The Development of Neural Network Based Rainfall-Runoff Model for Kashmir Pakistan

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Abstract

Flooding disaster happens almost annually in Pakistan. With no real solution to this incident, loss of human lives and wealth are inevitable. Heavy rainfall is an important aspect which contributes to flooding. Monitoring rainfall remains an integral part of flood defense system. One of the most leading method to predict flood is by developing a forecast model of rainfall-runoff. Rainfall and river flow relation are very much subjective with various affecting factors. Artificial Neural Network (ANN) is preferred to model hydro system because of its accountability of nonlinear dynamics of water flow. A case study is done on a flood-prone river basin in Jhelum river, in Kashmir. Rainfall data of 5 hydrologic stations and river level are used as the input. The performance of the learning algorithms involved were evaluated with a coefficient of determination (R) and Mean Square Error (MSE). The network configuration of the ANN which best fit each algorithm is determined. The results achieved showed the promising advantage of LM as compared to BR and PSO.

Keywords
Rainfall, affect, flood, threat, disaster

1. Introduction

Flooding is a natural disaster which has been occurring annually. It is a universal problem throughout the whole world. Flooding which comes from rivers, seas, and threaten the lives of millions, especially during extreme climate The disaster, such as other natural catastrophe could only be mitigated rather than it being thoroughly solved. Runoff prediction is one of the vital elements in pre-flooding. It is a key resource for flood defines in coastal areas. Runoff level is highly affected by precipitation and landscape factors which includes topography, soil Figure 1: Kashmir (left) and rainfall stations throughout rivers (right) (Graff. et al 2013).

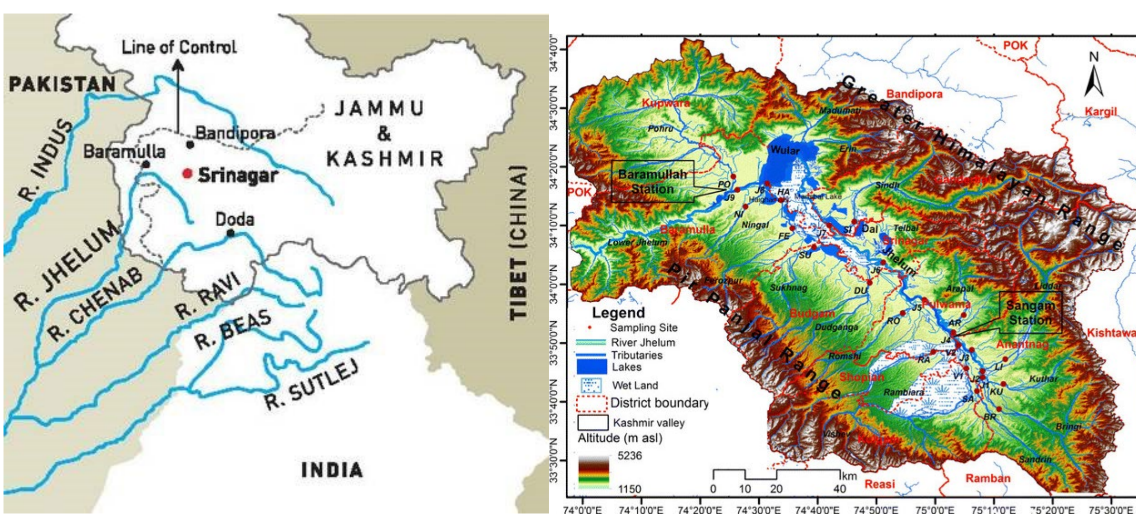


Figure 1. Kashmir rivers and lakes with rain fall

1.1 Objectives
This research is focused on rainfall run-off model, applications and properties.

2. Literature Survey
Geographically, Kashmir is surrounded by bodies of water. Seas, lakes and rivers are a major geological feature of the country.Over the past decades, Kashmir is prone to muddy floods at the riverbanks and flash floods in the city. During climate change, sea levels and rainfall increased, thus resulting towards flood risk. Other than LM, the ANNs were trained by Bayesian Regularization learning algorithm. Bayesians methods are broadly used in astronomy and cosmology, and are earning reputation in other fields (Figure 2). It is an efficient and robust learning algorithm for large or deep feed-forward neural network (Shabir, et al., 2023). Bayesian approach are more common in hydrology nowadays(Graff. et al 2013). The performance of Bayesian technique in hydrological system when compared to other learning algorithms is evaluated. Bayesian method offers a supervised learning method to boot with statistical method for classification(Graff. et al 2013). Researcher claim that among the advantages of Bayesian methods are

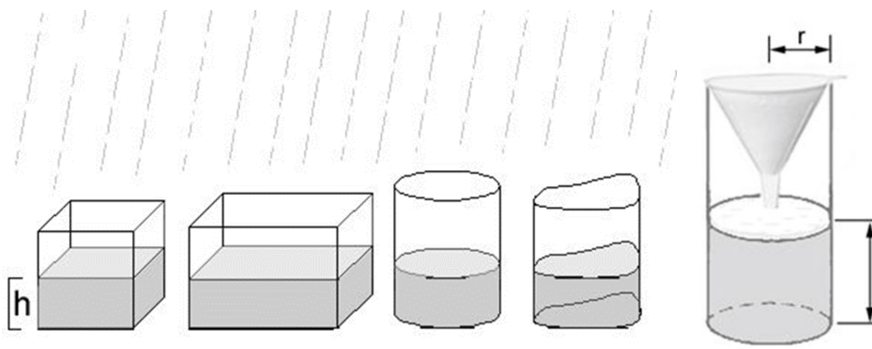


Figure 2(a): Container which collects rain.The containers shown are with varying shapes and sizes.
Figure(b): Obtaining height from volumetric formula.

simultaneously enabling uncertainty analysis and scrutiny of model integrity[4].The third learning algorithm to be evaluated is Particle Swarm Optimization. PSO was built to simulate flock of birds[5]but as it behaves more of a swarm, thus the name Particle Swarm Optimization. PSO have some similarities with Genetic Algorithm as it works on population of potential solutions to examine the search space (Shabir, et al., 2023).

