time-series and where quick model response and ability to extrapolate is vital for decision making in application such as flood warning and forecasting systems, real time operation, etc. Its better accuracy means that it has application in water resources planning and management.

5.5 Summary

The application of ELM was demonstrated in the prediction of hydrological flows from three different catchment sizes from three different climatic conditions (Tryggevælde Catchment, Denmark; Mississippi River, USA and Duckmaloi Weir catchment, Australia). Literature shows that EC-SVM performed better than ANN, ANFIS, Fuzzy Logic in the prediction flows. ELM's performance was compared with EC-SVM and GP. The results showed how ELM improved prediction accuracies and reached the solutions very quickly compared to other techniques (e.g. EC-SVM). ELM resolves the output analytically in a single iteration which reduces the computational run time. The study also concluded that:

- ELM showed reasonable results with all combination of lagged input variables (flows) for 1-day lead prediction in terms of CC (>0.9) and NSE (>0.8). The minimum errors in terms of RMSE and NRMSE were obtained where 2-4 lagged flows were applied as input variables. For smaller catchment, higher number of lagged variables (2 or more for Tryggevælde Catchment) produces better prediction as the catchment responses rapidly to change in climatic condition. A bigger catchment (Mississippi River) has a slow response and similarly accurate results were obtained with 2 lagged variables;
- ELM produced satisfactory results very rapidly from less than a second where the number of hidden nodes of the hidden layer were ten to two minutes for maximum number of hidden nodes (number of training samples). A higher number of hidden nodes (above 1000) generally produced better results in ELM. However, higher number of hidden nodes increased the computational run time significantly (from less than a second to two minutes) with a minor improvement in accuracy (<3%);
- ELM was able to extrapolate reasonably well where the input variables with highest flows were excluded from training dataset;
- ELM showed improved results when the parameter of regularization coefficient was fine-tuned; and
- ELM produced similar or better results compared to GP and EC-SVM with a shorter computational time.

The study demonstrates ELM's ability for rapid prediction and has potential application in real-time forecasting and in water resources planning and management. However, the ELM (node based) applied in this chapter is further improved using Kernel function. The application of Kernel based ELM and comparison with node based ELM and other published techniques are investigated and reported in Chapter 6.

CHAPTER 6

KERNEL AND NODE BASED EXTREME LEARNING MACHINES TO PREDICT HYDROLOGICAL TIME-SERIES

This chapter includes the major part of

- Atiquzzaman, M. and Kandasamy, J. (2019). "Kernel and node based extreme learning machines to predict hydrological time-series.", Paper prepared for the submission to a journal.

6. Kernel and Node Based Extreme Learning Machines to Predict Hydrological Time-Series

6.1 Introduction

Prediction of flows from a catchment depends on many complex hydrological parameters. Traditionally, numerical modelling was a popular method to determine these parameters for estimating catchment yield. With the advent of high-performance computers and the availability of catchment data including hydrological flow-series, researchers and water managers have moved their focus to data-driven modelling techniques, mainly to accelerate the water management process analysis and evaluation and hasten their decision making.

Extreme Learning Machines (ELM) has become popular due to its ability to quickly learn and solve complex problems. The hydrological flow time-series were predicted using node based ELM (NELM) in the previous chapters. In addition, Kernel based ELM (KELM) is applied in this chapter. The predictive capabilities of both NELM and KELM were presented using data from Tryggevælde catchment (Denmark), Mississippi River at Vicksburg (USA) and Duckmaloi catchment (Australia). The results were compared with those obtained with Genetic Programming (GP) and with evolutionary computation based Support Vector Machine (EC-SVM), the later obtained from literature. The results show that both NELM and KELM predictions were better than GP and EC-SVM. KELM ran faster than any other model. KELM can be a viable alternative for real-time forecasting of hydrological variables.

6.2 Model Data

The model data for this analysis consist of the same three catchments as described in Chapter 4 and Chapter 5 which are Tryggevælde catchment (Denmark), Mississippi River at Vicksburg (USA) and Duckmaloi catchment (Australia).

6.3 Modelling Technique

ELM and GP were applied to estimate the catchment runoff using the past and current information of rainfall data and past catchment flow as input data. Mathematically, the relationship can be expressed as:

$$Q_{t+\Delta t} = f(Q_t, Q_{t-\Delta t}, \ldots. Q_{t-m\Delta t}) \tag{1a}$$

if only the past historical flow series is considered.

$$Q_{t+\Delta t} = f(R_{t+\Delta t}, R_t, R_{t-\Delta t}, \ldots R_{t-m\Delta t}, Q_t, Q_{t-\Delta t}, \ldots. Q_{t-m\Delta t}) \tag{1b}$$

if current rainfall, past rainfall and the past historical flow series are considered.

where, Q is the flow (m^3/s), R is the rainfall (mm), and m represents how far back the recorded time series (flows) affects the flow prediction. Δt is time interval.

The GP algorithm used in this analysis is called Eureqa (Schmidt and Lipson, 2009) which has the ability to discard the input variables that do not have a significant impact on the output.

6.4 Model Parameters and Input Variables

NELM requires two parameters namely the number of hidden nodes and *C*. Usually, the accuracy of NELM improves with a larger number of hidden nodes. Huang et al. (2012) obtained good generalization capability with more than 1000 hidden nodes. In this chapter, the number of hidden nodes of 500, 1000 and the number of training samples (6204) in NELM (refer to Section 5.3.2), were considered for comparison purpose. Further investigation of NELM with number of hidden nodes of 6204 was undertaken. Initially, the *C* value was set at 1. Subsequently the *C* value was changed in a series of iterations to achieve a better training model and prediction result.

