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# The River Runoff Forecast Based on the Modeling of Time Series

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**Abstract**—Discussed are the methods of stochastic modeling the precipitation runoff time series and fields. Discussed are the structural attributes, scope, boundary conditions and various improvements of the univariate Autoregressive Integrated Moving Average (ARIMA) and the multivariate Transfer Function Model (TFM). Presented are the comparative studies of existing models of the neural network. An attempt is made to investigate various geographical locations and various applications of the river runoff forecast.

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## 1. INTRODUCTION

Right through the history of mankind, we learnt that precipitation and consequent river runoff brought myriad wealth and prosperity. However, excess and uncontrolled rainfall and runoff always resulted in tremendous losses and untold sufferings to people. Focused efforts are required to reduce the risk of river runoff and utilize it for the benefits of society [36]. Generation of the systems of river runoff forecasting and warning is one solution which leads towards the above said objective [6, 97]. An accurate forecasting of peak values of precipitation and resulting river flow plays an important role in hydroinformatics for the flood disaster management and for assessing of the risk of failure of dependable capacities of hydraulic structures [79, 91]. Suitable modeling of temporal variations of precipitation and associated river runoff can be used for flood and drought studies, for optimal operation of reservoir systems, for planning and design of water supply and hydraulic systems, for inventing alternative water supply strategies, and for many other purposes [83].

Papers [71, 98] discuss the details of the models of various types that deal with the spatiotemporal variations of precipitation runoff. These models have various degrees of complexity, capabilities, structure, strength and limitation, and each has its own objecive, its advantages and disadvantages. Among various methods of precipitation runoff calculation, the time series analysis suggested by Box and Jenkins [12, 13, 37, 40] is worth mentioning.

The objective of this article is to study various stochastic models of precipitation runoff based on the analysis of time series and used for the estimation and forecast of river runoff in various watersheds. The attempt is made to take precipitation in account during the forecast of river runoff. Various modifications of models and methods of stochastic analysis are considered in order to provide more reliable and accurate calculation of precipitation runoff.

## 2. STOCHASTIC NATURE OF RAINFALL RUNOFF PROCESS

The description of river runoff variations is most often based on stochastic methods that use ARMA, ARIMA, transfer functions, neural networks and system identification [11]. Paper [83] suggests to treat the stream flow process as the integration of stochastic and deterministic components. Dynamic relationships are described using transfer functions whereas the stochastic component explains the anomalies of the systems that do not seem to be inherently stochastic. For the purposes of modeling river runoff is assumed to be either a totally linear stochastic process or fully nonlinear deterministic chaos [33, 44].

A stochastical model is structurally adapted to local conditions and hydrological data in real time. Using the stochastic model allows understanding the physics of the process through the data analysis and elucidating it through the interpretation of data. In the analysis of stochastic time series, the important systematic patterns and trends of a phenomenon are recognized and separated, and the random fraction of data which is also called noise, is left out. The structure of a model should be simple (with the least possible input requirements), and the approach towards the data processing should ensure the accurate result. The analysis of stochastic time series allows exploring possible realistic scenarios of a given precipitation runoff system using suitable simulation techniques [51].

Extensive reviews of the several classes of stochastic models proposed for operational hydrology can be found in [15, 55]. In this paper we shall discuss only the Autoregressive Integrated Moving Average (ARIMA) models developed using the analysis suggested by Box and Jenkins [12–14]; these models are the basic tool in the today's modeling of time series [82].

## 3. METHODOLOGY

### *3.1. The ARIMA Models*

The earlier studies of the precipitation runoff process consisted of the synthesis of available annual hydrologic data on time dependent or independent stochastic components and the identification of trends and cycles. A lot of studies applied simple and multiple regression techniques before 1970. Kisiel [48] first applied the procedures of autoregression and moving average in the time series of hydrological data. Later, in about four decades, stochastic models (belonging to the ARIMA class) became the main choice of the researchers of river runoff forecasting.