3. Development of electronic raingauge system
Methods of Rainfall Precipitate Measurement:
There are two ways of measuring rain water or precipitate. One is height measurement and the other is volume measurement shakil. et al 2023. By measuring height, the opening of the rain gauge does not need to be particular. Funnels with the opening of any shape are applicable as long as the shape is similar from bottom to top
The second type of rain gauge measures the volume of rain fall water. As the volume of rainfall water is obtained, height increment can easily be retrieved. For example a cylindrical container is used to collect rain fall.
The volume of water inside a cylindrical (Shabir, et al., 2023)

container is as follows

$$V = \pi r^2 h \tag{1}$$

Thus, the height of rainfall water can be calculate

$$h = \frac{V}{\pi r^2} \tag{2}$$

Types of Rain Gauges:

There are several rain gauges which is common in meteorological and weather forecast system (Figure 3). For instance, tipping bucket rain gauge is commonly used all over the world (Shabir, et al., 2023). Tipping bucket rain

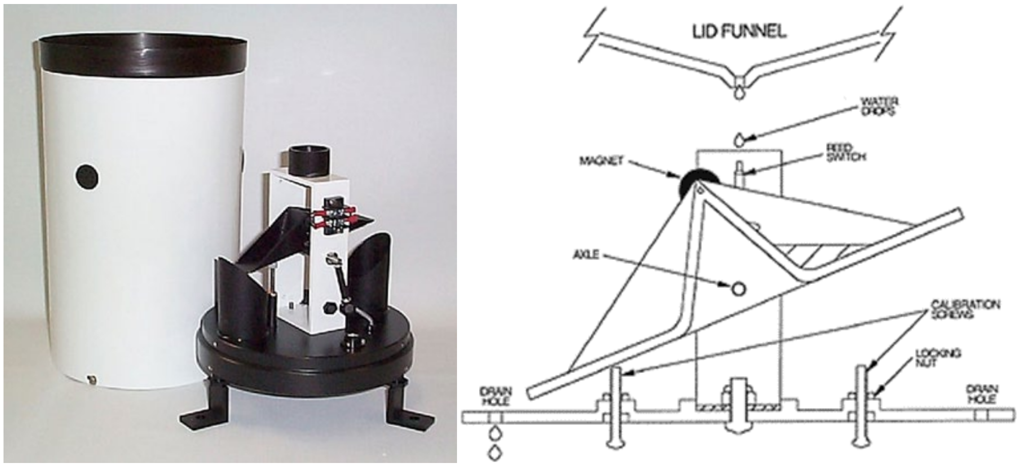


Figure 3 : Tipping bucket rain gauge and its mechanism

gauges are used in countries which do not experience winter season. The sensor which is used in tipping bucket rain gauges are usually hall effect sensor and reed sensor (Figure 4, 5 and 6).

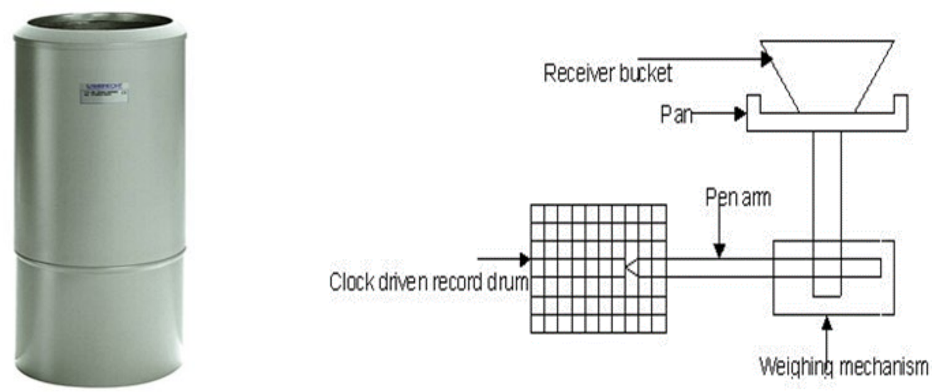


Figure 4 :weighing rain gauge and its mechanism

Mechanical Design*:*

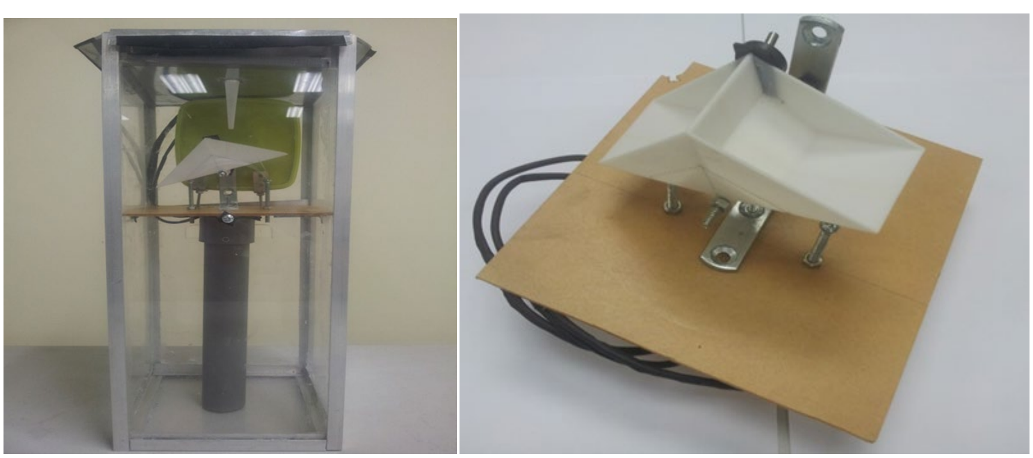


Figure 5(a): Electronic tipping bucket rain gauge. Figure(b): Tipping bucket design.

