Soft Computing techniques for Rainfall-Runoff modeling: A Review

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Abstract—Rainfall-Runoff models are dependent on the physiographic, climatic and biotic characteristics of the basin. These factors induce either a linear, non-linear or highly complex behaviour among the rainfall and runoff parameters. Rainfall-Runoff relations are unstructured nature which diverted the attention of researchers towards Soft Computing tools for reasoning, consciousness, intuition and wisdom possessed by human beings. These are multi-disciplinary field uses a diversely of statistical, optimization and probabilistic tools which complement each other to produce its three main branches viz., Fuzzy Logic, Artificial Neural Networks and Genetic Algorithms. Soft computing techniques either complementing each other or working on their own. They are able to model complex or unknown relationships which are either nonlinear or noisy. These review paper explains an introduction to these techniques and discusses their applications in modeling Rainfall-Runoff relations replaces time-consuming conventional mathematical techniques with intelligent and time-saving computing tools.

Keywords— Artificial neural networks, fuzzy logic, genetic algorithms, hybrid soft computing, Rainfall-runoff modeling, soft computing.

I. INTRODUCTION

Rainfall and equivalent runoff generated are most important hydrological processes which depends on the local physiographic, biotic and climatic factors. Rainfall over a catchment is the fall of precipitation from the atmosphere to the earth's surface in liquid form (rainfall) or frozen form (snow, hail, sleet, freezing rain). Runoff of a catchment area in any specified interval is the total quantity of water draining into a reservoir or into a stream in that interval, which can be expressed as millimetre of water over a catchment area or the total volume of water in cubic meter or hectare meter. Water available in a specific time period at a specific location in a specific area in a river basin can be determined with the help of the rainfall-runoff regression model. The essential components of a hydrological model are precipitation, infiltration, stream flow, interception, evaporation, transpiration, variability in time and space. When the rainfall intensity overreach the infiltration rate than the runoff starts immediately. Physiography of the local area predominately affects the rainfall and the generated runoff from the catchment. The infiltration capacity of the land depends on porosity of a soil which also calculates the resistance of water flow into the deeper layers. Volume of runoff per unit area decreases with the increasing size of the catchment is called runoff efficiency. Lower flow velocity in flat area, vegetation cover density, thick layer of mulch of leaves or grasses provides longer time absorption hence low runoff generation. Flat land has less runoff than undulating land due to getting the less energy received from the slope and more time for infiltration. The smaller drainage density gives less runoff. Distribution coefficient, i.e. ratio of maximum rainfall at a point to the mean rainfall in the catchment. It also affects the runoff generated. Direction of the prevailing wind decreases or increases the flowing velocity and indirectly affects the runoff. The average basin characteristics, i.e. wind velocity, temperature, annual rainfall and relative humidity also affect the rainfall runoff relation in the basin.

The operation, maintenance, optimum design and use of proposed or existing water resources projects in a particular river basin requires comprehensive knowledge of the rainfall and the equivalent runoff generated in a particular time interval. Apart from planning and development of water resources projects, the rainfall-runoff models helps in formulating drought management, flood control measures, water supply, optimization of reservoir operation etc. In addition to its wide applicability and multifaceted in judging the overall water balance scenario of an area under study, the functional relationships between rainfall and runoff are extremely complex and non-linear. The conventional mathematical techniques in the form of regression equations do not provide a perfect representation of the rainfall-runoff phenomenon. Soft computing tools offer a simplified techniques over conventional hard computing with the real life phenomenon associated with noisy, imprecise, ambiguous and complex nature of information. The review paper is an attempt to provide a comprehensive introduction to major fields of Soft Computing viz., Fuzzy Logic, Artificial Neural Networks and Genetic Algorithms and their applications in modelling rainfall-runoff relationships.