In 1970 and 1976 Box and Jenkins presented an orderly, well demonstrative and comprehensive approach that is the basic tool in the today's analysis of time series aimed at the modeling of stationary and non-stationary time series of runoff. Since then the methods of time series have been used more and more widely for the modeling of precipitation runoff. In order to characterize precipitation and runoff, the model of stochastic time series can be divided into two groups. One is essentially stochastic univariate (where only one independent variable is used) and multivariate (where more than one series are used). Stochastic univariate series are modeled using ARIMA while the impact of more than two series (where dependent series are associated with other series through random errors) is incorporated using transfer function models (TFM). The concept of analytical solution of modeling stochastic time series for the analysis of both univariate (ARIMA) and multivariate (TFM) time series was suggested by Box and Jenkins and was further promoted in [14, 27, 60, 101, 105].

### *3.2. Univariate ARIMA Modeling*

The Box–Jenkins approach to the modeling of the univariate stochastic time series of river runoff includes four steps: identification, estimation, diagnostic verification and the forecast. Data series should be stationary in order to fit the model of stochastic time series; i.e., the mean and variance should be constant in time. Therefore, at the stage of identification data series are analysed in order to remove any trend, seasonal, cyclic and periodic components; it is accomplished using the appropriate methods of transformation (standardisation) or filteration as discussed further [40]. The next step is to plot the autocorrelation function (ACF) and partial autocorrelation function (PACF) in order to identify a tentative order of the model and its parameters. The ARIMA model is described with the following equation

$$ {}_{p}(B)(1 \quad B)^{d} \quad {}_{p}(B^{s})(1 \quad B^{s})^{D} y_{t} \qquad {}_{q}(B) \quad {}_{Q}(B^{s})a_{t}, \tag{1}$$

where (B) and (B) are non-seasonal polynomials of the order $p$ (auto regression), $q$ is the moving average, and $d$ is differencing; $B^{s}$) and ($B^{s}$) are seasonal polynomials of the order $P$ (auto regression), $Q$ is the moving average, $D$ is seasonal differencing, and $S$ is the length of the season. Random errors $a_t$ are assumed to be independently or identically distributed with the constant (or zero, = 0) mean and the constant variance .

Once a tentative model is identified, the values of the model parameters are estimated using the method of least squares, and then diagnostic verification of the model adequacy is accomplished. This process is repeated until the satisfactory model is finally selected. Then the forecasting model is used to compute the selected values and forecast values.

The temporal and spatial variability that characterizes a river system makes the forecast of river runoff a very demanding task. In the most suitable and reliable forecasting model, residuals (difference between observed and forecasted values) should satisfy the requirements of the white noise process, i.e., a residual should be independent and normally distributed around the zero mean. The independence of the model forecast is tested by the Ljung–Box–Pierce statistics, and the adequacy of the model (goodness of fit) is evaluated by the Akaike information criterion [5, 17, 84].

ARIMA models provide great flexibility and potential for modeling the time series of precipitation runoff. ARIMA models were used jointly with such models as nonlinear regression (NLR), multiple linear regression (MLR), exogenous input data (ARMAX), and variations of autoregressive moving average (VARMA), etc. This resulted in the development of the improved and efficient model of the mixed ARIMA class including NLRMA, MLRMA, ARMAX, and VARMA, respectively [65, 83, 103]. Another class of the ARIMA models of river runoff includes derived linear models such as ARMA (Auto Regressive Moving Average), SARIMA (Seasonal ARIMA) and PARMA (periodic ARMA), etc. [50, 61, 95]. The hybrid class of stochastic models of ARIMA class that were widely used in the past for modeling hydrologic time series, includes auto regressive models, the fractional model of Gaussian noises, moving average models, broken-line models, short-noise models, the model of intermittent processes, disaggregation models, the Markov models, the ARMA–Markov models, and general mixture models [82]. These improved versions of the ARIMA model require less computation time, ensure more accurate forecasts and are useful for real-time forecast of river runoff. However, the applicability of ARIMA models is limited to the basins in which runoff has been measured for a long period and no significant changes in watershed conditions have occurred.