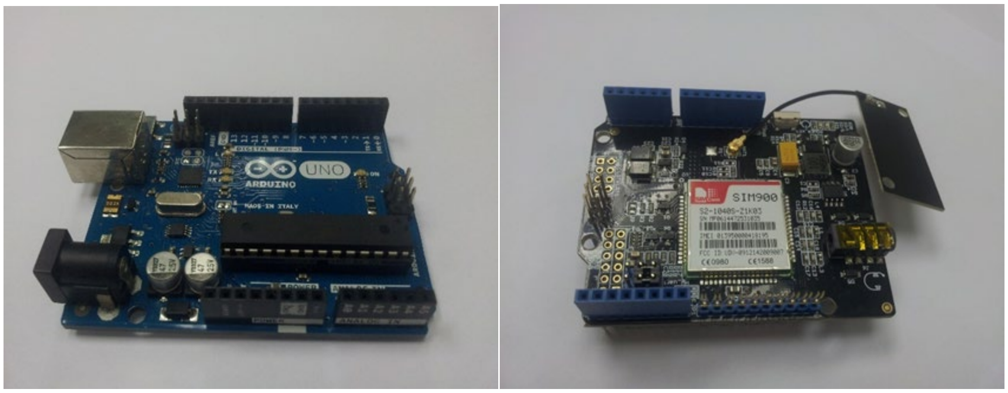


Figure 6: Arduino Uno (left) and Arduino GSM Shield (right).

Communication Module: For the water level data transmission, a GSM shield is selected for wireless communication. The purpose is to enable monitoring activities through mobile phones. Sim card is placed on the back of the shield and the Arduino are powered by 9V external power source.

By using wireless data transmission, multiple rain gauges can be subsequently monitored by a single user. Real time reading of rainwater can be acquired according to the request from the user. By proper coding of the microcontroller, hourly, daily or weekly updates can be made available. As our priority is to be able to transmit data from afar, GSM module is selected. Data transmission via Bluetooth and Wireless transmission can be easily disrupted, and it also has lower transmission range (shakil. et al 2023).

To complete the research, hardware development of electronic rain gauge system is constructed. Even though data is not taken from the rain gauge that we build, it is a decent design which provide good functionality, wireless data transmission and low cost of production(Shabir, et al., 2023).

As the rainfall runoff forecast model requires large sum of data, various geographical places and long period of time as the input, we opted to acquire Department of Irrigation and Drainage (DID) for the input of the rainfall and runoff level information (shakil. et al 2023).

4. Neural Network Trained by Levenberg Marquardt, Bayesian Regulization and Particle Swarm Optimization

There are two varying variable which have been selected to determined best network model for each learning algorithm. They are numbers of neuron in hidden layer and type of model order. Finally rainfall-runoff forecast are done with 12 hours of lead time (Graff. et al 2013).

Artificial Neural Network (MLP-NN): The performance of MLP-NN is determined by initial weight setting (Figure 7). The learning rule or algorithm alters the weight connection between units of neuron in response to data supplied

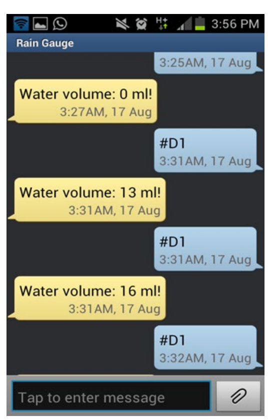


Figure 7: Rain gauge output display through mobile phone.

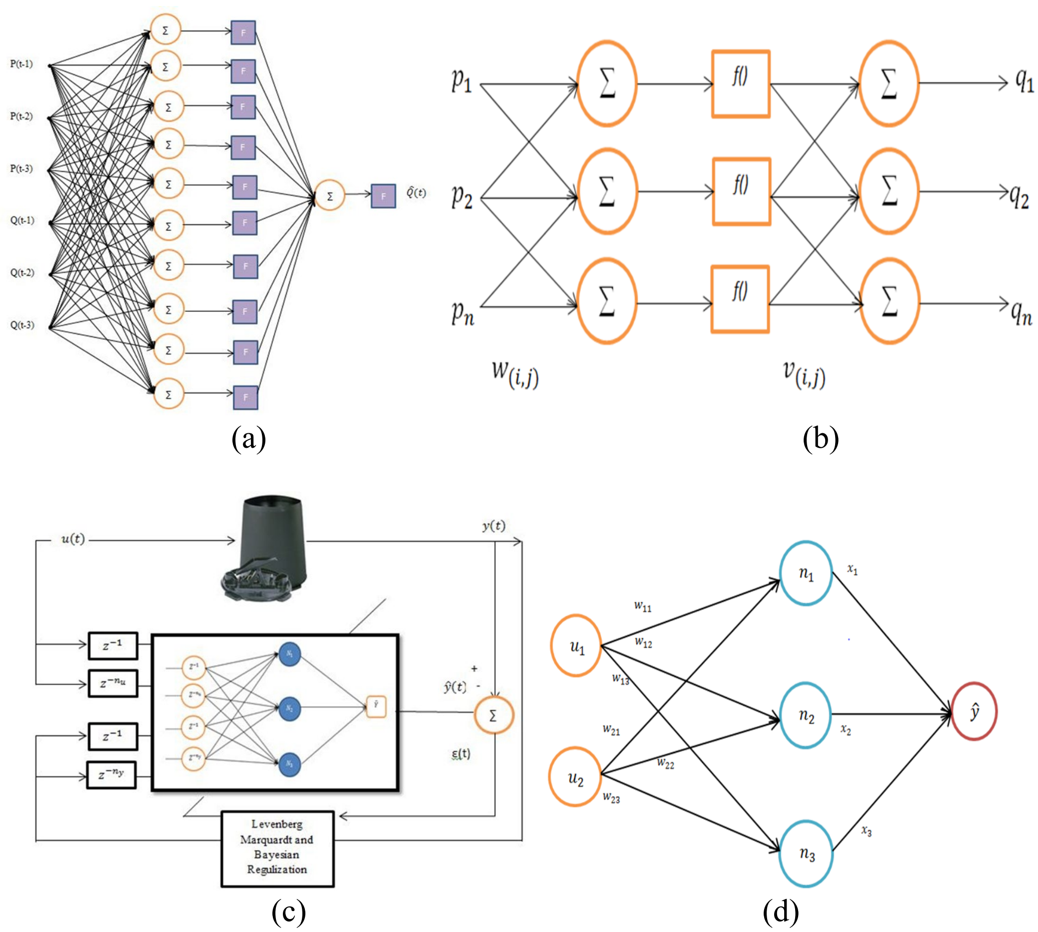


Figure 8. (a) Levenberg Marquardt Algorithm, (b) Neural network with two-layered hidden neuron, (c) Particle Swarm Optimization Algorithm, (d) Multilayer perceptron with interconnecting weights.

externally (shakil. et al 2023). Learning process of the neuron occurs when weights between interconnecting nodes are changed, in order to acquire least value of error when the outputs are compared to the expected outcome. MLP have at least three layers with at least one hidden layer (Figure 8). In this study, one layer of neuron are selected for experimental setup with varying no of neuron in said hidden layer (shakil. et al 2023).

