

Application of Data Driven Techniques in Discharge Rating Curve - An Overview

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Citation: Zakwan, M, Muzzammil, M. and Alam, J. (2017). Application of Data Driven Techniques in Discharge Rating Curve - An Overview. *Aquademia: Water, Environment and Technology*, 1(1), 02. doi: 10.20897/awet.201702

Published: June 30, 2017

ABSTRACT

Establishing a reliable rating curve is an integral part of water resource engineering. The present paper is a review of data driven techniques used for modelling the stage discharge relationship over the last two decades. Over the year's several data driven techniques such as ANN, SVM, MT, fuzzy logic and GA have been applied by researchers in quest of arriving at a reliable technique to model the stage discharge relationship. Although, during this period several techniques have been used to establish the stage discharge relationship but the application of modern optimization tools such as ACO, PSO or PS has remained limited in this field. Therefore, application of modern optimization techniques and their comparison with existing literature would be appreciated in near future.

Keywords: data driven techniques, optimization, rating curve, review

INTRODUCTION

Management of water resources require input in the form hydrologic variables such as rainfall, runoff or discharge in streams. Over any given region, the quantity of water flowing in streams may vary widely in both time and space. The fluctuation in discharge and water level results from variation in duration, frequency, intensity, areal cover of precipitation and variation in the catchment characteristics. Knowledge of river flow and its variability is an essential requirement for assessment, management and control of surface water resources. Records of discharge measurement in a river are the basic data required for flood frequency studies, flood inundation modelling, design of flood protection and warning systems, river sediment management, water supply engineering, drought studies and geomorphologic studies.

Stage discharge relationships or rating curves are generally modelled by two approaches. One is the numerical approach which requires accurate information regarding channel geometry and flow boundary conditions. The other approach is a data driven approach based on non-linear regression. The review of the later approach is the main focus of this paper.

Conventional method of establishing stage discharge relationship through application of linear regression on log transformed data often fails to provide a reliable estimate of discharge. This led to the application of several data driven techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM), MT, Takagi-Sugeno (TS) fuzzy inference, Genetic Algorithm (GA) and Generalized Reduced Gradient (GRG) by researchers in quest of reliable modelling of stage discharge rating curves. Several researchers have compared various modelling techniques applied for modelling stage-discharge relationship but the comparison among the modelling techniques yielding functional form of stage-discharge has been limited. Although machine learning techniques such as ANN and SVM have been found to estimate discharge with fair accuracy yet, at times when functional form of stage-

discharge relationship is required their application appear to be futile. In such cases application of nonlinear optimization techniques appear to be suitable however, their application for setting up the stage discharge relationship has remained limited.

POTENTIAL OF AI TECHNIQUES

Artificial Intelligence (AI) techniques used in hydrological modelling include artificial neural networks, Bayesian networks, evolutionary programming, fuzzy systems and agent-based models. AI have potential for modelling, optimizing and decision support applications in various aspect of science and engineering (Kingston et al. 2008 a). AI methods are population-based and evolutionary in nature making use of information contained in the population to find better solutions. AI methods base their search on objective function, rather than on information about this function itself (e.g. gradient information, derivatives), which make them applicable for wide variety of problems whether the objective function is continuous or discontinuous. One of the main advantages of AI approaches that they generally do not require an in-depth mathematical understanding of the problems in water resource such as rainfall-runoff, channel routing, stage-discharge rating, sediment rating, water distribution design, reservoir operation and groundwater inverse flow problem (Kingston et al. 2008 b).

MATERIALS AND METHODOLOGY

Continuous measurement of discharge in a river is a very costly, time consuming and impractical exercise during floods. Usually, to overcome these limitations of continuous discharge measurement observed stage data is converted into river discharge by means of a stage-discharge relationship, commonly known as the rating curve. Rating curve is considered as an epitome of all the channel characteristics. A single valued relation is derived for majority of non-alluvial rivers using the assumptions mentioned below.