For KELM, the model requires two parameters namely, *C* and γ (see Sections 2.3.3). These parameters were changed linearly to optimize the model and achieve better results.

The input and output data were normalized to the interval [-1, +1] using the following equation to non-dimensionalise the variables.

$$x' = 2\frac{x-x_{min}}{x_{max}-x_{min}} - 1 \qquad (3)$$

where, x_{max} and x_{min} represent the maximum and minimum values in the original datasets.

6.5 Performance Measures

The model prediction accuracies were determined based on Correlation Coefficient (CC), Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE) (see Atiquzzaman and Kandasamy, 2016b). The mathematical equations of these are described below:

$$CC = \frac{\sum_{t=1}^{N}(Q_{Ot}-\overline{Q_O})(Q_{Mt}-\overline{Q_M})}{\sqrt{\sum_{t=1}^{N}(Q_{Ot}-\overline{Q_O})^2\sum_{t=1}^{N}(Q_{Mt}-\overline{Q_M})^2}} \qquad (4)$$

$$NSE = 1-\frac{\sum_{t=1}^{N}(Q_{Ot}-Q_{Mt})^2}{\sum_{t=1}^{N}(Q_{Ot}-\overline{Q_O})^2} \qquad (5)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(Q_{Ot}-Q_{Mt})^2} \qquad (6)$$

$$NRMSE = \sqrt{\sum_{t=1}^{N}(Q_{Ot}-Q_{Mt})^2 / \sum_{t=1}^{N}[(Q_{Ot}-\bar{Q}_O]^2} \qquad (7)$$

where, Q_{Ot} and Q_{Mt} denote observed and modelled flows at time t; N is the number of observations and $\overline{Q_O}$ and $\overline{Q_M}$ represents the mean observed and modelled flows, respectively. CC provides information on linear dependence between observed and simulated values (Kisi et al., 2013). The CC lies between 0 and 1 where 0 means no correlation whereas and 1 means that the dispersion of prediction is equal to that of the observation. RMSE represents the forecasting error and estimates the sample standard deviation of the differences between predicted values and observed values. A RMSE value of zero indicates perfect match whereas higher values represents a smaller match between the observed and modelled output. It is a good measure when large model errors are not desirable. NSE is frequently used and provides a measure of the model's ability to predict observed values. In general, high values of NSE (up to 100%) and small values for RMSE indicate good model predictions.

6.6 Results

6.6.1 Tryggevælde Catchment

Three NELM model results (NELM1, NELM2, NELM3) (refer to Section 5.3.2) each with different number of hidden nodes (500, 1000 and 6204) in terms of CC, NSE, RMSE and NRMSE for both training and testing dataset are presented in Table 6. 1. Table 6. 1 shows good predictions with all having CC and NSE values of more than 0.9 and 0.8 respectively for training and testing datasets. The RMSE ranged from 0.498-0.512 for training and 0.495-0.515 for testing data. The corresponding NRMSE varied from 0.364-0.365 for training and 0.339-0.353 for testing data. The lowest RMSE of 0.495 and NRMSE of 0.339 (Table 6. 1) for the testing dataset were obtained when the highest number of hidden nodes (number of training samples) was applied (i.e. in NELM3). In all these runs, the training time was relatively short as no further iteration was required and varied from less than a second (for 500 nodes) to 99sec (6204 nodes) on a Windows Intel i7@2.67GHz machine (Table 6. 1).

Table 6. 1: Prediction accuracy for Tryggevælde Catchment

Model Run		Hidden Nodes	*C*	*γ*	CC	NSE	RMSE	NRMSE	Iterations	Training Time
NELM1	Training	500	1	-	0.927	0.867	0.512	0.365	1	<1sec
	Testing				0.936	0.867	0.515	0.353		
NELM2	Training	1000	1	-	0.929	0.869	0.507	0.362	1	3sec
	Testing				0.938	0.869	0.508	0.348		
NELM3	Training	6204	1	-	0.931	0.867	0.498	0.364	1	99s[a]
	Testing				0.941	0.885	0.495	0.339		
NELM4	Training	6204	1E3	-	0.937	0.878	0.477	0.349	4	6m 21s[a]
	Testing				0.943	0.889	**0.486**	0.333		
KELM	Training	-	1E2	1	0.936	0.876	0.474	0.347	3	21s[a]
	Testing				0.942	0.887	**0.487**	0.334		
EC-SVM[1]	Testing	-	-	-	-	-	0.514	0.352	151,668	207.67s[b]
EC-SVM[2]	Testing	-	-	-	-	-	0.501	0.344	824	5h 25m[b]
GP	Testing	-	-	-	-	-	0.551	0.378	77,082	202.8sec[a]

(Yu et al. 2004)[1]; (Yu and Liong, 2007)[2]; [a]Windows Intel i7@2.67GHz; [b]Linux Pentium II@333MHz

The highest number of hidden nodes was then fixed (number of training samples = 6204) and the *C* value was changed sequentially in a series of iterations. Commencing with a value of 1, *C* was changed in each iteration by a factor of 10. Within 4 iterations, a *C* value of 1.00×10^3 was found which gave CC and NSE values above 0.9 and 0.8 for both training and testing dataset (see NELM 4 in Table 6. 1). *C* values higher than 1.00×10^3 did not further improve the accuracy (for details refer to section 5.3.3). The RMSE and NRMSE values were 0.477 and 0.349 for training dataset and 0.486 and 0.333 for testing dataset. In this analysis, NELM4 required 6min 21sec from 4 iterations to learn the input data on the same Windows machine (Intel i7@2.67GHz).