The review paper has been splits into sections. A brief introduction to three major soft computing techniques, fuzzy logic (FL), artificial neural networks (ANN) and genetic algorithms (GA) is given in Section II. Section III deals with numerous applications of soft computing applied to rainfall runoff modelling. This section has been further sub-divided to give a comprehensive review about the application of individual and hybrid soft computing techniques in rainfall-runoff modeling. The literature review conclusions have been briefly discuss in Section IV.

II. SOFT COMPUTING TECHNIQUES

Soft computing techniques is a set of "inexact" solutions, which are able to analyze and model very complex problems. They offer the solution with a tolerance of imprecision, uncertainty, approximation and partial truth. Soft computing techniques similar to biological processes more closely than traditional techniques, which are effectively based on formal logical systems such as sentential logic and predicate logic or rely heavily on computer aided numerical analysis (as in finite element analysis).These methodologies mimic cognition and consciousness in several important aspects: they learn from experience, they can universalize into domains where direct experience is absent and through parallel computer architectures that simulate biological processes. They can perform the mapping from inputs to the outputs faster than inherently serial analytical representations. Soft Computing render low cost solutions to imprecisely formulated problems and attempt to introduce the behaviour and learning ability of human beings into computers. The following sub-sections deal with an introduction to the fore techniques of Soft computing viz., Fuzzy Logic, Artificial Neural Networks and Genetic Algorithms.

A. Fuzzy Logic

According to Lotif A. Zadeh [1] in 1965, Fuzzy Logic (FL) reflects the computational methodology of solving and thinking problems inherent in human beings. FL approximates the decision making and reasoning ability of human beings in areas which are prone to inexact, imprecise and vague knowledge, therefore is a quantitative method of describing observations. FL has an ability to link many inputs to one output and does not require the linearity, normality needed by traditional methods such as principal and regression component analysis. This approach provides a simple method to draw definite conclusions from imprecise, vague or ambiguous information [2]. Based on linguistic principles, modelling using fuzzy logic involves fuzzification of variables, defining rule base, selecting inference method and finally applying defuzzification method for predicting responses. The fuzzification of variables is accomplished by defining the membership function, which represents the degree of belongingness of the element to the set. Its fuzzy set theory is synonymous to mathematical formulation dealing with classes without crisp boundaries. In variation to traditional logic that deals with either "False" or "True" logic or "0" or "1" logic. FL using the fuzzy set theory is able to deal with many valued logic that has prevailed due to vagueness and uncertainty inherent in real life phenomenon which allows characteristic function to a membership function. Fuzzy set theory and Fuzzy Logic theory provide an excellent means for representing uncertainty and imprecision in the decision-making process.

B. Artificial Neural Networks

Artificial neural networks (ANN) represents the architectures and learning algorithms inspired by the working and structure of the human brain. They represent a simplified version of the human brain but these computational models inspired by biological neural network has provided new approach to solve problems arising in natural tasks. Haykin [3] has described a neural network as a heavily parallel distributed processor made up of simple processing units, which has a natural tendency for accumulating experiential knowledge and making it available for use. They present an information learning pattern comprising of processing elements called "artificial neurons" or "neurons", which are arranged in layers. Flood and Kartam [4] has described neurons performs individually trivial functions, but collectively in the form of a network, they are capable of solving complicated problems. The architecture of ANN comprises of three basic identities viz., the weighted connections between the neurons, the learning algorithm for updating the weights and the activation function acting on the weighted sum of input signal fed into the neuron. ANNs are well suited for problems whose solutions require knowledge that is difficult to specify but for which there are enough data or observations. ANN's potential to offer model free, parallel processing of noisy adaptability and data to changing instances of the problem, give it an edge over conventional dataprocessing techniques. The multidisciplinary applications of ANN is attributed to its ability of deriving non-linear, complex and unknown relationships among dependent and independent variables through a learning process, therefore working as a universal function approximator and has been a field of interest for predicting behaviour of natural and engineering systems.

