

RAINFALL-RUNOFF FORECAST MODEL

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Abstract

Flood is a matter of rainfall-runoff process. Runoff volume from rainfall has been found to be nonconsistent over a given catchment area. Rainfall-Runoff is addressed as complex hydrological problem because of contributions of multiple variables involve in the process. If we are to control flood then we need to be able to forecast rainfall-runoff accurately. Generally, because of the non-linearity of the process of rainfall-runoff and the fact that details of various subprocesses involve are not yet known makes modelling the only solution to the problem. Existing models for rainfall-runoff include: Statistical models which was not acceptable as linear functions were used for nonlinear process, conceptual models in which the modeller's view of the process is represented. However, over parameterisation and non-availability of certain variables limited the operational applications of such models. Other recent approaches in the developed world has resolved to use of Artificial Neural Network amidst other methods. However, in developing part of the world manual method is still operational. There is need to adopt softcomputing techniques so as to improve accuracy of forecast. Fuzzy logic also takes care of uncertainty . between the parameters without detail knowledge of the subprocesses. In this work, further improvement of rainfall-runoff forecast is being proposed using combination of the Artificial Neural Network and Fuzzy logic called neurofuzzy. The work examined the accuracy of Fuzzy Inferential System that can further be trained to improve accuracy of rainfall-runoff forecast along side with Artificial Neural Network.

Keyword: Catchment, Hydrology, Softcomputing

INTRODUCTION

Rainfall is a natural phenomenon and runoff is generated by rainstorm. Runoff generation begins when rainfall intensity exceeds the actual infiltration capacity of the soil. When

rain begins to fall, the first drops of water are intercepted by the leaves and stems of vegetation which varies with the type of vegetation and growth stage of the vegetation. This is called the interception storage. As the rain continues, water

reaching the ground surface infiltrates into the soil until it reaches a stage where the rate of rainfall (intensity) is greater than the infiltration capacity of the soil. Thereafter, surface puddles, ditches, and other depressions are filled (depression storage), after which runoff is generated. The infiltration capacity of the soil is a function of soil texture, structure and the antecedent soil moisture content (previous rainfall or dry season). Soil usage is another variable that affects all other variables aforementioned. Rainfall intensity, rainfall duration, rainfall distribution and catchment also affect the occurrence and volume of runoff. This explains why rainfall runoff process is a complex hydrological phenomenon. How to accurately relate all the parameters that determine runoff requires a great deal. These variables of runoff also vary from catchment to catchment thereby making model develop for one catchment area extremely unapplicable to others.

When runoff volume increased in a particular catchment, water can overtop the banks of the river since the water cannot be stocked in the soil. This results to flood that is capable of destroying the ecosystem. Flood is a matter of rainfall-runoff. Flood and droughts as one of the natural disasters kill more people than any other natural disasters[1].

But nowadays, urbanisation has increased population concentration and economic activities around river. Flooding therefore renders untold

havoc than ever before. The global climate change contributed to increase flood thereby increasing damage due to flooding. This now becomes a real threat and especially in flash flood events. There is heavy likelihood that this will continue to the future.

Flood however can have great usefulness. The Egyptian civilisation was well known for taking advantage of the Nile's river that regularly covered their lands and deposited fertile sediments. Hydrologists suggest structural solution to the problem of flood. This include building new flood defence structures such as barrages and reservoirs, dams and multi purpose reservoirs etc.

However, the safety and life span of such structures also depend on the accuracy of forecast of runoff. The use of such flood defence structures for defending vulnerable areas can also have serious financial implications when such structures were being stressed beyond runoff capabilities. It can even lead to more loss of lives and properties of the adjoining regions. Water harvesting and water resources management that attempt to divert excess water from flood to various positive ways for humanity also requires the need to know accurate forecast of runoff. If the efforts in water harvesting and water resources management is successful, then runoff can be used for productive purposes.