Number of Neuron in Hidden Layer:
Various input combinations are used in order to determine the best model to estimate runoff in using ANN. The optimum number of neurons in hidden layer is determined based on trial and error. Number of hidden neuron of 3, 6 and 10 were chosen for the varying variables (Shabir, et al., 2023).

Type of model:

Model I :

$$Q(t) = f(P(t-1), Q(t-1))$$

Model II :

$$Q(t) = f(P(t-1), P(t-2), Q(t-1), Q(t-2))$$

Model III :

$$Q(t) = f(P(t-1), P(t-2), P(t-3), Q(t-1), Q(t-2), Q(t-3))$$

Three models were developed to examine the effect of adding delays to neural network configuration. The input data of the model consist of antecedent rainfall, and antecedent river level data (Graff. et al 2013). The sign denotes time, where

denotes input rainfall and is the sign for runoff level. The number of delay to be investigated are
n =1, n =2 and n =3**.**

Rainfall runoff forecast:

Based on the optimum number of hidden neuron and type of model, the best neural network configuration trained by both Levenberg Marquardt and Bayesian Regularization are determined distinctively for each rain station. For each rain station data, comparisons were made between the learning algorithms of the neural network. In order to produce runoff forecast 12 hours in advance, the input data of river levels used for ANNs are the data of 12 hours ahead of the predicted time (Green. Et al., 2014). As the result, we can determine, which learning algorithms serves better for the rainfall runoff forecast system (shakil. et al 2023).

Neural networks with Multi-Layer Perceptron which consist of input, hidden and output layer are implied on the prediction model. The modeling of nonlinear dynamic system is done through Nonlinear Autoregressive Network with Exogenous Inputs (NARX). NARX time series prediction is suitable to predict future values of a time series y(t) from past value time series (Green. Et al., 2014). The output of the NARX network is the estimation of the output of some nonlinear dynamic system of rainfall-runoff relation that we are trying to model. Different learning algorithms are proposed for the study to determine the best prediction model (Green. Et al., 2014). The training algorithms of Levenberg Marquardt produce faster solutions, while Bayesian Regularization gives better results with more time consumed. Particle Swarm Optimization edges with its simplicity and offers solution for neurons trapped in local minima which results towards early stopping (Shabir, et al., 2022).

5. Neural Network Modelling and Prediction Experimental Result

Figure 9 and 10 shows the regression plot between target and output of forecasted river level for 5 rainfall stations. The output give good results in compare to the real observation as correlation coefficient are recorded high. Networks trained by LM outperform other training algorithm as each individual trained model shows correlation coefficient no less than 0.996. High accuracy are achieved for all training algorithm. ANN trained with LM shows average correlation coefficient of 0.996514. ANN trained by BR gives 0.996186 and finally ANN trained by PSO produce average correlation coefficient 0.981378. From the scatter plot it can also be seen that certain data points have lower fit especially data trained by PSO algorithms (Green. Et al., 2014). Exceptional accuracy of correlation coefficient were attained as the result of abundant input data available as well as filtering out missing data in the rainfall and river level input beforehand. Rather than interpolating missing data (Figure 11, 12, 13, 14, and 15), we omitted any part of

Rain Station	Neuron no	1st ORDER			2ND ORDER			3RD ORDER		
		TRAINING	VALIDATION	TESTING	TRAINING	VALIDATION	TESTING	TRAINING	VALIDATION	TESTING
RF 3430097	3	4.24392e-1	4.23392e-1	3.88261e-1	4.13685e-3	4.22270e-3	4.42124e-3	2.85791e-3	2.69998e-3	2.52620e-3
	6	1.39982e-2	1.31978e-2	**1.34006e-2**	3.92946e-3	4.08366e-3	3.78586e-3	2.52433e-3	2.50721e-3	2.61535e-3
	10	1.37141e-2	1.41414e-2	1.37963e-2	3.66099e-3	3.60835e-3	**3.48213e-3**	2.55305e-3	2.45518e-3	**2.46696e-3**
RF 3431099	3	1.37833e-2	1.39890e-2	1.36302e-2	4.13685e-3	4.22270e-3	4.42124e-3	2.85791e-3	2.69998e-3	**2.52620e-3**
	6	1.39982e-2	1.31978e-2	**1.34006e-2**	3.92946e-3	4.08366e-3	3.78586e-3	2.52433e-3	2.50721e-3	2.61535e-3
	10	1.37141e-2	1.41414e-2	1.37963e-2	3.66099e-3	3.60835e-3	**3.48213e-3**	2.54888e-3	2.60111e-3	2.58146e-3
RF 3532101	3	1.38289e-2	1.32776e-2	1.41167e-2	4.13685e-3	4.22270e-3	4.42124e-3	2.85791e-3	2.69998e-3	**2.52620e-3**
	6	1.39982e-2	1.31978e-2	**1.34006e-2**	3.92946e-3	4.08366e-3	3.78586e-3	2.52433e-3	2.50721e-3	2.61535e-3
	10	1.37141e-2	1.41414e-2	1.37963e-2	3.66099e-3	3.60835e-3	**3.48213e-3**	2.54888e-3	2.60111e-3	2.58146e-3
RF 3533102	3	1.38289e-2	1.32776e-2	1.41167e-2	3.81793e-3	3.77280e-3	3.89066e-3	2.80252e-3	2.86843e-3	2.65428e-3
	6	1.37419e-2	1.33706e-2	1.44309e-2	3.53824e-3	3.73035e-3	**3.2726e-3**	2.60643e-3	2.73359e-3	2.66719e-3
	10	1.38094e-2	1.37993e-2	**1.36654e-2**	3.53493e-3	3.79295e-3	3.72534e-3	2.45167e-3	2.47158e-3	**2.47614e-3**
RF 3534103	3	1.38289e-2	1.32776e-2	1.41167e-2	4.27247e-3	4.13365e-3	4.35186e-3	2.63708e-3	2.79765e-3	2.84682e-3
	6	1.37419e-2	1.33706e-2	1.44309e-2	4.06502e-3	3.80342e-3	4.14820e-3	2.62851e-3	2.59160e-3	2.84503e-3
	10	1.38094e-2	1.37993e-2	**1.36654e-2**	3.67084e-3	3.73534e-3	**3.75016e-3**	2.28573e-3	2.40461e-3	**2.48872e-3**