In KELM, the value of *C* and *γ* were selected by changing them sequentially in a series of iterations initially commencing with a value of 1. First *C* was changed by a factor of 10 in each iteration. Once *C* was selected, *γ* was changed by a factor of 10 in subsequent iterations. The results were less sensitive to values of γ and therefore it was changed only after *C* was selected. Within a few iterations (3), KELM produced RMSE and NRMSE of 0.474 and 0.347 for training dataset and 0.487 and 0.334 for testing dataset (Table 6. 1) with the values *C* and *γ* of 100 and 1 respectively. The CC and NSE values were above 0.9 and 0.8. The model did not show any improvement with further increase of *C* and *γ* values. Figure 6. 1 and Figure 6. 2 depict the comparisons of observed and predicted KELM flows in terms of scatter plot for training and testing dataset respectively. The results from KELM are similar to that obtained from NELM4 although KELM ran faster and required 21sec to train the model.

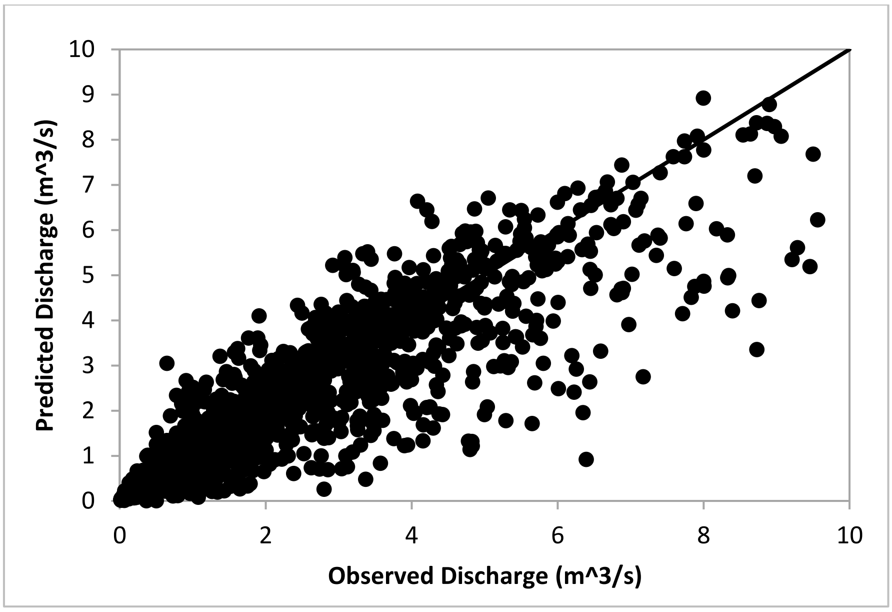


Figure 6. 1 Comparison of Observed and Predicted Flows from KELM for Tryggevælde Catchment - Scatter Plot for Training Dataset

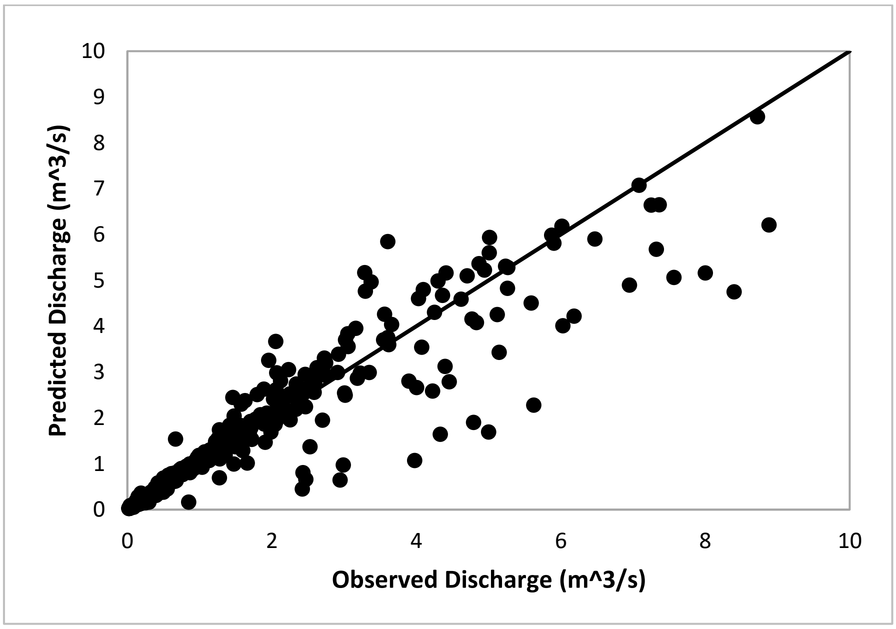


Figure 6. 2: Comparison of Observed and Predicted Flows from KELM for Tryggevælde Catchment - Scatter Plot for Testing Dataset

The performances of NELM and KLEM were compared in Table 6. 1 with GP and previously published results of EC-SVM by Yu et al. (2004) and Yu and Liong (2007). GP model was run with the same input variables (lagged flows) for comparison. All ELMs (NELM and KLEM) yielded better results (minimum RMSE of 0.486 and NRMSE of 0.333) compared to GP (0.551 for RMSE and 0.378 for NRMSE), EC-SVM (Yu et al., 2004) (RMSE = 0.514, NRMSE = 0.352) and EC-SVM (Yu and Liong, 2007) (RMSE = 0.501, NRMSE = 0.344). Compared to GP, EC-SVM (Yu et al., 2004) and EC-SVM (Yu and Liong, 2007), NELM4 reduced RMSE by 11.90%, 5.4% and 3.2% respectively and KELM by 11.64%, 5.11% and 2.9% respectively. KELM ran faster and took 21sec, while NELM4 took 6min 21sec. NELM3 ran faster (99 sec) than NELM4, being marginally less accurate. GP failed to reach a better solution. GP required 77,082 iterations and a training time of 202.8sec on the same windows machine. EC-SVM (Yu et al., 2004) and EC-SVM (Yu and Liong, 2007) required 151,668 iterations and 207.66sec (see Table 2 in Yu et al., 2004) and 824 iterations and 5hr 25min (see Table 6 in Yu and Liong, 2007) respectively on a Linux Pentium II@333mHz machine.