### *3.3. Multivariate Modeling with Transfer Functions*

The river runoff process is the result of several temporal (meteorological processes) and spatial (hydraulic characteristics) factors. This phenomenon can be described as the system of multivariate transfer functions in which the input series exert influence via the transfer function TFM on the output series during the long time period [21, 60]. In the transfer function model, river runoff (dependant variable $Y_t$) is correlated with various temporal and spatial independent variables (represented by different time series $X1_t$, $X2_t$, $X3_t$, etc.); it is also correlated with the error $N_t$ (that cannot be explained by $X_t$) in the following form

$$Y_t \quad X_t \quad N_t. \tag{2}$$

In equation (2) the noise term $N_t$ is considered to be generated by the ARIMA process of the order ($p$, $d$, $q$) which is statistically independent from the input function $X_t$. Equation (2) can be represented as

$$Y_t \quad \frac{(B)}{(B)} X_{t \quad b} \quad \frac{(B)}{(B)} a_t \text{ or } Y_t \quad \frac{{}_0 \quad {}_1 B \ldots \quad {}_r B^r}{1 \quad {}_i B \ldots \quad {}_t B^t} x_{t \quad b} \quad \frac{1 \quad {}_t B \ldots \quad {}_p B^q}{1 \quad {}_t B \ldots \quad {}_q B^q} a_t. \tag{3}$$

Here, $a_t$ is white noise; in the stochastic process of precipitation runoff it is usually assumed to have normal distribution with the zero mean and variance ${}^2_a$.

The application of the TFM procedure usually includes several stages, e.g., tests for stationarity, identification, fitting, and diagnostic checking. First, the structure of the model has to be determined assuming that the distribution of data is normal and estimating the initial values of the parameters related to ACF, PACF and CCF [56]. The cross-correlation and cross spectral analyses show that there is a linear relation between annual cycles and the independent stochastic components of river runoff, temperature, precipitation etc. The estimate of the response function is used to determine the suitable values of operators in the TFM, and the fitness of the preliminary TFM is tested using the Akaike information criterion [5] and the Schwarz information criterion [86].

## 4. SIGNIFICANT STUDIES ON STOCHASTIC PRECIPITATION AND RUNOFF

Below discussed are univariate and multivariate stochastic models of the ARIMA class for estimation and forecast of precipitation and river runoff. This paper does not provide the review of all technical issues associated with the modeling of precipitation runoff. However, attempts are made to cover the most part of problems associated with differences in the capabilities and procedures of modeling. Some comparative studies (with ANN and other conceptual models) were included in the discussion to justify the applicability of various modifications in order to enhance the forecast efficiency.

### *4.1. Univariate Modeling*

Soon after the development of the Box–Jenkins approach researchers started applying other methods of precipitation runoff modeling. McKerchar and Delleur [63] applied seasonal parametric linear stochastic models to account for the variability of data on mean monthly runoff. First studies in this area (forecasting of precipitation and river runoff) are those by Ozis and Keloglu [75] and Graupe et al. [38]; they used the ARIMA methods for runoff simulation in karstic basins of Turkey. Todini [97] used the ARIMA model to generate a unit hydrograph in the form of exogenous variables (ARMAX) in the flood forecasting system based on the Kalman filter.

River runoff is highly dependant on the accuracy of the estimation of meteorological variables (mainly, of precipitation). Therefore Salas et al. [82] and Shiiba et al. [90] have forecasted river runoff in the conjugation with the estimation and forecasts of precipitation and other meteorological parameters that influence the runoff of the main catchment area. Similarly, Chang et al. [23–26] and proposed the Discrete Autoregressive Moving Average (DARMA) model for the short-term forecast of river runoff combining subsequent precipitation and delayed runoff. Noakes et al. [73] developed the periodic autoregressive (PAR) model with seasonally varying order and established the superiority of the PAR model in a course of the comparative study of the runoff forecast using the ARIMA and SARIMA models for the mean monthly runoff of thirteen rivers of North and South America.