It is obvious that non-structural solutions are needed to sustain structural solutions. The

non-structural solution will help determine in advance what likely volume of runoff can be i.e. forecast runoff. When the two solutions can complement each other then runoff can be effectively put into productive uses. Non-structural solutions lead to development of models that can be used to forecast runoff. In an attempt to forecast rainfall-runoff, various models have been developed. There are numerous multi-models on rainfall-runoff as certain details of this natural phenomenon is not perfectly understood[2]. This is because the detail of the processes involve in rainfall-runoff have not been perfectly understood and the models also vary. The degree of representation of the physical processes of rainfall-runoff also explains the wide variation in different categories of models use for rainfall-runoff. Current flood forecasting and warning systems have several limitations, such as insufficient lead time to provide accurate flood warnings, inadequate spatial and temporal resolution of real-time rainfall observations and forecasts for flood producing storm, little integration of different sources of forecast information. Moreover their ability in considering the uncertainties in estimating and forecasting precipitation and flood discharges is very limited.

Statistical models have been used for rainfall-runoff. Various conceptual models have also been developed but were not operational because the required parameters could not be

obtained. In recent time, Artificial neural network has been used for modelling rainfall-runoff. However several studies have argued for more cautious approaches to make Artificial Neural Network more useful for operational hydrological problems. Various studies have shown the need for further attention in developing model with suitable network architecture and parameter estimation[3].

Basic Theoretical consideration

Rainfall-runoff is a complex hydrological phenomenon. Let us consider some of the variables involve in the process of rainfall-runoff for any given catchment area:

- (i) Atmospheric conditions over the cathment (wind speed, direction, temperature, humidity etc).
- (ii) The surface cover (type, distribution, interception, takeup, evapotranspiration etc)
- (iii) Surface soil (type, permeability, porosity etc)
- (iv) Terrain (slope, surface texture etc).
- (v) Geology (structure distribution, permeability, porosity, ground water levels)

Major processes identified in the rainfall-runoff process:

- (a) Evapotranspiration at the surface

- (b) Surface infiltration
- (c) Overland flow
- (d) Unsaturated zone flow
- (e) Saturated zone flow (groundwater)

Each process is made more complicated by other more detailed sub-processes.

Rainfall-runoff modelling finds a description for transformation of the total rainfall volume to the corresponding reduced runoff volume in a catchment area. The relationship between rainfall volume in a given catchment may be expressed as

Where W_{rf} represents the total rainfall volume during one rainy event,

A represents the catchment Area

Hr represents the average height of rainfall

$$W_{rf} = A \int i * dt$$

i represents the rainfall intensity in meter per second

T0 represents the starting time of the rainfall event

Tr represents the ending time of the rainfall event.

Runoff volume, WQ can be estimated by

$$WQ = A \int_{T0}^{Tr} i * dt$$

Q represents hydrograph runoff ordinate on the outlet of the watershed.

i_e is net or effective intensity of the rainfall.

Wrf WQ is the retained water volume (water volume deficit) that varies with time, ie similar rainfall volumes may result in significantly different runoff volumes on the same watershed structure. This internal structure is a composition of a large number of relatively permanent and changeable essential features. More than ten factors invariably participate in the rainfall-runoff process, hence the need for modelling.

Conceptual models have been used for understanding of the hydrologic processes. In conceptual models, the internal descriptions of the various subprocesses are modelled attempting to represent, in a simplified way, the known physical processes. The input (precipitation values) is divided into components that are routed through the subprocesses either to the watershed outlet as streamflow or to the surface and deep storages or to the atmosphere as evapotranspiration. Even if not applying the exact differential laws of conservation, conceptual models attempt to describe large spatial and temporal scale conservation and response laws that are in accordance with the observed large-scale behaviour of water in hydrologic drainage basins. They attempt to provide reliable approximation of physical mechanisms, which determine the hydrologic cycle. Conceptual models usually try to find a trade off between complexity of the modelling approach and output