Rain Station	Neuron no	1st ORDER			2ND ORDER			3RD ORDER		
		TRAINING	VALIDATION	TESTING	TRAINING	VALIDATION	TESTING	TRAINING	VALIDATION	TESTING
RF 3430097	3	4.24392e-1	4.23392e-1	3.88261e-1	9.95561e-1	9.95481e-1	9.95117e-1	9.96905e-1	9.97265e-1	9.97191e-1
	6	9.84857e-1	9.85762e-1	**9.85360e-1**	9.95760e-1	9.95598e-1	9.95961e-1	9.97285e-1	9.97328e-1	9.97147e-1
	10	9.85118e-1	9.84706e-1	9.85197e-1	9.96064e-1	9.96070e-1	**9.96261e-1**	9.97265e-1	9.97273e-1	**9.97372e-1**
RF 3431099	3	9.85165e-1	9.84281e-1	9.85334e-1	9.95561e-1	9.95481e-1	9.95117e-1	9.96905e-1	9.97265e-1	**9.97191e-1**
	6	9.84857e-1	9.85762e-1	**9.85360e-1**	9.95760e-1	9.95598e-1	9.95961e-1	9.97285e-1	9.97328e-1	9.97147e-1
	10	9.85118e-1	9.84706e-1	9.85197e-1	9.96064e-1	9.96070e-1	**9.96261e-1**	9.97265e-1	9.97234e-1	9.97147e-1
RF 3532101	3	9.85099e-1	9.85563e-1	9.84422e-1	9.95561e-1	9.95481e-1	9.95117e-1	9.96905e-1	9.97265e-1	**9.97191e-1**
	6	9.84857e-1	9.85762e-1	**9.85360e-1**	9.95760e-1	9.95598e-1	9.95961e-1	9.97285e-1	9.97328e-1	9.97147e-1
	10	9.85118e-1	9.84706e-1	9.85197e-1	9.96064e-1	9.96070e-1	**9.96261e-1**	9.97265e-1	9.97234e-1	9.97147e-1
RF 3533102	3	9.85099e-1	9.85563e-1	9.84422e-1	9.95898e-1	9.96003e-1	9.95693e-1	9.96990e-1	9.96763e-1	9.97239e-1
	6	9.84921e-1	9.85752e-1	**9.85039e-1**	9.96168e-1	9.96022e-1	**9.96475e-1**	9.97184e-1	9.97171e-1	9.97062e-1
	10	9.85066e-1	9.85385e-1	9.84738e-1	9.96237e-1	9.95698e-1	9.95969e-1	9.97370e-1	9.97261e-1	**9.97365e-1**
RF 3534103	3	9.85099e-1	9.85563e-1	9.84422e-1	9.95369e-1	9.95568e-1	9.95415e-1	9.97166e-1	9.97006e-1	9.96902e-1
	6	9.84921e-1	9.85752e-1	**9.85039e-1**	9.95617e-1	9.95872e-1	9.95581e-1	9.97178e-1	9.97169e-1	9.96949e-1
	10	9.85066e-1	9.85385e-1	9.84738e-1	9.96032e-1	9.96177e-1	**9.95814e-1**	9.97547e-1	9.97356e-1	**9.97341e-1**

(9) (10)

Figure 9: MSE of ANN model trained by Levenberg Marquardt

Figure 10: R(correlation) value of ANN model trained by Levenberg Marquardt

Rain Station	Neuron no	1st ORDER TRAINING	1st ORDER VALIDATION	1st ORDER TESTING	2ND ORDER TRAINING	2ND ORDER VALIDATION	2ND ORDER TESTING	3RD ORDER TRAINING	3RD ORDER VALIDATION	3RD ORDER TESTING
RF 3430097	3	1.37338e-2	0e-0	1.41181e-2	3.92823e-3	0e-0	3.97276e-3	2.57729e-3	0e-0	2.79521e-3
	6	1.36786e-2	0e-0	1.44289e-2	3.57487e-3	0e-0	**3.35954e-3**	2.42037e-3	0e-0	2.357474e-3
	10	1.38145e-2	0e-0	**1.36588e-2**	3.45833e-3	0e-0	3.74005e-3	2.25699e-3	0e-0	**2.14132e-3**
RF 3431099	3	3.95195e-0	0e-0	4.92513e-0	3.73624e-0	0e-0	5.98362e-0	2.65055e-3	0e-0	**2.49376e-3**
	6	3.79736e-0	0e-0	5.43829e-0	3.85880e-0	0e-0	**4.13874e-0**	2.44198e-3	0e-0	2.60280e-3
	10	3.87785e-0	0e-0	**4.50762e-0**	3.60573e-0	0e-0	5.28343e-0	2.36654e-3	0e-0	2.53404e-3
RF 3532101	3	1.38147e-2	0e-0	1.36569e-2	3.77627e-3	0e-0	3.59608e-3	2.55689e-3	0e-0	2.88004e-3
	6	1.38506e-2	0e-0	**1.34431e-2**	3.50501e-3	0e-0	3.69313e-3	2.39680e-3	0e-0	2.60905e-3
	10	1.37196e-2	0e-0	1.41935e-2	3.47444e-3	0e-0	**3.55445e-3**	2.31531e-3	0e-0	**2.42228e-3**
RF 3533102	3	1.37338e-2	0e-0	1.41181e-2	3.79712e-3	0e-0	3.47273e-3	2.65055e-3	0e-0	2.49376e-3
	6	1.36786e-2	0e-0	1.44289e-2	3.53274e-3	0e-0	3.54000e-3	2.59098e-3	0e-0	2.72119e-3
	10	1.38632e-2	0e-0	**1.33798e-2**	3.55524e-3	0e-0	**3.31041e-3**	2.25699e-3	0e-0	**2.14132e-3**
RF 3534103	3	1.37846e-2	0e-0	1.38273e-2	3.92626e-3	0e-0	3.99115e-3	2.76603e-3	2.91512e-3	2.80203e-3
	6	1.38354e-2	0e-0	1.35392e-2	3.57357e-3	0e-0	**3.30346e-3**	2.47936e-3	0e-0	2.71874e-3
	10	1.38480e-1	0e-0	**1.34658e-2**	3.49867e-3	0e-0	3.40910e-3	2.36608e-3	0e-0	**2.27403e-3**