Chiew et al. [30] simulated daily, monthly and annual river runoff in eight unregulated catchments using six modeling approaches belonging to three groups: black box models, process models and conceptual models. They concluded that the approach to the modeling of stochastic time series provides better estimates of monthly and annual runoff of rivers in the catchments. In the same year Kuo and Sun [52] demonstrated that the intervention analysis of data on the Tanshui River (Taiwan) runoff caused by typhoon precipitation and similar abnormalities of the weather in the catchment area, has greatly improved the forecast accuracy and confinement of runoff patterns as compared to the traditional ARMA model. Burlando et al. [20], Jakeman and Hornberger [42], and Langu [53] also used the ARIMA processes by means of varying the low-order parameter to model short-term precipitation and runoff; they tried to detect changes in precipitation and runoff patterns. Maidment [59] considered periodic components in river runoff and developed a periodic autoregressive (PGAR) model to simulate the multiple periodic time series of river runoff. Bartolini and Salas [10] and Claps et al. [32] also used periodic variations to obtain more accurate forecast using the stochastic ARMA model.

Adaptation of the modified ARIMA process and the comparison of the forecast results with the alternative model inspired the researchers to continue experiments with the ARIMA method in order to enhance it. At present, the problems of the river flow forecast are tackled using the simple linear (e.g., AR, ARMAX, and the Kalman filter) and seasonal linear (e.g., SARIMA) techniques as shown by Awwad et al. [8], Cheng [29] and El-Fandy et al. [35]. Lardet and Obled [54] and Takasao et al. [94] used both the statistical and stochastic methods to estimate precipitation in real time and predicted the runoff potential of a river using the ARIMA model and the Kalman filter. Porporato and Ridolfi [76, 77] have performed nonlinear analysis of river runoff for flood forecasting to identify the hidden deterministic behavior of the process and to understand the cause and effect relationships in hydrological problems. They concluded that the ARIMA model combined with the nonlinear concept is the best choice for the accurate forecasting.

Weeks and Boughton [104] and Brockwell and Davis [16] demonstrated that the ARIMA model provides better forecast efficiency when using random data even if the input data do not correspond to the Gaussian pattern. Madsen et al. [57] and Toth et al. [99] demonstrated that the efficiency of short-term runoff forecast in real time using the ARIMA model can be improved due to the adoption of suitable techniques of data assimilation instead of the preliminary transforming of data to make them closer to the Gaussian pattern.

Till the 20th century, the ARIMA model and its derivatives such as SARIMA, PAR, etc. were successfully used for the simulation of precipitation and runoff in order to solve various hydrological and water resource problems. It was due to the use of the linear regression. ARIMA models do not allow to identify and, hence, to simulate the intricate characteristics of precipitation and runoff process sufficiently enough. Therefore, in the 21st century researchers shifted their attention to new forecasting methods that enabled analyzing and simulating natural phenomena (e.g., precipitation and runoff) basing on the nonlinear approach. This idea affected the ARIMA processes, and the improvements of the conventional approach can be well understood by the following categorizing the studies on stochastic river runoff based on ARIMA:

—studies based exclusively on ARIMA or on its derivatives;

—real time studies;

—studies using hybrid models;

—comparative studies using models based on the neural network and artificial intelligence.

