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Artificial Intelligent Techniques in Rainfall-Runoff Process

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Abstract: The use of rainfall-runoff (R-R) models in the decision making process of water resources planning and management has become increasingly indispensable. R-R modeling is still one of the most difficult issues in hydrological sciences due to the dynamic, uncertain and non-linear characteristics and relationship among the processes. In the broad sense R-R modeling has started at the end of 19th century and till today various types of models have been developed and applied based on their mechanism, input data and other modeling requirements. Fairly a large number of empirical, conceptual and physically based models having their own merits and demerits have been developed and applied to map the R-R relationship. In the real world, temporal variations in data do not exhibit simple regularities and thus R-R process is difficult to analyze and model accurately by conventional modeling approach. Hence R-R modeling approach has been shifted from process based technique to data-driven based Artificial Intelligent (AI) techniques like Artificial Neural Network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS), Genetic Programming (GP) and Model Tree (MT). The primary aim of this paper is to highlight the merits and demerits of those recent works on R-R modeling using AI techniques. As a value addition, a graphical user interface (GUI) has been developed as a decision support system.

Key words: Rainfall-Runoff process · Artificial Neural Network · Adaptive Neuro Fuzzy Inference System · Genetic Programming · Model Tree

INTRODUCTION

Rainfall-runoff (R-R) modeling is a very important research topic in the water resources planning, management and development which is being used among hydrologists and the engineers for a very long time. The determination of R-R process over catchment is a complex hydrologic phenomenon due to the underlying non-linear sub processes and well explained by many authors [1-3]. Over the last 25 years, a large number of studies have been undertaken to enhance the understanding of R-R process. The R-R modeling techniques can be broadly classified into two classes: the theory-driven (conceptual and physically based) approach and the data-driven (empirical and black box) approach [4]. Although the theory-driven models provide reasonable accuracy, the implementation and calibration of such models can typically present various difficulties [5] requiring sophisticated mathematical tools and some degree of expertise. Conventional systems theoretic models like autoregressive models and their variations [6] suffer from being based on the linear systems theory and may only be marginally suitable in capturing the highly complex, dynamic and non-linear rainfall-runoff process [7]. Owing to the difficulty associated with parameter optimization in non-linear systems, the development of non-linear system theoretic models are very limited [8]. It is reported that most of the hydrologic models are still far from perfect and hydrologists need to put the models in better compliance with observations prior to use in forecasting [9]. In this context, data-driven models (DDM), belongs to Artificial Intelligent (AI) techniques which discover relationships from input-output data without having the complete physical understanding of the system, may be preferable.

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Artificial Intelligent Techniques in Rainfall-Runoff Modelling: In recent years, many AI techniques have emerged to overcome the shortcomings of conventional modelling technique. These AI techniques are based on extracting and re-using information implicitly contained in hydrological time-series without directly taking into account the physical laws that underline the process [10]. During the last few decades the area of empirical modelling received an important boost due to development in the area of machine learning and classified separately as AI modelling techniques [11]. These models have been developed with the contributions from artificial intelligent, data mining, knowledge discovery in databases, computational intelligent, machine learning, soft computing, pattern recognition, etc. AI or soft computing is an emerging field that consists of complementary elements of neural computing, fuzzy logic, evolutionary computation, machine learning and probabilistic reasoning. In the last decade, artificial neural network (ANN) has been successfully employed in modelling a wide range of hydrologic processes especially rainfall and runoff due to their ability to model non-linear system efficiently [12-16]. It is proved that the soft computing techniques are excellent to model the complex R-R process and is better than the conventional modeling techniques. These techniques improve the model performance, help faster model development and calculation times [17-20]. Even though many types of R-R forecasting models are available, the problem of accurate estimation and forecast still persist at field level. All the models developed in the laboratory need to be tested and used in field, where field engineers would also be able to understand, handle and apply the model. With the advancement of computer facilities, there is a wide scope for developing site-specific graphical user interface (GUI) interactive software as a decision support system for field engineers.