6.6.2 Mississippi River at Vicksburg

Three NELM model results (NELM1, NELM2, NELM3) (refer to Section 5.3.2) each with different number of hidden nodes (500, 1000 and 6204) in terms of CC, NSE, RMSE and NRMSE for both training and testing dataset are presented in Table 6. 2. All models were run with a *C* value of 1. These models showed good predictions with the values of both CC and NSE above 0.9 for all training and testing datasets. The RMSE ranged from 396.55 to 403.33 for training and 320.15 to 331.28 for testing data. The corresponding NRMSE was 0.040-0.041 for training and 0.041-0.042 for testing data. The lowest RMSE of 320.15 for testing dataset was obtained when the highest number of hidden nodes (i.e. 6204 in NELM3) was applied (Table 6. 2). The training times for all three NELM were relatively short varying from less than a second (for 500 nodes) to 104sec (6204 nodes) on a Windows Intel i7@2.67GHz machine (Table 6. 2).

The *C* value of NELM3 model was modified in the same manner as outlined in the previous case. Within a few iterations (i.e. 9), an optimum *C* value of $1.00\text{x}10^8$ was obtained with CC and NSE above 0.9. This model is called NELM4 in Table 6. 2. The results of NELM4 (Table 6. 2) improved significantly and the RMSE and NRMSE reduced to 353.89 and 0.036 for the training dataset and 297.91 and 0.038 for the testing dataset. The training time for the model was 14min and 55sec on the same Windows machine.

Table 6. 2: Prediction accuracy for Mississippi River Flow, Vicksburg

Model Run		Hidden Nodes	*C*	*γ*	CC	NSE	RMSE	NRMSE	Iterations	Training Time
NELM1	Training	500	1	-	0.999	0.998	403.33	0.041	1	<1sec
	Testing				0.999	0.998	331.28	0.042		
NELM2	Training	1000	1	-	0.999	0.998	399.53	0.041	1	3sec
	Testing				0.999	0.998	324.07	0.041		
NELM3	Training	6204	1	-	0.999	0.998	396.55	0.040	1	104s[a]
	Testing				0.999	0.998	320.15	0.041		
NELM4	Training	6204	1E8	-	0.999	0.999	353.89	0.036	9	14m 55s[a]
	Testing				0.999	0.999	**297.91**	0.038		
KELM	Training	-	1E8	1	0.999	0.998	327.81	0.033	9	57s[a]
	Training				0.999	0.998	**297.25**	0.038		
EC-SVM[1]	Testing	-	-	-	-	-	306.58	0.039	1,732,579	53.93m[b]
EC-SVM[2]	Testing	-	-	-	-	-	320.44	0.041	1,214	8h 40m[b]
GP	Testing	-	-	-	-	-	321.70	0.041	181,892	8m 20s[a]

(Yu et al. 2004)[1]; (Yu and Liong, 2007)[2]; [a]Windows Intel i7@2.67GHz; [b]Linux Pentium II@333MHz

Similarly, in KELM the values of *C* and *γ* were selected in the same manner as outlined previously. Table 6. 2 shows KELM produced RMSE and NRMSE of 327.81 and 0.033 for training dataset and 297.25 and 0.038 for testing dataset with the *C* and *γ* values of $1.00\text{x}10^8$ and 1 respectively. The CC and NSE values were above 0.9. Figure 6. 3 and Figure 6. 4 show a very good agreement between the observed and predicted KELM flows for training and testing dataset respectively. The results from KELM were slightly better than that obtained using NELM4. However, KELM ran faster and took only 57sec to train the model on the same Windows machine.

Table 6. 2 provides comparisons of Mississippi River flows prediction from different

ELM models, other previously published results of EC-SVM (Yu et al., 2004; Yu and Liong, 2007) and GP. GP model was run with the same input variables for comparison. Table 6. 2 shows that the two ELM models (NELM4 and KELM) yielded better solutions (RMSE < =297.91 and NRMSE of 0.038) than GP (321.70 for RMSE and 0.041 for NRMSE), EC-SVM (Yu et al., 2004) (RMSE = 306.58, NRMSE = 0.039) and EC-SVM (Yu and Liong, 2007) (RMSE = 320.44, NRMSE = 0.041). The prediction error (RMSE) using KELM was smaller by 7.60%, 3.0% and 7.23% compared to GP, EC-SVM (Yu et al., 2004) and EC-SVM (Yu and Liong, 2007) respectively. NELM4 also performed similarly.