### *4.1.1. Studies based exclusively on ARIMA or on its derivatives*

Damle [33] applied the methodology of time series data mining (TSDM) to the data on river runoff in order to study the embedding process delayed in time. It was aimed at predicting floods using the univariate ARIMA model. The TSDM combines the methods of phase space reconstruction and data mining aimed at revealing hidden patterns which are capable to predict future events in nonlinear nonstationary time series. Yurekli et al. [110] analyzed daily data on maximum runoff from three gage stations on the Chekerek River in order to simulate monthly maximum runoff using ARIMA stochastic approaches. DeSilva [34] used the model of time series for predicting the runoff of the Kalu Ganga basin (SriLanka). Naill and Momani [70] used the seasonal ARIMA model for predicting monthly precipitation totals at Amman airport (Jordan) in order to estimate future water budget to manage water demand in arid areas; they also determined the peak values of precipitation through intervention analysis. Rabenja et al. [80] forecasted both monthly precipitation and the discharge of the Namorona River in the Vohiparara River basin in Madagascar using ARIMA and SARIMA models; they also concluded that the SARIMA model is more reliable for runoff forecast. Otok and Suhartono [74] forecasted precipitation and consequent runoff in Indonesia and suggested that seasonal ARIMA (SARIMA) models are better to analyze data on seasonal precipitation than ARIMA and TFM; SARIMA models also provide better runoff forecasts. Mauludiyanto et al. [62] modeled tropical rain attenuation in Surabaya (Indonesia) adopting the ARIMA model. The authors of [9, 39, 58, 87] used the stochastic SARIMA model to forecast river flow as the consequence of meteorological parameters (e.g., temperature, humidity, and precipitation) in India (Vellore in Tamil Nadu), Czech Republic, Iran (the Abadeh Station), and Bangladesh (Dhaka), respectively. They compared the results of the forecast with the data of conceptual hydrological model depending on local conditions and suggested that the SARIMA model provides better forecasting results with less complex computation. Nigam [71] developed the runoff forecast model for the perennial Kulfo River in the tropical region of Ethiopia and the seasonal Narmada River in the subtropical region of India using the ARIMA model. It is shown that ARIMA model provides better forecast for the perennial river and it is the quality of data (data with least perturbations) rather then their length ensures better results. Meher and Jha [64] have developed the general ARIMA model for simulating and forecasting mean precipitation using Theissen weights and mean precipitation for 38 rain-gage stations located in the Mahanadi River basin in India. Modarres and Ouarda [66] used the model of generalized autoregressive conditional heteroscedasticity (GARCH) to analyse runoff series in nonlinear manner and compared the results with the ARMA model. They also suggested various parametric criteria for evaluating the results of runoff forecasting through the model.

### *4.1.2. Real time studies*

In the studies dealing with real time forecasting of runoff, the model automatically generates the online forecast of river runoff with the varying dynamics of river influence. In these studies the way of obtaining input data for the model and the quality of data are significant for achieving accurate results. Shiiba et al. [89] and Young [108] designed the automatic precipitation–runoff model that depends on local conditions and is capable of calibrating input parameters. They concluded that overparameterized complex models cannot be identified with sufficient accuracy, hence, relatively simple models are more functional. Tachikawa et al. [93] developed the stochastic model of real-time prediction of precipitation runoff based on the analysis of the frequency distributions of the prediction error. Bruen and Yang [19] and Yu et al. [111] proposed a scheme that combined the chaos theory and regression analysis to predict the daily discharge in rivers.

### *4.1.3. Studies using hybrid models*

Tseng et al. [100] proposed a hybrid forecasting model which combines the seasonal model of time series (SARIMA) and the models of back propagation in the neural network (BP) known as SARIMABP which can be used to forecast river runoff series. Broersen and Weerts [18] studied the possibilities of the automatic error correction in the time series of precipitation runoff for flood forecasting. They developed a computer program called ARMAsel using the MATLAB software for the detection and correction of outliers in univariate stochastic data. In this program past error signals were chosen to give the best predictions during sudden and abrupt changes in runoff which are the most important for timely flood warnings.

Mohamad and Mojtaba [67] generated a hybrid system using the analysis of neuro wavelet time series and multilayer ANN to forecast the runoff of the Halil River in southern Iran and concluded that the conjuction model significantly enlarges the possibility to forecast maximum runoff. Yoon et al. [107] forecasted monthly hydrological data (precipitation, evaporation, and runoff) in the Andong dam basin using the SARIMA model, conducted long-term simulations of runoff through the forecasted results of the TANK model, and developed another joint ARIMA+TANK model. Basing upon their conclusions, they suggested the models of mid- and long-term runoff forecasts for application to water resources.