accuracy[4]. Generally, the use of conceptual models require a great amount of information regarding the physical properties of the catchment area which unfortunately can be expensive and not available. This then limits the accuracy of conceptual models in the forecast of rainfall-runoff. Another approach that has been given to rainfall-runoff is the use of statistical models. Statistical models generally require a dataset of past observations sufficiently large to allow the system to be adequately parameterized. Statistical modelling techniques have been used to obtain systematic empirical methods for simulating and forecasting of rainfall-runoff and streamflow. These models are spatially lumped i.e. they treat the catchment as a single unit. The established transfer functions are characteristics of the basin and do not necessarily have a physical interpretation. The main limitation of these models is that the structure of the model is generally taken as linear while rainfall-runoff process is non-linear [5]. The formulation of real-time flood forecasting using statistical and stochastic models are based on the assumption of linearity whereas the quantity of runoff resulting from a given rainfall event depends upon a number of factors and is dominantly non-linear.

Artificial Neural Network has also been found useful in solving hydrological problems as it is able to capture the nonlinear relationship between the variables of rainfall-runoff. Artificial

Neural Network are large class of parallel processing architectures which are useful in specific types of complex problems. Recent works revealed the accuracy and robustness of Artificial Neural Network over regression and conceptual models. In extreme cases, where certain parameters required by conceptual models cannot be found, Artificial Neural Network is able to predict result, thereby making the use of Artificial Neural Network a popular choice for modelling rainfall-runoff among others[6]. The most commonly used ANN for hydrological modelling is a Feed-forward network with the Back Propagation training algorithm. Some work also compared ANN and conceptual models. Previous works reviewed include Precipitation Runoff Modelling using Artificial Neural Network and conceptual models. Conceptual models compared with ANN include: The Sacramento Soil Moisture Accounting (SAC-SMA) model; Water Balance Model (WATBAL); Simple Conceptual Rainfall-Runoff Model. The works demonstrated the accuracy of ANN over conceptual models. Accuracy of Artificial Neural however depends on large sets of training data sets and use of appropriate transfer functions.

In the recent time, fuzzy logic approach became a preferable tool for dealing with uncertainties and imprecise information. Fuzzy modelling is the application of fuzzy set theory to the representation of essential features of a

system. Fuzzy systems can be regarded as a generalization of crisp systems. Fuzzy logic represents a broader class of theoretical tools which is termed as method of granular knowledge representation. It enables the use of formal mathematical models for imprecise and ambiguous defined terms, relations and mechanisms of approximate inference, resemblance of human reasoning and capable of perception of the environment in human form [7]. The small computational time requirement, the numerical robustness, transparent programming of rule base systems, and the ability to handle non-probabilistic uncertainties are the essential features of fuzzy systems. Fuzzy logic has also been applied in solving hydrological problems such as stream flow forecasting, water level forecasting, flood forecasting among other hydrological problems. The limitation of using only fuzzy logic is the inability to efficiently tune fuzzy system to give precise outputs for several, possibly contradictory, input combinations.

Recent work has further shown that combination of Artificial Neural Network and fuzzy logic can result to network that exploit both technique to further improve accuracy. This is referred to as neurofuzzy. While fuzzy Inference System establishes rule base approach among various inputs and map them to various output space, Artificial Neural Network can further train

the rulebase so that knowledge from the rules can further be used to some unknown scenario. This approach is data driven. This also reduces the limitations of the two systems as their features are combined. Past records of hydrological and meteorological stations in this tropical region can then be used to develop a model for rainfall-runoff process as against the manual measurement.. Features present in Neural Network and Fuzzy logic include: distributed representation of knowledge, model-free estimation, ability to handle data with uncertainty and imprecision etc. However, fuzzy logic has tolerance for imprecision of data, while neural networks have tolerance for noisy data. A neural network's learning capability provides a good way to adjust expert's knowledge and it automatically generates additional fuzzy rules and functions to meet certain specifications. On the other hand, the fuzzy logic approach possibly enhances the generalisation capability of a neural network by providing more reliable output when extrapolation is needed beyond the limits of the training data [8].