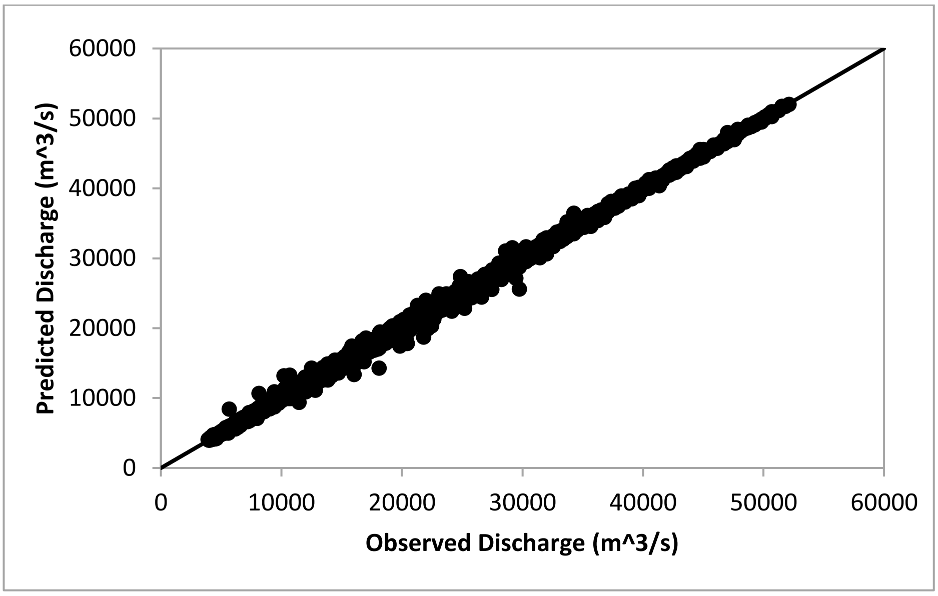


Figure 6. 3: Comparison of Observed and Predicted Flows from KELM for Mississippi River Catchment, Vicksburg - Scatter Plot for Training Dataset

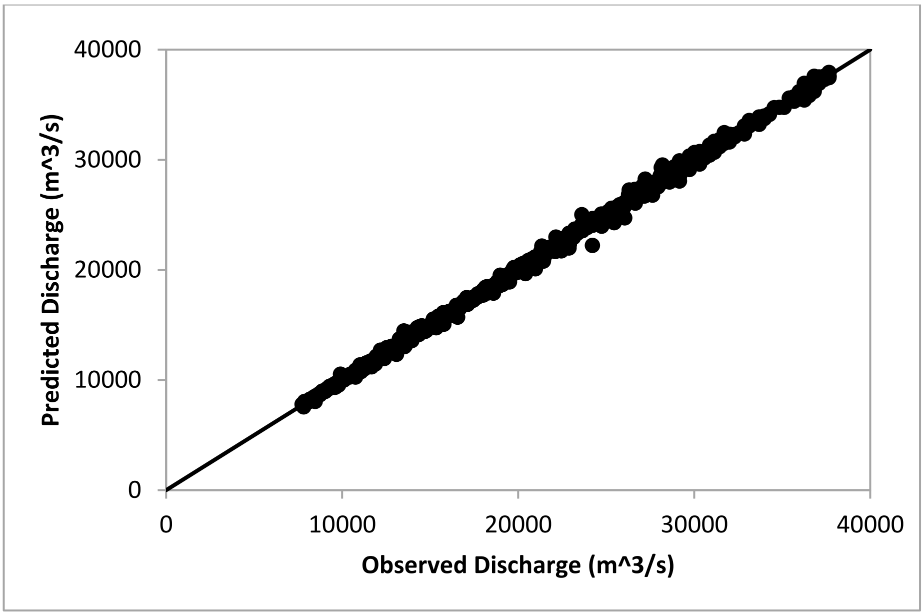


Figure 6. 4: Comparison of Observed and Predicted Flows from KELM for Mississippi River Catchment, Vicksburg - Scatter Plot for Testing Dataset

The time required by NELM4 and KELM to train input data were 14min 55sec and 57sec respectively from 9 iterations on a Windows Intel i7@2.67GHz machine. On the same machine, GP took 8min 20 sec and 181,892 iterations to train the model. The number of iterations and the training time required for EC-SVM (Yu et al., 2004) were 1,732,579 iterations and 53.93min respectively (see Table 4 in Yu et al., 2004) and for EC-SVM (Yu and Liong, 2007) were 1,214 iterations and 8hr 40min (Table 6, Yu and Liong, 2007) respectively on a Linux Pentium II@333mHz machine. KELM produced the best results converging very quickly in a few iterations (< 10) to achieve the best results among the models compared.

6.6.3 Duckmaloi Catchment

ELM was applied to the Duckmaloi catchment with the lagged flow and rainfall data as inputs (equation 1b). The number of hidden nodes in NELM1, NELM2 and NELM3 were 500, 1000 and 7745 respectively (refer to section 5.3.2 for details). These models used a *C* value of 1. All three models ran fast and the maximum time required to train the model (NELM3) was 3.14min (Table 6. 3) on Windows Intel i7@2.67GHz machine. The models predict well and the lowest RMSE and NRMSE for the testing dataset were obtained in the model with the highest number of hidden nodes (7745 in NELM3). The CC and NSE values were above 0.9 and 0.8 respectively for all training and testing datasets. The RMSE ranged between 47.124-49.733 for training and 33.099-41.165 for testing data (Table 6. 3). The corresponding NRMSE was between 0.382-0.404 for training and 0.284-0.353 for testing results.