#### *4.1.4. Comparative studies using models based on the neural network and artificial intelligence*

Abrahart and See [1, 2] as well as Zaldнvar et al. [112] compared forecasting efficiency of nonlinear (ANN) and linear (ARIMA) models for real-time estimation of runoff in the course of the stochastic study of dynamic routing of floods; they suggested that inaccuracies in the forecasting results are due to the unavailability of representative historical data. A year later Cigizoglu [31], Kim and Valdes [47], and Sana et al. [85] used ARMA and ANN models to forecast river runoff. They suggested the following measures to increase the forecasting accuracy: the use of synthetically generated data, the extension of input and output data sets in the training stage, the use of delayed response variable, the use of transformed data, and the introduction of periodic components to the input layer.

Castellano et al. [22] and Kihoro et al. [46] compared the ANN and ARIMA models using river runoff data at various time scales (daily, monthly, quarterly, and annual) and the model algorithm; they confirmed the supremacy of the ANN model over the ARMA model when applied to runoff forecast. Kisi [49] and Mohammadi et al. [68] also compared ARIMA and ANN methods for in order to estimate the efficiency of the runoff forecast. Somvanshi et al. [92] studied behavioral patterns of precipitation basing on past observations and using ARIMA and ANN. In order to increase the prediction efficiency they used data on mean annual precipitation in the Hyderabad region (India) obtained in 104 years, from 1901 to 2003. The models were trained basing on the data on annual precipitation for 93 years. Karim et al. [45] forecasted daily river runoff of the Black Water River and the Gila River in the USA and enumerated the advantages of the ANN process over ARIMA models, namely, less computational difficulties in the estimation of the process parameters, smaller effect of uncertainty and outliers in the measurements etc. Reddy et al. [81] modeled the precipitation–runoff process by the linear autoregressive (ARX) and ANN model. They found out that the quality of runoff simulation by the ANN model can be improved by introducing the residuals of ARX models as inputs in the ANN model.

Wu et al. [106] have studied the quality of five data-driven models of ARMA, K-Nearest-Neighbors (KNN), Crisp Distributed ANN (CDANN), ANN and Crisp Distributed Support Vectors Regression (CDSVR) with data-preprocessing techniques, namely, the analysis of the singular spectrum and moving average using two real series of monthly data on river runoff. Volkan and Onkur [102] predicted daily mean runoff of the Anamur River using data obtained from 1989 to 2003 by applying the methods of multivariate linear regression (MLR), autoregressive integrated moving average (ARIMA) and the methods of the radial basis function neural network (RBFNN). They suggested that the RBFNN model provided more reliable results than other methods. Abudu et al. [3] compared ARIMA, SARIMA, and Jordan–Elman ANN models for forecasting the monthly runoff of the Kizil River in Xinjiang, China. They failed to reveal significant improvement relative to time series models and suggested that ARIMA and SARIMA models can be used in the forecast of monthly runoff with a simple and explicit model structure; they produced performance similar to those of Jordan–Elman ANN models. Chattopadhyay and Chattopadhyay [28] forecasted the Indian Summer Monsoon Rainfall (ISMR) using the univariate ARIMA model and compared these results with the autoregressive neural network (ARNN) model for the same data. As a result of thorough statistical analysis the supremacy of ARNN over ARIMA model has been established. Sharma et al. [88] first used ANN to generate spatially distributed data on precipitation for various periods and locations at the absence of the Next-Generation Weather Radar (NEXRAD) data, then used the multilinear regression (MLR) and ANN to forecast runoff of the Saugahatchee River runoff in southeast Alabama.