C. Genetic Algorithms

Genetic algorithms (GA) is a optimization tool and computerized search whose methodology is inspired by the "Survival of fittest" heuristic. Heuristic explains adaptability and durability because it provides a flexible balance between necessary and effective characteristics for survival in different conditions and environments [5]. GA's performs the efficiency of conventional optimization techniques in searching non-continuous and non-linear spaces, which are characterized by poorly understood expert knowledge. In compare with traditional optimization techniques which start from a single point in the solution search space, GA starts its search process using a group of solutions indicated as the chromosomes population at a time and navigates the search space using its three evolutionary operator's viz., selection, crossover and mutation to gain the global optimum. Based on the fitness of each chromosome, the selection operator filters the fitter chromosomes from a pool of chromosome population and allows them to represent themselves in the succeeding generation. The crossover works on the pair of chromosomes and selects a crossover point along the length of the chromosome. The genetic characteristics are then exchanged across the pair of chromosomes following the cross site, in the hope of generating better off springs. In variation to crossover that performs the exploitation of the present population, the mutation operator explores the entire population and tries to bring forth any possibility of improvement in the search that has largely connected. GA operators help in improving the quality of the solution with every successive generation, therefore increasing the probability of finding global optima.

III. APPLICATIONS OF SOFT COMPUTING FOR RAINFALL RUNOFF MODELING

A. Fuzzy Logic applications

FL is an easier way of developing rainfall-runoff model based on the linguistic variables which governed by highly complex linear and non-linear hydrological processes. Hundecha et al. [6] employed fuzzy rule based routines for generating runoff from precipitation. The methods were applied to modular, conceptual and semi-distributed model to prove the effectiveness of FL. Nayak et al. [7] used fuzzy computing for real time flood forecasting. The study proved that fuzzy models have the potential to simulate the unknown relationships between the hydrological data. Fuzzy model study the sensitivity of prediction and assess the deal between the precipitation, upstream runoff and total watershed runoff. FL for rainfall-runoff modelling using soil moisture measurements presented by Casper et al. [8]. Fuzzy rule-based system (FRBS) using the Sugeno-Takagi-Kang approach has been developed using rainfall and soil moisture as input parameters to predict the actual discharge at the catchment area. The study proved that the measurements of soil moisture at particular locations could be used as description for the actual system state, allowing for an entirely data driven prediction of the runoff using rainfall. Wang and Altunkaynak and Wang [9] compared the FL with storm water management model (SWMM) frequently used for rainfall-runoff simulation. The study proved that FL model outperformed the SWMM for large rainfall. However, fuzzy logic is subject to limitation of the methodology whereas the SWMM can produce the time varying hydrograph.

B. Artificial neural networks applications

ANN has been a best choice among the various soft computing techniques for modelling non-linear complex rainfall runoff phenomenon. Tokar and Johnson [10] used neural networks for modelling daily runoff as function of daily snowmelt, temperature and precipitation. The study proved that ANN model provided better prediction accuracy than compared with conceptual and regression models. The study also showed that for obtaining sufficiently reliable predictions, the data should characteristic of the watershed and the climatic conditions. Rajurkar et al. [11] employed the daily rainfall and runoff data for Narmada catchment for development of a model for transforming rainfall into runoff. A linear multi-point single output model (MISO) has been effectively used for deriving the response function relating rainfall to runoff. MISO model predicted runoff is then improved by a multi-layer feed forward neural network. The study showed that combination of MISO with ANN led to better prediction accuracy than non-linear and linear MISO models. Wilby et al. [12] developed evaporation, precipitation and discharge data for progressing neural network and conceptual rainfall-runoff model. Different experiments were conducted with successively decreasing amount of information, to determine the extent to which neural networks can safely assimilate the hydrological processes. The study proved that a neural network with seven input nodes and three hidden nodes were able to grasp the behaviour of the conceptual model. The correlation analysis proved that the two hidden nodes corresponded to the quick flow and base flow components whereas, the third hidden node represented the seasonal variations in the soil moisture deficit.