(11)

Rain Station	Neuron no	1st ORDER TRAINING	1st ORDER VALIDATION	1st ORDER TESTING	2ND ORDER TRAINING	2ND ORDER VALIDATION	2ND ORDER TESTING	3RD ORDER TRAINING	3RD ORDER VALIDATION	3RD ORDER TESTING
RF 3430097	3	9.85177e-1	0e-0	9.84420e-1	9.95751e-1	0e-0	9.95817e-1	9.97223e-1	0e-0	9.97006e-1
	6	9.85069e-1	0e-0	**9.85042e-1**	9.96144e-1	0e-0	**9.96410e-1**	9.97395e-1	0e-0	9.97464e-1
	10	9.85117e-1	0e-0	9.84746e-1	9.96271e-1	0e-0	9.95999e-1	9.97567e-1	0e-0	**9.97718e-1**
RF 3431099	3	4.96609e-1	0e-0	**4.38906e-1**	5.05120e-1	0e-0	4.39490e-1	9.97143e-1	0e-0	9.97336e-1
	6	5.11226e-1	0e-0	4.35978e-1	5.25619e-1	0e-0	5.20590e-1	9.97369e-1	0e-0	9.97212e-1
	10	5.32561e-1	0e-0	4.23390e-1	5.32130e-1	0e-0	**5.35252e-1**	9.97450e-1	0e-0	**9.97450e-1**
RF 3532101	3	9.85117e-1	0e-0	9.84748e-1	9.95941e-1	0e-0	9.96085e-1	9.97260e-1	0e-0	9.96819e-1
	6	9.84971e-1	0e-0	**9.85589e-1**	9.96217e-1	0e-0	9.96068e-1	9.97410e-1	0e-0	9.97249e-1
	10	9.85143e-1	0e-0	9.84599e-1	9.96248e-1	0e-0	**9.96229e-1**	9.97510e-1	0e-0	**9.97376e-1**
RF 3533102	3	9.85177e-1	0e-0	9.84420e-1	9.95901e-1	0e-0	9.96303e-1	9.97143e-1	0e-0	9.97336e-1
	6	9.85069e-1	0e-0	9.85042e-1	9.96221e-1	0e-0	9.96034e-1	9.97209e-1	0e-0	9.97077e-1
	10	9.84979e-1	0e-0	**9.85549e-1**	9.96166e-1	0e-0	**9.96457e-1**	9.97567e-1	0e-0	**9.97718e-1**
RF 3534103	3	9.85059e-1	0e-0	9.85087e-1	9.95791e-1	0e-0	9.95583e-1	9.96999e-1	9.96835e-1	9.97118e-1
	6	9.85005e-1	0e-0	9.85412e-1	9.96140e-1	0e-0	**9.96502e-1**	9.97321e-1	0e-0	9.97135e-1
	10	9.84995e-1	0e-0	**9.85444e-1**	9.96233e-1	0e-0	9.96320e-1	9.97459e-1	0e-0	**9.97518e-1**

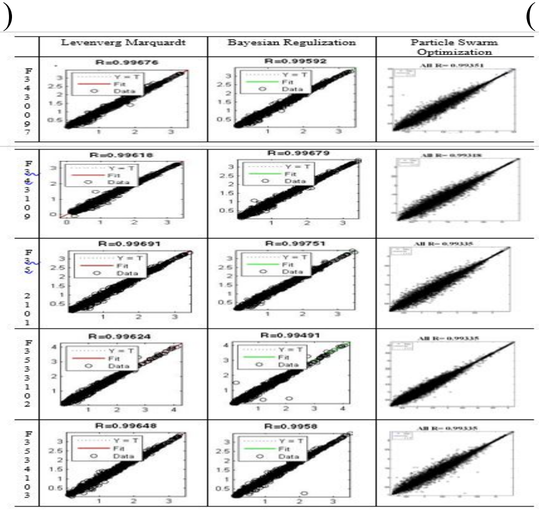
(12)