Table 6. 3: Prediction Accuracy for Duckmaloi Weir Catchment

Model Run		Hidden Nodes	C	γ	CC	NSE	RMSE	NRMSE	Iterations	Training Time
NELM1	Training	500	1	-	0.915	0.837	49.733	0.404	1	1.31sec
	Testing				0.936	0.876	41.165	0.353		
NELM2	Training	1000	1	-	0.919	0.844	48.659	0.395	1	3.95sec
	Testing				0.944	0.892	38.412	0.329		
NELM3	Training	7745	1	-	0.924	0.854	47.124	0.382	1	3.14m[a]
	Testing				0.959	0.920	33.099	0.284		
NELM4	Training	7745	10	-	0.929	0.862	45.766	0.371	2	6m 3s[a]
	Testing				0.962	0.923	**32.487**	0.278		
KELM	Training	-	1E3	10	0.929	0.862	45.748	0.371	5	1m 6s[a]
	Testing				0.961	0.923	**32.404**	0.278		
GP	Testing	-	-	-	-	-	60.715	0.520	255,473	12.52m[a]

[a]Windows Intel i7@2.67GHz

The C value was then selected in a manner similar to previous cases and took two iterations (see mode NELM4 in Table 6. 3) to improve the results with CC and NSE values above 0.9 and 0.8 respectively. The RMSE improved by 2.9% (from 47.124 to 45.766) for training samples and 1.8% (from 33.099 to 32.487) for testing samples compared to NELM3 (see Table 6. 3). The NRMSE also reduced by 2.8% (from 0.382 to 0.371) for training dataset and 2.1% (from 0.284 to 0.278) for testing dataset respectively. NELM4 took 6min 3sec to train the model.

The selection of parameters (C and γ) in KELM took five iterations to improve the results with CC and NSE values above 0.9 and 0.8 respectively. The minimum RMSE values obtained from this model were 45.748 and 32.404 and NRMSE were 0.371 and 0.278 for training and testing datasets respectively (see Table 6. 3). Figure 6.5 and Figure 6.6 show the graphical representation of scatter plot between the observed and predicted flows for training and testing dataset. KELM required a short time (1min 6sec) to obtain this result.

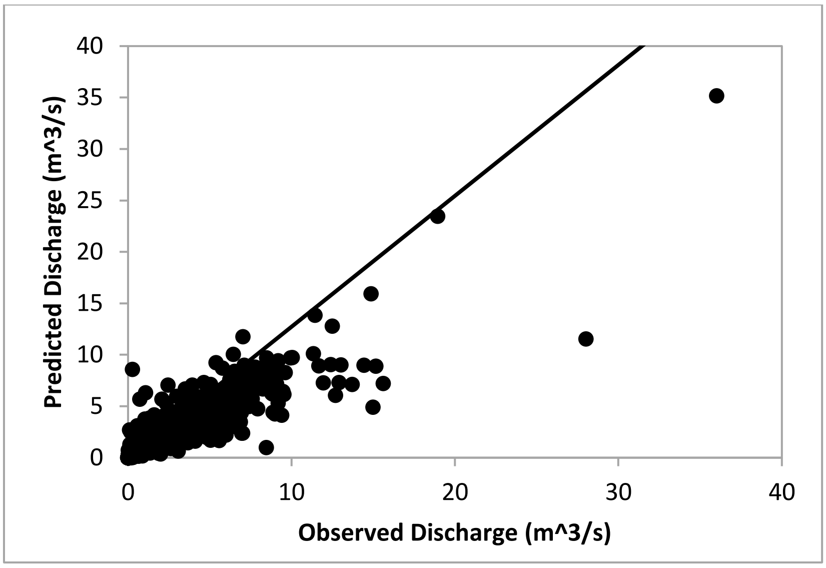


Figure 6. 5: Comparison of Observed and Predicted Flows from KELM for Duckmaloi Weir Catchment - Scatter Plot for Training Dataset

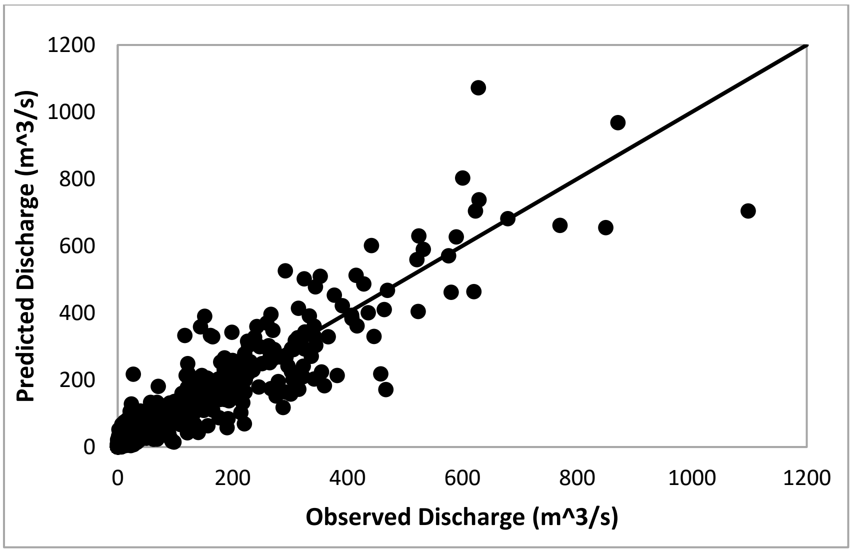


Figure 6. 6: Comparison of Observed and Predicted Flows from KELM for Duckmaloi Weir Catchment - Scatter Plot for Testing Dataset

The performances of different ELM and GP models are compared in Table 6. 3. No results were available for EC-SVM (Yu et al., 2004) or EC-SVM (Yu and Liong, 2007). ELM models performed better than GP. Specifically, NELM4 and KELM reduced RMSE by more than 46% compared to GP. GP required 255,473 iterations and 12.52mins to generate results with a RMSE of 60.715 and NRMSE of 0.520. Both NELM4 and KELM produced similar results. NELM4 ran slower than KELM as the run time of the former depended on the number of hidden nodes in hidden layer.