The intuitive consideration of forecasting results using the model based on ARIMA analysis, revealed that this model provides good results for data on mean runoff and consistent random data. However, the loss of physical characteristics increases as included are various input and output techniques and the nonlinear nature of data that are applied to develop more accurate and parsimonious model [98]. Also, the method needs to be improved to be able to accommodate variations of data occurring due to natural or anthropological disturbances and abnormalities. It was noted by the Hsu et al. [41] that the ARIMA models do not describe the nonlinear dynamics of the transformation of precipitation into runoff; hence, they could not always rely on the good performance of the model. The behavioural response functions of other hydrological and site specific factors that make precipitation–runoff processes a complex system, can be expressed by advanced autoregressive models using spectral correlation, cross correlation and the analysis of the transfer function noise. There is a stochastic model developed in this way that includes intricacies affecting precipitation and variables that well express the process of dynamic river runoff. It is called the multivariate ARIMA model or transfer function model [34, 109]. These models are good enough to incorporate the variables of exogenous time series and to include the impact of concerned parameters in order to express the integrated performance of river runoff attributes without the loss of the assumption on linear data. The applications of TFM models in the river runoff forecasting are described below.

### *4.2. Multivariate Modeling*

Thompstone et al. [96] compared ARIMA, Periodic AutoRegressive (PAR), and Transfer Function (TF) models utilizing precipitation and snowmelt inputs, with a conceptual model. They found that the TF model performs better than other models when forecasting quarter-monthly runoff. Yu et al. [109] have applied the transfer function model to the runoff process of reservoir runoff. Awadallah and Rousselle [7] used sea-surface temperature signals of the El Niño–Southern Oscillation (ENSO) as exogenous input variables to develop a TFN model for the forecasting of the summer runoff of the Nile River. They suggested that the ENSO input explained 63% of the variability of summer runoff of the Nile River. Porporato and Ridolfi [78] developed multivariate nonlinear prediction of river runoff based on their studies on the nonlinear river runoff analysis. Mondal and Wasimi [69] proposed a periodic TFN model and applied it to the monthly forecasting of the Ganga River runoff using monthly data on precipitation in northern India. The results demonstrated that the methodology has the potential capability of capturing the seasonally varying dynamic relationship between monthly precipitation and runoff processes. Todini [98] discussed the relative merits of physical and data driven models of precipitation runoff. He recognized that Box and Jenkins approach shows the link between the transfer function model (TFM) and the autoregressive model of exogenous variables (ARX) although it introduces a loss of 'physicality' in the model. Agrawal et al. [4] have modeled and forecasted runoff and sediment from the Vamsadhara River basin (situated between the Mahanadi and Godavari River basins in South India) during the monsoon period for daily and weekly time periods using the model of back propagation in artificial neural network (BPANN). The models with the single input and linear transfer function (SI-LTF) for runoff and sediment yield forecasting were more efficacious than the multi input linear transfer function (MI-LTF) and the ANN model. Nigam [71] developed the TFM model for predicting river runoff of the tropical and subtropical Kulfo River in Ethiopia and the Narmada River in India in conjuction with data on precipitation in the river catchment area. TFM performed equally well for both cases.

## 5. DEVELOPMENT PROSPECTIVES

The system of decision support in real time may be developed for emergency flood warning, planning hydraulic structures and estimation of losses.

The stochastic model can be used in conjunction with Numerical Weather Prediction (NWP) models, artificial intelligence models etc. to predict both the time and magnitude of floods in the best way. This will help to alert in real time and to plan loss mitigation.

The use of multiple parameters related to the depth of a river, the subsurface water level, snowmelting, surface (basin) characteristics etc. may be tried for higher prediction accuracy. The precipitation runoff prediction may be experimented with different time delays in order to observe the effect of elapsed time on the prediction accuracy. A multivariate integrated model of time series may be experimented for modeling the phenomenon of translation and rotation of precipitation fields.

Stochastic forecast modeling requires that design data be trained depending on local conditions (not according to the general blueprint). Therefore, there is a need to improve the stochastic ARIMA process for assimilating all-purpose data on precipitation runoff.

The prediction results from Time Series Data Mining can be used as a tool for making decisions for the authorities who are responsible for planning and control.

Application and incorporation of the Fourier analysis, spectra analysis, regression analysis etc. can be enhanced due to the effective use of ARIMA models in order to analyze large data sets of precipitation runoff events using readymade software, e.g., MATLAB, SPSS, SAS, etc.