Artificial Neural Networks: ANN is essentially a group of interconnected computing elements, or neurons that has certain performance characteristics resembling biological neural networks of the human brain [21]. ANNs were proposed approximately 75 years ago by [22] inspired by a desire to understand functions of the human brain and to simulate their functioning [23-25]. Werbos [26] proposed the first back propagation (BP) ANN in 1974. Nevertheless, the powerfulness of BP networks was not recognized until [27] modified the architecture of BP networks. These efforts made BP networks gain attention and become the most popular network-training algorithm. With all the efforts researchers have developed more sophisticated ANN algorithms. ANNs have been consequently developed into a promising computation tools which can be used to solve complex problems such as pattern recognition, non-linear modelling, classification and others [25]. ANN models are able to learn the underlying patterns between the inputs and outputs. This feature makes ANN suitable for modelling natural systems where complex relationship exist between the inputs and outputs and data are often incomplete or noisy [19]. ANNs are inherently non-linear, generalisable and noise tolerant. They have been found to be a robust tool for simulating many non-linear hydrologic processes, such as RR, stream flow, water quality, reservoir operation, inflow forecasting and others [8, 28].

Neuro-Fuzzy Models: Fuzzy theory is extremely effective in handling dynamic, non-linear and noisy data, especially when the underlying physical relationships are not fully understood. Fuzzy theory has proved to be a very attractive tool enabling to investigate problems that are uncertain and in case of vague data. Fuzzy logic and fuzzy set theory, founded by [29] are used to identify the characteristics of decision making through a set of logical rules. Sugeno and Yasukawa [30] developed a fuzzy logic based approach to qualitative modeling and have proposed the use of fuzzy clustering method for structure identification of models. The past decade has witnessed a few applications of fuzzy logic approach in water resources [31-35]. However, the applicability of ANN and fuzzy models suffered from several weaknesses of the individual models. Therefore, combinations of neural networks with fuzzy systems have been proposed, where both models complement each other [36]. This approach has been tested and evaluated in the field of signal processing and related areas, but researchers have begun evaluating the potential of this neuro-fuzzy hybrid approach in hydrologic modeling studies and found to be successful [37-40].

Genetic Programming: In spite of various advantages of applying ANN and ANFIS technique, transferring the knowledge particularly the relationship between input and output to the field engineers is rather limited. Hence researchers are seeking other data based techniques where the knowledge can be extracted very easily. The Darwin's natural selection theory of evolution based genetic programming (GP), is relatively a new technique and is the member of evolutionary algorithm family [41]. GP is an inductive form of machine learning as it evolves a computer program to perform an underlying process defined by a set of training samples [42]. GP has been successfully applied to complex non-linear problems and its solution describes the input-output relationship. Linear genetic programming (LGP) is a recently emerged subset of GP. Comparing LGP to the traditional Koza tree-based GP, there are some main differences such as the graph-based functional structure of LGP, evolvement of these programs in an imperative programming language (like C/C ++) [43] and machine code [44] rather than in expressions of a functional programming language (like LISP) and the coexistence of structurally ineffective codes with effective codes in LGP. The name 'linear' refers to the structure of the (imperative) program representation and does not stand for functional genetic programs. LGP represents highly non-linear solutions in this meaning [43, 44]. The main advantage of LGP is its ability to produce models that build an understandable structure given that the LGP model exhibits a great potential to screen and prioritize the input variables. The various LGP parameters involved are population size, mutation rate and its different types (block mutation rate, instruction mutation rate and data mutation rate), crossover rate, homologous crossover, function set, number of demes and program size. LGP provides inherent functional input-output relationships as compared to traditional black box models and found to be more suitable in developing a physical relationship between a set of input and output data in the form of a computer program [45, 42].

Model Tree: Model tree (MT) is a machine learning technique based on an idea of splitting the input data into sub areas and building "local" linear regression models in each of them. Model trees combine a conventional decision tree with the possibility of generating linear regression functions at the leaves. This representation is relatively perspicuous because the decision structure is clear and the regression functions do not normally involve many variables. The M5 tree is a piecewise linear model and hence takes an intermediate position between the linear models as ARIMA and truly non linear models as ANNs. It means that input space can be divided into a number of subspaces or regions for each of which a separate specialized model is built [46]. Such models are called experts and the combinations of experts are called a committee machine. The derails of M5 model tree is shown in Figure 1.

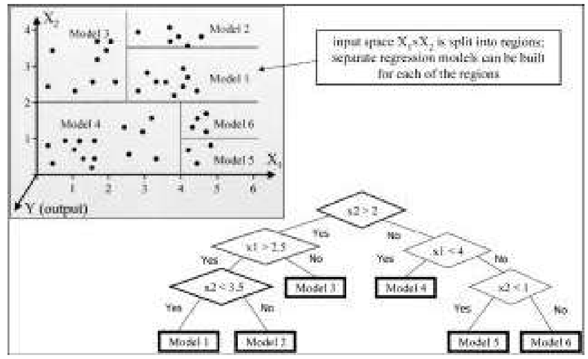

Fig. 1: Example of M5 Model Tree [47]