6.7 Discussion

This chapter demonstrates the application of a fast AI technique called ELM. Predictions of yields were undertaken for three catchments located in different continents each with different climates namely the Tryggevælde catchment in Denmark, Mississippi River Flow at Vicksburg in USA and Duckmaloi catchment in Australia. In the former two, lagged flows were used as input consistent with other published techniques. In the later lagged flows and rainfall were used as input. Performances of different types of ELMs (node based and kernel based) were assessed in terms of CC, NSE, RMSE and NRMSE.

All NELM models generated good results (CC > 0.9 and NSE > 0.8). The best results were obtained where the number of hidden nodes was set to the number of training samples in node based ELM (NELM3). The performance was further improved by fine tuning the *C* parameter in NELM4. It was found that within a few trials, the RMSE reduced to 0.486 (1.8%) for Tryggevælde catchment, 297.91 (6.9%) for Mississippi River Catchment and 32.487 (1.8%) for Duckmaloi catchment compared to NELM3. KELM produced similar or better results compared to NELM4.

Both NELM4 and KELM produced better results compared to GP and EC-SVM when predicting flow series for all three catchments. Compared to GP, KELM improved the prediction accuracy by between 7.6-46.6% for these catchments. Similarly, KELM's results were better than that of EC-SVM (Yu and Liong, 2007) and showed improvement of 2.8% for Tryggevælde catchment and 7.2% for Mississippi River catchment. KELM was also better than EC-SVM (Yu et al., 2004). The performance of NELM4 was similarly better.

KELM was computationally much faster in training models than NELM, GP and EC-SVM for all catchments noting that the computational time was not completely comparable since two different types of machines were used. The performance of EC-SVM using Linux Pentium II@333mHz machine was obtained from literature. ELM's learning algorithm is much simpler, and the learning speed is extremely fast as it avoids iterative tuning to determine the input weights (Huang et al., 2006). KELM ran faster than NELM4 (Table 6. 1- Table 6. 3) as KELM does not require information on the number of hidden nodes.

This analysis shows that even when using a simple parameter selection technique, KELM produced results with better accuracy in much faster run time than any other model studied here. Indeed, using a more sophisticated optimization techniques to select parameters C and γ may further improve the performance of KELM (and NELM4) in terms of prediction accuracy.

The major strength demonstrated in this analysis was KELM's ability to reach similar or better solutions much faster than NELM, GP and EC-SVM. It adds to its attractiveness for use in actual river and flood operations and its potential for real-time prediction of hydrological time-series and where quick model response is vital for decision making in application such as flood warning and forecasting systems. It can make significant contribution in real-time control applications.

6.8 Summary

The application of node and kernel based ELMs (NELM and KELM) were applied to predict flows from three different catchments (Tryggevælde catchment, Denmark; Mississippi River, USA and Duckmaloi catchment, Australia). The performances from different ELM models were also compared with GP and EC-SVM. Predictions of daily flow time series from all catchments showed how ELM could improve the prediction accuracies and reached the optimal solutions faster than GP and EC-SVM. The study findings concluded that:

- KELM and NELM obtained good prediction accuracies for all catchments where CC and NSE were greater than 0.9 and 0.8 respectively;

- NELM produced good results for all catchments where the number of hidden nodes was greater than 1000. However, better results are obtained where the number of hidden nodes was the same as the number of training samples. The time required to train the model varied from less than a second to a few minutes.
- KELM produced similar or better results than NELM;
- Both NELM and KELM models were capable of producing better results compared to GP and EC-SVM; and
- KELM computationally runs faster than NELM and other models as KELM does not require hidden nodes.

This analysis shows that KELM produced more accurate results in much faster run times than other models studied. The study demonstrates ELM's ability, especially KELM's, for rapid prediction and has potential application in real-time river and flood forecasting and in water resources planning and management.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

7. Conclusions and Recommendations

7.1 Summary

Application of Artificial intelligence (AI) techniques to resolve complex nonlinear hydrological flow prediction problem was demonstrated in this study as calibration of such physical hydrological models using a trial and error method or optimization algorithm requires considerable effort and experience particularly when the number of the calibration parameters is large. AI based machine learning techniques have proven superior by the researchers in this modeling process (e.g. flow prediction) compared to other conceptual and stochastic models including Autoregressive (AR), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Autoregressive moving average with Exogenous Inputs (ARMAX) and Sacramento model. However, many of the AI based data-driven modelling methods including traditional ANN learning algorithms are slow requiring numerous iterations to generate optimal solutions and may not be suitable for real-time prediction where fast response is desirable (e.g. flood control). In this study, GP was first applied to fill the data gaps and predict long term flows from a dam catchment using a hybrid approach (linked with MIKE11-NAM). While the application was successful and produced better results, it was found that GP suffered from computational overhead in the learning process. A relatively new machine learning technique, called Extreme Learning Machine (ELM) was proposed in this study. Three different catchments from three different continents were considered.

Initially, AI model using GP was developed for the daily real-time flow prediction at the Duckmaloi Weir catchment located in Oberon, Australia considering present and past rainfalls and past measured flows. GP model showed better results than ANN and Sacramento model. GP model is further improved by using hybrid method with MIKE11-NAM (refer to Chapter 3). This approach is used when the measured or gauged flows are not complete or missing and long-term inflow prediction is required for reservoir management. The future 100 year flows were predicted assuming two hypothetical rainfall time series. The results from this hypothetical rainfall analysis show how the flow conditions vary in the dam catchment in drought conditions. The analysis provides information about the potential application of the GP and hybrid models in operation and management of water resources.