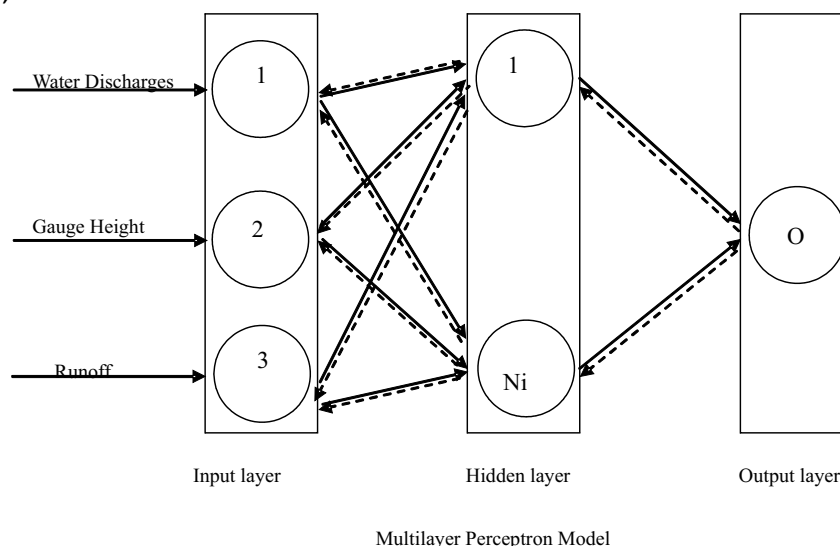
Popular among the various network used for solving hydrological problem is the Multilayer Feed Forward Neural network that make use of backpropagation algorithm for training. Various training functions that are used for training neural network include: `trainlm`, `traingd`, `traingda`, `traingdx` etc while mathematical transformation function for building the neural network include

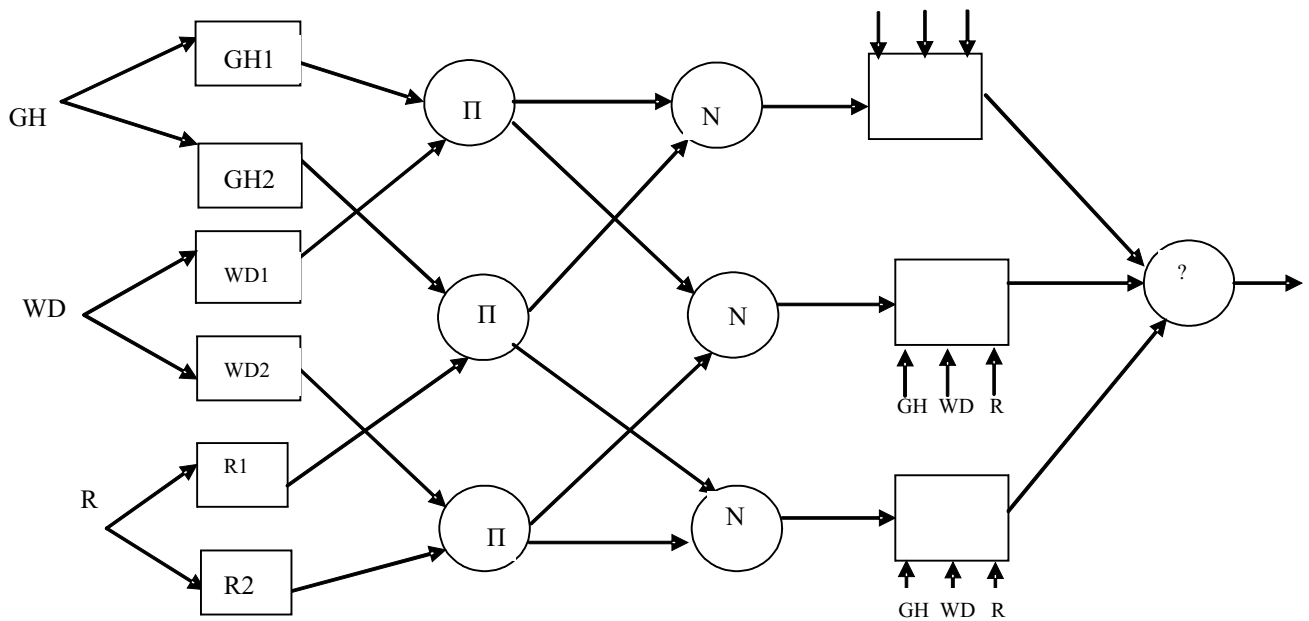
logsig, tansig, purelin etc. Fuzzy inference system can be built up using data clustering and grid partitioning methods.