Rain Station	No of Neuron	MSE 1ST ORDER	MSE 2ND ORDER	MSE 3RD ORDER	R correlation 1ST ORDER	R correlation 2ND ORDER	R correlation 3RD ORDER
RF 3430097	3	0.0050838	0.016943	**0.025377**	9.9348e-001	9.8377e-001	**9.6325e-001**
	6	0.0050575	**0.016607**	0.031138	9.9348e-001	**9.8377e-001**	9.6325e-001
	10	**0.0049081**	0.016986	0.02802	**9.9348e-001**	9.8377e-001	9.6236e-001
RF 3431099	3	0.0052845	0.0055636	0.025826	9.9280e-001	9.831e-001	9.6424e-001
	6	0.0051116	**0.0054173**	0.029833	**9.9337e-001**	**9.8310e-001**	9.6424e-001
	10	**0.0046445**	0.0064286	**0.02116**	9.280e-001	9.8166e-001	**9.6756e-001**
RF 3532101	3	0.0053179	**0.0053217**	**0.02813**	9.9446e-001	9.8113-001	**9.6594e-001**
	6	0.0047323	0.0068572	0.039246	9.9429e-001	**9.8344e-001**	9.6435e-001
	10	**0.004731**	0.0069904	0.028486	**9.9446e-001**	9.8113e-001	9.6564e-001
RF 3533102	3	0.0056701	0.01866	0.032484	9.9292e-001	9.8214e-001	**9.6264e-001**
	6	0.0054959	**0.0069188**	0.041015	**9.9348e-001**	**9.8225e-001**	9.6149e-001
	10	**0.0052627**	0.018618	**0.029587**	9.9263e-001	9.8181e-001	9.5851e-001
RF 3534103	3	0.0049206	0.017592	**0.036155**	9.9347e-001	**9.8129e-001**	9.6541e-001
	6	0.0049793	0.017724	0.037518	9.9336e-001	9.8036e-001	**9.6833e-011**
	10	**0.0048728**	**0.0063823**	0.037446	**9.9354e-001**	9.8036e-001	9.6541e-001

(13)

Rain Station		*R correlation* *LM*	*R correlation* *BR*	*R correlation* *PSO*	*MSE* *LM*	*MSE* *BR*	*MSE* *PSO*
RF 3430097	Training	9.96824e-1	9.97002e-1	9.9348e-1	2.59128-3	2.43427e-3	4.9081e-3
	Validation	9.96782e-1	0.00e-0		2.63275e-3	0.00e-0	
	Testing	***9.96759e-1***	9.95916e-1		***2.61725e-3***	3.38755e-3	
RF 3431099	Training	9.96545e-3	9.96832e-1	9.9337e-1	2.284277e-3	2.59747e-3	4.6445e-3
	Validation	9.96949e-1	0.00e-0		2.53869e-3	0.00e-0	
	Testing	9.96179e-1	***9.96788e-1***		3.08242e-3	***2.67486e-3***	
RF 3532101	Training	9.96859e-1	9.97199e-1	9.9446e-1	2.57055e-3	2.30511e-3	4.731e-3
	Validation	9.95807e-1	0.00e-0		3.39490e-3	0.00e-0	
	Testing	9.96909e-1	***9.97508e-1***		2.59658e-3	***2.01518e-3***	
RF 3533102	Training	9.96195e-1	9.96828e-1	9.9348e-1	3.07685e-3	2.56150e-3	5.2627e-3
	Validation	9.96256e-1	0.00e-0		3.13789e-3	0.00e-0	
	Testing	***9.96235e-1***	9.94912e-1		***2.95130e-3***	4.16389e-3	
RF 3534103	Training	9.96867e-1	9.96822e-1	9.9354e-1	2.59796e-3	2.64180e-3	4.8728e-3
	Validation	9.95544e-1	0.00e-0		3.87501e-3	0.00e-0	
	Testing	***9.96480e-1***	9.95804e-1		***2.95575e-3***	3.62589e-3	

(14)



(15)

Figure 11: MSE (Mean Square Error) value for ANN model trained by Bayesian Regularization, Figure 12: R (correlation) value of ANN model trained by Bayesian Regularization, Figure 13:MSE and R (correlation) of ANN trained by Particle Swarm Optimization, Figure 14: R and MSE of rainfall-runoff forecast, Figure 15: Regression plot of ANN trained by varying learning algorithms

runoff data which corresponds to the missing rainfall data. Especially in some parts the gaps within either rainfall or runoff data received form Departments of Irrigation and Drainage (DID) Malaysia is consecutive. This can be caused by many factors such as equipment dysfunction, errors in measurements or faults in data acquisition. When this occurs, interpolating or filling in the missing value with estimated numbers in large scale is deemed incompatible (shakil. et al 2023).

6. MSE Performance Graph Analysis:

Figure 16 shows MSE performance of rainfall-runoff model for 5 rainfall stations. MSE against number of epochs.

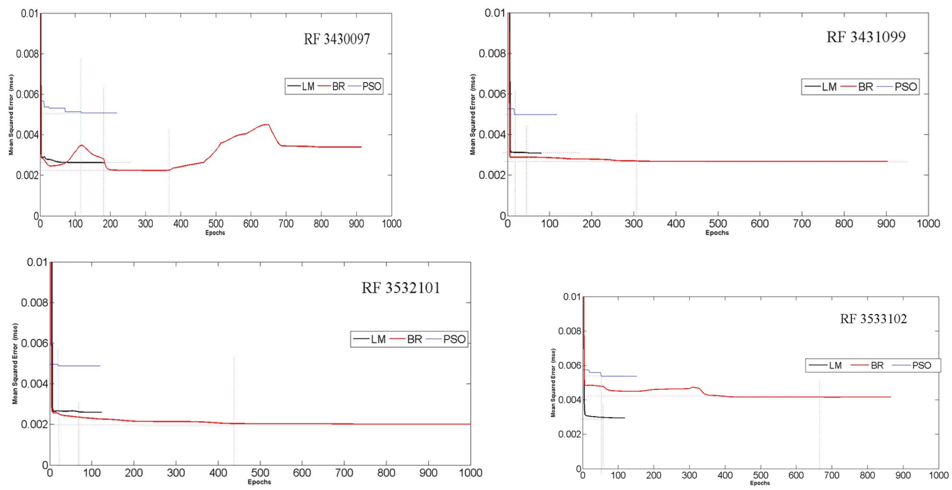


Figure 16: MSE performance of rainfall-runoff model for 5 rainfall stations. MSE against number of epochs as graph axis. Line/training algorithm: Black-LM; red- BR; blue-PSO.

Figure 17: Bar chart with blue coloured parts indicates training before best epoch reached, and red coloured part indicates continuation of iteration after best epoch achieved.