Chapter 4 presents the application of ELM for predicting hydrological flow time-series for the Tryggevælde Catchment (Denmark) and Mississippi River at Vicksburg (USA). It is demonstrated that ELM overcomes the slow learning issue and predicted hydrological time-series very quickly. The results also show that the prediction accuracies of ELM are better than ANN and other previously published techniques (e.g. EC-SVM, Standard Chaotic Approach and Inverse Approach). The real strength of ELM is the short computational run-time to reach solutions comparable with other techniques including EC-SVM. This is because ELM does not require iteration whereas other techniques (e.g. EC-SVM) may require thousands of iterations and much longer processing time to predict the same flow time-series and yet with less accuracy.

The robustness of ELM's capability in predicting flows is described in Chapter 5 using the same two catchments, e.g. Tryggevælde Catchment, Denmark and Mississippi River, USA and also Duckmaloi Weir catchment, Australia. ELM's performance is compared with EC-SVM and GP especially for the first two catchment obtained from the literature. The results showed how ELM improved prediction accuracies and reached the solutions very quickly compared to GP and EC-SVM.

In addition to general node based ELM (NELM), the performance of a kernel based ELM is reported in Chapter 6. The prediction accuracies from NELM and KELM are compared for the two catchments as described above plus another catchment, Duckmaloi catchment from Australia. The performances from different ELM models were also compared with GP and EC-SVM. Predictions of daily flow time series from all three catchments showed how KELM could improve the prediction accuracies and reached the optimal solutions faster than NELM, GP and

EC-SVM.

7.2 Conclusions

The conclusions of this study are described below:

Application of GP

- GP model showed better results than ANN and Sacramento model in the prediction of daily flow from Duckmaloi Weir catchment located in Oberon, Australia.
- The hybrid model by linking GP model with MIKE11-NAM improved the results further. This model is applicable when the measured or gauged flows are not complete or missing. and long-term inflow prediction is required for reservoir management.
- The future 100 year flows were predicted assuming two hypothetical rainfall time series using the hybrid model. These predicted flows can be used to manage extended drought or flood conditions.

Application of ELM

- The application of ELM in the predictions of flows for Tryggevælde Catchment (Denmark) and Mississippi River at Vicksburg (USA) showed better accuracies compared to ANN and other previously published techniques (e.g. EC-SVM, Standard Chaotic Approach and Inverse Approach).
- ELM predicted the same hydrological time-series faster than ANN and other previously published techniques (e.g. EC-SVM, Standard Chaotic Approach and Inverse Approach).

Robustness of ELM

- ELM showed reasonable results with all combination of lagged input variables (two or higher lagged variables) for 1-day lead prediction in terms of CC (>0.9) and NSE (>0.8). For smaller catchment, higher number of lagged variables (2 or more for Tryggevælde

Catchment) produced better prediction as the catchment responds rapidly to change in climatic condition (e.g. rainfall). However, a bigger catchment (e.g. Mississippi River) responds slowly and higher number of lagged variables have minimal impact on the prediction.

- ELM produced satisfactory results very rapidly when the number of hidden nodes was greater than or equal to 1000. The computational time required by ELM ranges from less than a second where the number of hidden nodes of the hidden layer were ten to two minutes for maximum number of hidden nodes (number of training samples). The number of hidden nodes higher than 1000 increased the computational run time significantly (from less than a second to two minutes) with a minor improvement in accuracy (<3%).
- ELM was able to extrapolate reasonably well where the input variables with highest flows were excluded from training dataset.
- ELM showed improved results when the parameter of regularization coefficient was fine-tuned.
- ELM generated reasonable results for higher number of lead days (e.g. second and third) predictions.
- ELM produced similar or better results compared to GP and EC-SVM with a shorter computational time for prediction of flow series from the same catchment.

Performance of Kernel ELM (KELM) compared to node ELM (NELM)

- KELM produced similar or more accurate results in much faster run times than NELM, GP and EC-SVM. The study demonstrates ELM's ability, especially KELM's, for rapid prediction and has potential application in real-time river and flood forecasting.
- ELM's fast learning capability from a training dataset means that it would be more suitable for on-line and real-time applications where quick processing is important or

vital. The study demonstrates ELM's ability for rapid prediction and has potential application in real-time forecasting and in water resources planning and management.

7.3 Limitations of the Study

Some of the limitations of the study are described below:

- Parameters including actual or potential evapotranspiration, antecedent precipitation index, temperatures were not included in the input data.
- Important catchment characteristics including initial loss, continuous loss, area, slope were not considered.
- The performances of the ELM model (NELM or KELM) were not tested for real time prediction.
- ELM was not applied for different regional local catchments with different climatic conditions.

7.4 Recommendations for Further Studies

The following recommendations are made for future extensions of this research work.

- Hydrological systems are generally complex and nonlinear. Time series of other important and sensitive variables, e.g. total precipitation, antecedent precipitation index, maximum temperature and evapotranspiration should be considered if they are available. These additional inputs information may further improve the prediction accuracies of the flows.
- This study has applied manual trial and error method to fine-tune some of the parameters related to relevant AI techniques. Evolutionary algorithms including both single-objectives and multi-objectives optimization are available. Single objective algorithms, e.g. SCE, GA and PSO and multi-objective algorithm, e.g.

non-dominated sorting genetic algorithm (NSGA-II) should be linked with ELM to automatically optimise the parameters such as regularisation coefficient (C) and kernel parameter. Applying these automatic optimization algorithms may improve the predictions significantly.

- ELM's application was limited to three catchments obtained from the literature. Further research will include ELM's application to catchments from a wider range of climatic condition and flow scenarios.
- ELM was applied to predict a single output. However, ELM's performance in predicting multiple outputs (objectives) should be investigated in the resolution of complex problem.

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