In this work, attempt is being made to develop Multilayer Feed Forward Network and Neurofuzzy model to forecast rainfall-runoff for tropical region using Benin-Owena river basin as the case study. The work further investigates the accuracy of selecting reduced number of variables of rainfall-runoff by the models in order to know the accuracy of forecast by the models. The accuracy of the model was tested using different number of input variable in order to show that with many or few variable the models' accuracy can be investigated. Three hydrological stations were selected. They are Ikpoba, Owan and Okhunwan stations. In all the three stations the same hydrological variables namely: Gauge Height, Water Discharges, Rainfall and Runoff were used in developing the models. Daily recordings of the three selected hydrological stations, Ikpoba, Owan and Okhunwan were used

to generate thousands of pairs of data. The Multilayer Perceptron Network has four inputs that made use of non-linear sigmoid function, Tansig at the hidden layer while the output made use of linear function, purelin to generate a single output at the output layer. The Multilayer Perceptron Network used Back propagation algorithm, Marquadt Levenberg, for the training of the neural network. The Neurofuzzy model made use of data clustering to generate Sugeno-type fuzzy inference system that will best model the data behaviour using minimum number of rules. Least Square and gradient descent algorithms were used for the training. The simulation of the model was carried out by using MATLAB 7.0. The performance evaluation of the proposed model was done using results from the model, existing models and observed data of selected gauging stations from Benin-Owena river basin by comparing the coefficient of determination (R^2).

The structure of the two models are shown below:

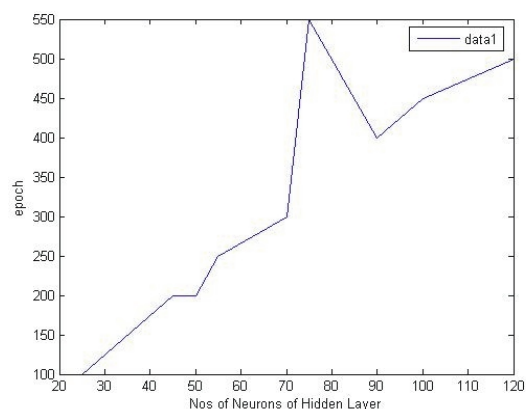
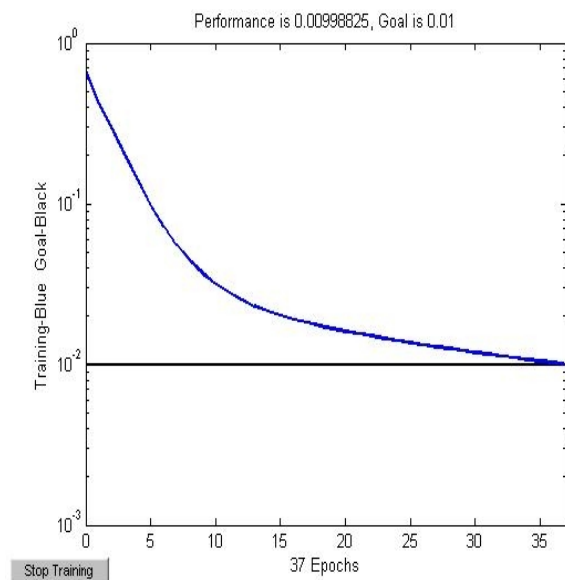