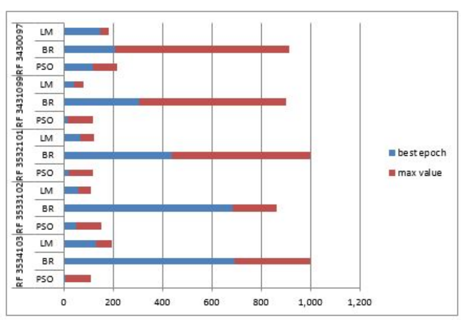


Figure 17. Factors of training termination:

Overfitting:

In terms of stability, training neural network by LM and PSO are prominent as the error recorded decreases over time (Figure 18). Meanwhile for BR, MSE graph plot recorded several troughs along the simulation. This is noticeable for simulation of rainfall station BR 3430097, and scarcely seen for RF 3533102. During training phase, the MSE shows steady decrement over time as the parameters, weights and biases are being predetermined. As it comes towards testing phase, the algorithms declined in performance. The MSE during training and testing is 2.43427e-3 and 3.38755e-3 for RF 3430097 respectively. The MSE during training and testing is 2.56150e-3 and 4.16389e-3 for RF 3533102 respectively (Shabir, et al., 2022).

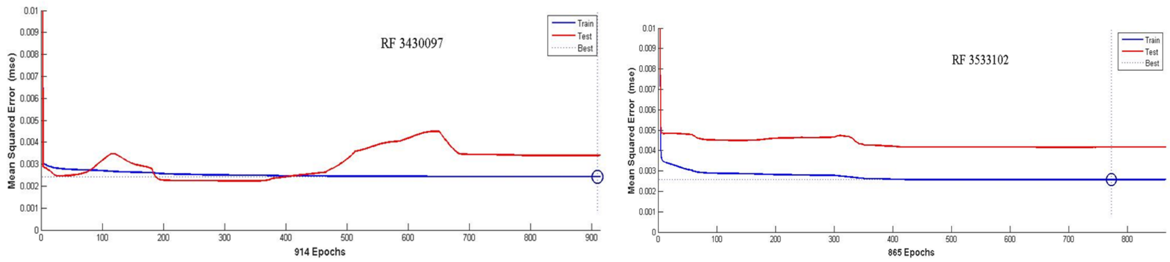


Figure 18: MSE plot graph of training and testing data set against number of epoch for RF 3430097 and RF 3533102.

From the analysis done, the best number of neuron in hidden layer and type of model order are obtained. Thus ANNs with best configuration for each learning algorithm are put into test for 12-hour rainfall-runoff forecast model. ANNs trained by LM produce best rainfall-runoff model prediction in Sungai Pahang, Pekan. It achieve best MSE and R value for 3 out of 5 rainfall stations available namely RF 3430097, RF 3533102 and RF 3534103. The early stopping method is implied to avoid overfitting. Trainlm are able to achieve good convergence rate with lower number of iterations (Shabir, et al., 2023).

ANNs trained by BR accomplished decent MSE and R value. For RF 3532101 and RF 3431099, it had recorded best performance result. Unfortunately, there is a tendency of overfitting. BR requires longer time for to converge, thus early stopping are not put into effect. Hence, iteration reached to higher number. This may have been the cause of overfitting to take place. In terms of time taken for simulation, trainbr are second to trainlm (Graff. et al 2013).

PSO learning algorithm produced lowest results in terms of performance. Though it achieved higher MSE and R value, it could be seen that performance is stable and achieve convergence faster. Trainpso consumes the longest time for simulation when compare to LM and BR.

In general, ANN trained with LM are best suited for rainfall-runoff model in Sungai Pahang in Pekan. It gives optimum performance, with the least time taken and the number of iteration is kept at a reasonable amount. LM algorithm demonstrated stable error in validation, training and testing phase graph plot. With early stopping method implemented, the problem of overfitting is avoided

7. Conclusions

The best configurations for each learning algorithms are attained. The configurations vary from one algorithm to another with no absolute number of neurons in hidden layer or delay (model order) which is dominant for all networks. This further proved the necessity of constructing a rainfall-runoff forecast model which is exclusive for a particular basin or river.12-hour forecast for rainfall-runoff prediction model in KASHMIR is developed. The results are satisfactory with prediction models producing low errors. The rainfall data and runoff data corresponds one another as the training generates good coefficient of correlation. Comparisons are made between ANNs with LM, BR and PSO as the learning algorithm. The algorithm which best suit to model Kashmir is determined. The performances of the networks are observed and the characteristics of each training algorithm, its advantages and disadvantages are analyzed and discussed.

The main objective of this paper is to investigate, develop, and compare between rainfall-runoff models for the case study in Jehlum River, in Pakistan Kashmir. It could be concluded that the objective has been successfully achieved. ANNs model have been develop with three different learning algorithm applied on the simulations. The configuration which best suited each learning algorithm are determined for it to produce optimum prediction model. The performances of the networks are acquired, analyse and finally comparison are made. The best learning algorithm with custom network configuration is obtained. This presents the conclusion drawn from the study and recommendations made for further study. These are the recommendations which can further improve future studies on rainfall-runoff prediction model. Hydrological studies are wide in scope and there are many rooms for improvement. Below are some suggestions on which particular field of work that could be explored.

A statistic study on how to estimate or interpolate incomplete information on rain intensity and river basin would be essential. There are gaps within the data given for rainfall and runoff. This may occurred because of rain gauge failure, measurement error or data acquisition deficiency. As missing values are discarded from the model, a portion of the data set is lost.

Rainfall-runoff model prediction which takes various factors as the input of the system. For this research the variable considered for the rainfall-runoff predictions are only rainfall and runoff level data. Other determining factors such as topology, soil condition and other hydrologic conditions were not taken into consideration.

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Biography

Madiha Mazhar received her bachelor's degree in chemistry from Pakistan's prestigious Government College University Lahore. Many articles detailing this study appeared in the field of organic chemistry. Materials, such as carbon emissions and their reduction, were the main topics of research. Lahore University of Management Sciences, among the greatest schools in South Asia, was where I earned my Master of Philosophy in chemistry. My master’s thesis work was in physical chemistry, and I hope to pursue doctoral studies in the field at the University of Florida USA in the near future.