Riad et al. [13] developed rainfall-runoff data at the Aghbalou station for constructing rainfall-runoff model using ANN. The inputs of the ANN of rainfall and runoff for the previous seven days as well as the rainfall expected for the day. The expected runoff for the day formed the output for ANN. The overall rainfall-runoff data of last seven years were divides into two parts. Rainfall-runoff data for six years composed the training data and the data for one year was used for testing the trained ANN. The performance of ANN was compared with multiple linear regression (MLR) model. The values predicted by ANN were found to be in close agreement with the observed data. The study proved that ANN has a good ability of modelling complex non-linear hydrological processes. Jeong and Kim [14] employed two neural network models viz., ensemble neural network (ENN) and single neural network (SNN) for providing better rainfall-runoff simulation. The study showed that ENN provided the least root mean square error (RMSE) and therefore performed efficiently than SNN. ENN compared with existing rainfall-runoff simulation model TANK based on certain probabilistic accuracy measures, ENN outperformed the TANK model in most of test cases. Abrahart and See [15] explored the applicability of neural networks for modelling non-linear rainfall-runoff relationships. The neural network modelling provided better results for producing non-linear transformations and can be helpful in case of scanty or difficult to obtain data-sets. Kalteh [16] developed rainfall-runoff model using ANN and compared that with the Garson's algorithm, Neural Interpretation Diagram and randomization approach. The study showed that ANN not only effectively learns the complex processes but also capable an understanding about the complex relationships within the processes. Solaimani [17] employed three different training algorithms for developing ANN models for forecasting rainfall. Efficiencies of Lavenberg-Marquardt, conjugate gradient and gradient descent training algorithms were compared. Monthly climatic and hydrometric data were used for development of the ANN model. The study showed that by combining computational efficiency with input nodes that describe the hydro-climatologic variables, an improvement in ANN prediction can be achieved. Machado et al. [18] used three ANN models prepared on the basis of monthly rainfall-runoff compared with the monthly time scale conceptual model IPHMEN. Back-propagation algorithm was used for training the neural network. The IPHMEN conceptual model was compared trained ANN during calibration and validation phases. IPHMEN model provided inconsistent results with large deviation of computed flows. The study proved that the trained ANN has better potential for accurately predicting the observed flows. Chen et al. [19] employed the rainfall-runoff model for typhoon using ANN. A three-layered neural network was constructed three rainfall stations of hourly rainfall data as inputs for modelling hourly flows of a station. The study proved that regression analysis is suitable for slight variation in data. But for substantial variation in data, ANN provided a promising methods. ANN proved to be easy and flexible to perform computational tool for modelling the complex hydrological phenomenon. Phukoetphim et al. [20] developed three different approaches viz., neural interpretation diagram, garson's algorithm and sensitivity analysis to understand the contribution of input variables and knowledge extraction approaches to neural network modelling of rainfall-runoff relationships. The study proved that the complexity in the rainfall-runoff models can be sufficiently reduced by removing the least significant input variables.

C. Genetic Algorithms applications

Genetic algorithms optimization and stochastic search has been harnessed for calibrating the rainfall-runoff models. Galeati and Franchini [21] developed GA for calibration of conceptual rainfall-runoff models. The parameters which cause minimum deviation were concluded using GA. Daniell and Ndiritu [22] presented an improved GA based on automatic search space shifting to achieve automatic search space reduction to effect timetuning, hill-climbing and the use of not dependent subpopulation search coupled with shuffling to deal with the occurrence of multiple regions of attraction for rainfall-runoff model. Cheng et al. [23] employed a parallel GA methodology for calibrating rainfall-runoff models influenced by a substantial number of parameters. The problem was partitioned into number of problems and run on number of computers through parallel genetic algorithm (PGA). The study proved that PGA methodology efficiently improves the time taken for produces a stable solution and optimization of solution. Li et al. [24] presented an improved GA to tackle the problem of inaccurate coding and low precision. An corrective objective function was used in the study to balance the hydrological elements present in the constraint relations, for accurate prediction of hydrological flow process. An automatic calibration tool to calibrate the ARNO conceptual rainfall-runoff model presented by Khazaei et al. [25]. For this a simple genetic algorithm was employed. The methodology provided sufficiently accurate predictions during calibration and validation and hence can be applied for continuous rainfall-runoff simulation.