## 6. LIMITATIONS OF STOCHASTIC MODELS OF PRECIPITATION RUNOFF

River runoff event is a complex process which is mostly governed by nonlinear patterns. Since the ARIMA model of stochastic process is linear, it cannot represent the nonlinear dynamics inherent in the transformation of precipitation to runoff. Therefore, the quality of the ARIMA analysis results is not always satisfactory.

ARIMA models are highly senstitive to the pattern of data, breach of stationarity, variance, outliers, missing observations etc. that all affect the forecast performance. Also, the ARIMA processes are skilled to capture past trends but for some intervals only. Therefore, in the stochastic ARIMA analysis the structure of the model is designed to encapsule what occured in the past supposing that no change will occur in the future. However, this is not true for the hydrological domain. As the ARIMA processes do not target future outcomes unlike the ANN method, all these reasons limit the efficiency of the forecast by the ARIMA models to a great extent. Some boundaries in the ARIMA process arise due to the characterizing all data on time series observations, the requirments to the stationarity of time series, to the normality and independence of residuals. Also the ARIMA process lacks the physical interpretation of the precipitation runoff phenomenon.

In order to include the dynamics of the precipitation runoff process, the univariate ARIMA process is modified to the Transfer Function Model in which the correlation among meteorological variables and runoff could be estabilished using cross correlation. The transfer of the attributes of dependant series is also possible but this makes the TFM process lengthy and computationally hard.

It could be deduced from the above discussion that over the years the ARIMA process was not improved enough to remove its shortcomings. Researchers introduced many modifications for higher efficiency of the forecast but their endeavor included alteration of input data rather than strengthening the process to adapt variations in data. It is also experienced that the ARIMA processes do not answer the present days requirements of precipitation runoff forecast in real time because they are mostly site dependant and require labour to design a parsimonious model. These methods are suitable for short-term prediction for next few periods. The prediction accuracy decreases as the prediction period increases. Also, these models are prone to giving unrealistic predictions during extreme events. Thus all these limitations lessen the applicability of the stochastic ARIMA process for the river runoff model. It is also observed that the development of ANN methods lead to the reduction of the use of stochastic ARIMA process in the modeling of precipitation and runoff process.

Stochastic modeling of precipitation and runoff phenomenon for river water management has been carried out in the last century and is still in use. With time the process of stochastic modeling has undergone many modifications to adapt the variety of data, elucidate the physics of the process, facilitate the analysis and to enhance the forecasting accuracy. Still the efficiency of the stochastic model always remained dependent upon the skill of a modeler who should know how to model a phenomenon (and this is more important that to develop an easy approach to it), what to model and how to guarantee an accurate result. The present review is intended to provide the better understanding of differences between available models, their applications, model inputs, and resulting outputs. This knowledge will be beneficial for those who use models for regulating river runoff and may be helpful in the development of guidelines for runoff modeling.

## 7. CONCLUSIONS

The authors recommend to continue the use of stochastic ARIMA model and its derivatives. For the forecasting of runoff in small rivers the authors recommend the parsimonious ARIMA model. For large size rivers seasonal ARIMA models or models with suitable transformation of data should be applied. In this case the forecast efficiency is important for making decisions. When the physical interpretation of the runoff is desirous, it is recommended to apply the multivariate ARIMA model and the ARIMA model coupled with the conceptual model. Stochastic modeling aimed at high-quality irrigational applicatons requires combining the surface runoff model with groundwater and soil moisture flux either at the process level or at the data application stage.

The analysis of precipitation runoff phenomenon and subsequent river runoff forecasting is of great significance for the management and planning of water resources. Medium- and long-term forecasting at weekly, monthly, seasonal, or even annual time scales is enviable for the forecasting purposes such as proper operations with reservoirs and irrigation management. The institutional and legal aspects of management and planning of water resources also have their specific requirements for researches. Information can be modeled by assimilation of more and more relevant characteristic attributes in order to get more precise description of the precipitation–runoff process. The scope of the analysis should be widened to synthesize the model outcomes with the physical consistency of a phenomenon.

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