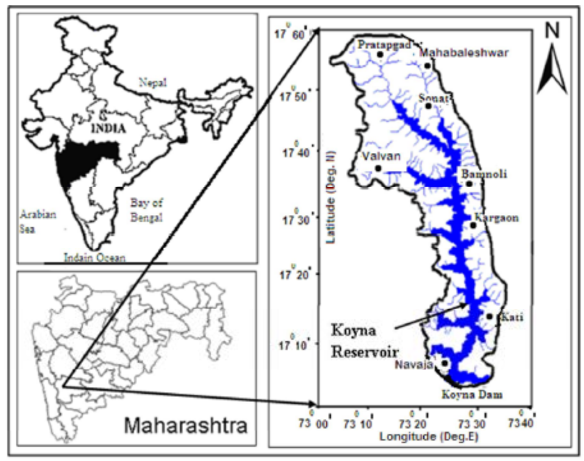

Fig. 2: Location of Koyna watershed, Koyna reservoir and the rain-gauge stations [48]

Study Area: The study area selected for the present study is Koyna watershed, situated on the West Coast of Maharashtra, India, lies between the latitude of 17°00'N to 17°59'N and longitude of 73°02'E to 73°35'E. The location of the study area along with nine rain-gauge stations in Koyna watershed is shown in Figure 2. The Koyna project is a multipurpose project, but primarily designed as a hydro-electric project that supplies hydro-electric power to Maharashtra state, India with an installed capacity of 1920 MW. Koyna watershed has an elongated leaf shape, about 64 km in length and about 13 km width with an area of 891.78 km^2. Nearly 99% of the annual rainfall in this basin occurs during south-west monsoon (June to October) and varies from 2972 mm to 6694 mm annually over the valley.

Graphical User Interface: Thus in the present study, this input and output relationship given by LGP in the form of C++ program has been used in the development of GUI software to be used in the field. In order to implement

Fig. 3: Splash Screen of KRIFS

Fig. 4: Main module of GUI

the developed reservoir runoff prediction models in real life at Koyna reservoir a GUI has been developed as a decision support system and is named as Koyna Reservoir-Inflow Forecasting System “KRIFS”. “KRIFS” is a user friendly graphical interface developed using Microsoft’s Visual Studio.NET as front end and Microsoft’s Access 2003 as back end. A rich look of the software and the charting controls are developed using DevExpress, DXperience 9.1.5. This software is developed with intent to forecast daily and hourly inflow into the Koyna reservoir by using the data from access Table and passing it through the developed rainfall-runoff (RR) models in this study. The user can enter the input data, forecast the inflow, compare, print or save the results in tabular as well as graphical form in various file formats. Figure 3 presents the sample screen of the main module of the GUI. This GUI is specifically designed such that even beginners can handle the software. All the procedures and tools required to prepare the input data, run the model and visualize the results are included in the module. As the splash screen window is clicked, main window or the functional area of the software begins. It is a menu driven single document interface (SDI), i.e. user can work on one window at a time, thus making the software easy to handle and the main window appears as shown in Figure 4.

CONCLUSION

Thus various tools are used to model the relationship between rainfall and runoff. Some of the recent soft computing models which have been proved as better tools are ANN, ANFIS, GP and MT. Even though, large work has been carried out on ANN, ANFIS, GP and MT, they do have many attractive features, but they suffer from some limitations. The difficulty in choosing the optimal network architecture and time-consuming effort involved thereof is one of the key issues. In other words, the user has to predetermine the structure of the ANN network and the training algorithm to optimize specific parameters of the network. On the other hand the advantage of GP is that optimize both the structure of the model and the parameter. It is not expected that a “single model’’ will perform better than the others for all types of catchments and under all circumstances. Also there is a shift in the use of single approach such as ANN, ANFIS and GP etc. to the hybrid use (combination of more than one technique). These hybrid approaches like combination of conceptual and soft computing techniques give better prediction. However GP provides a program relating input and output variables, it has the advantage to provide an inherent functional relationship explicitly over ANN. A key advantage of GP as compared to traditional modelling approaches is that it does not assume any *a priori* functional form of the solution. A major advantage of the GP approach is its automatic ability to select input variables that contribute beneficially to the model and disregard those that do not. GP can thus reduce substantially the dimensionality of the input variables. Model trees have several advantages since it can be trained faster and has transparent results which are easily understood by the users, unlike ANN. The LGP model has edge over the all the models and hence the output of LGP model resulted in the form of C++ program has been used in development of GUI software for real-time reservoir runoff prediction.

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