D. Hybrid soft computing applications

There has been enormous inclination towards hybrid soft computing techniques in the past few years for dealing with problems meets in real life. The hybridization of the techniques covers up the limitations of the individual ones and leads to development of robust computational methods. Jain and Srinivasulu [26] compared the back-propagation neural network trained using real coded GA (RGA) and self organizing map (SOM) classified input-output rainfall-runoff data. The study proved that ANN trained using a RGA provided accurate generalization of the non-linear and complex rainfall-runoff process. Nasseri et al. [27] represented hybridization of ANN with GA for short term rainfall forecasting, by utilizing the global search ability of GA for selection of suitable input parameters and optimal neural network architecture. The study proved that hybrid ANN outperformed the prediction ability of multi-layer perceptron (MLP) neural network.

Talei et al. [28] employed Adaptive Network-based Fuzzy Inference System (ANFIS) for event-based rainfall-runoff modelling. ANFIS results were compared with an established physical-based model. The study showed that ANFIS is comparable to the physical model and is found to give accurate peak flow estimation compared to the physical model. Dorum et al. [29] used the rainfall-runoff data using ANN and ANFIS methods. A multi regression model was also used to compare the results obtained from ANN and ANFIS models with traditional methods. The study showed that ANN and ANFIS models can be used in calculation of rainfall runoff relationships of susurluk basin except peak situations. Asadi et al. [30] showed GA for evolving the weights of the neural network used for rainfall-runoff process modelling. The data were preprocessed by input variable selection, data transformation and data clustering for improving the prediction accuracy of the model. The study showed that by adopting this methodology, faster training, high degree of accuracy and good adaptation of nonlinear complex relationships between rainfall and runoff is achieved.

IV. CONCLUSIONS

Rainfall-runoff interactions and their accurate assessment form an integral part of any hydrological study. The ambiguous, complex and non-linear factors affecting the rainfall-runoff relations, makes its mathematical modelling a tedious task. Such conditions demand for nature inspired computational tools to deal with the real life phenomenon which are always subjected to ambiguous, imprecise and noisy information. Soft computing through combination of statistical, optimization and probabilistic techniques into the computing environment has presented a suitable replacement substitute to traditional mathematical techniques. Fusion of these methods has given a new dimension to computing, in which human behaviour resembling capability of intuition, reasoning, consciousness and wisdom can be combined through software programming. Though these computational techniques do not offer exact answers, yet they provide a sound decision oriented solutions to the problems influenced by noisy and vague information.

The review paper has presented a brief introduction to three major soft computing techniques viz., Fuzzy Logic (FL), Artificial Neural Networks (ANN) and Genetic Algorithms (GA) and their application in rainfall-runoff modelling. The review has shown that by applying these techniques the complex analytical method can be avoided to certain extent. ANN learning from historical or experiential data can form a backbone for unknown, complex and difficult to describe functional relationships between rainfall and runoff. GA through its optimisation ability and stochastic search can be used for calibration of these rainfall-runoff models. FL simulation of human reasoning and decision making ability can be exploited for modelling problems governed by vague, inexact and imprecise information. The paper has also significantly attended the hybrid soft computing techniques. The complementing nature of soft computing approaches has given the benefit of deriving the best from these techniques to the user. Hybridization is a technique of improving the original procedures and covering up the limitations of the individual methods and therefore opens up the avenues for solving new problems. It is hoped that the combine use of soft computing will surely be step beyond the cognitive skills implicit in human beings.

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