ANFIS for the Neurofuzzy model

Sample rules generated by the NEUROFUZZY modell

1. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) then (output is out1mf1) (1)
2. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) then (output is out1mf2) (1)
3. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf3) then (output is out1mf3) (1)
4. If (input1 is in1mf1) and (input2 is in2mf2) and (input3 is in3mf1) then (output is out1mf4) (1)
5. If (input1 is in1mf1) and (input2 is in2mf2) and (input3 is in3mf2) then (output is out1mf5) (1)
6. If (input1 is in1mf1) and (input2 is in2mf2) and (input3 is in3mf3) then (output is out1mf6) (1)
7. If (input1 is in1mf1) and (input2 is in2mf3) and (input3 is in3mf1) then (output is out1mf7) (1)
8. If (input1 is in1mf1) and (input2 is in2mf3) and (input3 is in3mf2) then (output is out1mf8) (1)
9. If (input1 is in1mf1) and (input2 is in2mf3) and (input3 is in3mf3) then (output is out1mf9) (1)
10. If (input1 is in1mf2) and (input2 is in2mf1) and (input3 is in3mf1) then (output is out1mf10) (1)



Variation of the Number of neuron with epoch for the Multilayer Neural Network

Model Evaluation and Result Discussion

Coefficient of determination, R^2

n

=

$$\frac{[\sum_1^n (Q_{obs} - Q_{ay})(Q_{cal} - Q_{cal} - av_i)]^2}{[\sum_1^n (Q_{obs} - Q_{ay})(Q_{cal} - Q_{cal} - av_i)]}$$

is the number of observations, Q_{obs} and Q_{cal} are

the

l and calculated values respectively, and Q_{cal-av}

mean of the observed and calculated values.

The summary of the results is shown in the table below

NG	Coefficient of <i>NEUROFUZZY</i>	
	<i>Determination MODEL</i>	
ANN		
A	0.75	0.93
I	.62	.92
NWAN	.94	.71

Fig 5.2

GING	Coefficient of <i>NEUROFUZZY</i>	
	<i>Determination MODEL</i>	
ION		
BA	0.86	0.97
N	.64	.99
UNWAN	.94	.81

From the results produced by the models, Neurofuzzy models outperformed the Multilayer Feed Forward Network while the results of the Multilayer Feed Forward model is relatively close to that of Neurofuzzy model in some cases. the coefficient of determination reveals that Neurofuzzy model is much more reliable. Two models of Multilayer Feed Forward Neural networks were built, the first model made use of four inputs variable while the second model made use of two inputs (i.e two variables of rainfall runoff process). Two models of Neurofuzzy were also built up such that the first model requires four input variable and the second model only requires two input variable to forecast result.

All the four models were trained using the same samples of data values that represents the required number of variables by the network. All the four models were tested using the same sample of input in other to determine the forecast accuracy of the model. The models were first tested with four input variables and they all forecast results. When the trained models of Multilayer Feed Forward network and Neurofuzzy models were tested with two input variables, some of the results obtained were the same as that of four input models however some models' accuracy increase, the accuracy of Neurofuzzy models was very high with two input variables as its coefficient of determination increase to 0.99 meaning the model can explain 99% of the

variation in the model. This results has shown clearly that softcomputing models can be used as substitute for determining nonlinear relationship of rainfall-runoff and to overcome some inestimable variables that contribute to the nonlinearity of the rainfall-runoff process. Neurofuzzy models generally gives improved accuracy over Feed Forward Multilayer Network.

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