In a channel of irregular shape, assuming that at higher stages Manning's roughness coefficient (n) is constant and the energy slope (S) tends to become constant. Further, area (A) is approximately equivalent to depth (H) times the width (W). Under these assumptions the Manning's equation may take the form

 $Q = CHWR^{\frac{2}{3}}$

(1)

Assuming hydraulic radius (R) equal to depth and width as constant equation (1) can be presented as

$$Q = KH$$

(2)

However, unless the stream is very wide, hydraulic radius is generally less than the depth (H) this has an effect of reducing the exponent of equation (2) (Herschy, 2009). So, the general form of equation for discharge in channel control becomes

$$Q = K(G-a)^n \tag{3}$$

Q = Stream discharge; G = Stage or height of water surface above arbitrary datum; a = Constant representing the gauge reading corresponding to zero discharge; K and n are the rating curve parameters.

Sometimes due to the presence significant unsteadiness in the flow, as in case of floods, for the same stage at the gauging site two discharge values may be observed corresponding to rising stage and falling stage of the flood, this affect is commonly known as hysteresis affect. Under such situation, a looped rating curves are formed which cannot be traced through the single valued stage discharge relationship. Generally, Jones formula has been adopted in most of the standard hydrologic literature (Peterson-Øverleir (2006)) for modelling looped rating curves.

In general estimation of discharge requires stage as an input, however, many researchers have used various combination of inputs to estimate discharge which include preceding discharges and water levels. The attempts to model discharge rating curves using data driven techniques may be summarised as follows.

Tawfik et al. (1997) introduced the use of multilayer artificial neural network (ANN) for modelling the hysteresis affected rating curve for two sites Melut and Malakal of river White Nile. Data set of daily stage and discharge hydrograph for 1975-77 was used to model the relationship for either site. A three-layer back propagation neural network employing two neurons in single hidden layer with stage and gradient of stage as input was used. Based on the comparative analysis of Boyer's approach, falling and rising approach and ANN modelling, they concluded ANN based modelling as the most accurate among the three.

Analysing the stage-discharge data of 1993 flood for four stations in middle Mississippi Westphal et al. (1999) reported a difference between measured flow rate for fixed stage value varied from 6.4% to 8.3%, thereby demonstrating the hysteresis effect. Developing single valued stage-discharge relationship using power law and polynomial of degree two, they found these approaches could not satisfactorily mimic the discharge curves in case

of floods. Further they analysed the effect of scour/fill at the cross sections on the stage-discharge relationship, but no significant correlation could be found either with stage or discharge.

Bhattacharya and Solomatine (2000) applied the ANN to model the stage discharge relationship at Swarupgunj site on river Bhagirathi, India. A simple network consisting of four input nodes and four hidden nodes was used to model the rating curve. Water levels of two earlier time steps and discharge at previous time step in addition to current water level were used as an input to the network to get the best results. Considering the data of six years for modelling and three years for testing they demonstrated that use of ANN has led to significant improvement in the estimation of discharge when compared with the conventional method. Further, generally significant error was observed in over estimation domain than that in underestimation stage.

Jain and Chalisgaonkar (2000) used back propagation feed forward ANN for modelling stage discharge relationship for Kolar river (tributary of Narmada river) and Jamtara site on river Narmada in India. For the data set of Kolar river 531 pairs of stage-discharge were used for training and 120 pairs were used for validation. Similarly, for Jamtara site 198 sets were selected for training and 61 pairs for testing. To estimate the discharge various combination of input were employed using a three-layer network. Number of neuron in the hidden layer were selected by trial-error process. Comparing their results with the conventional rating curve they emphasized on the capability of ANN to model the rating curves. They also successfully utilised back propagation feed forward ANN to model the hypothetical hysteresis loop curve in unsteady flow condition.

Jain (2001) introduced the concept of developing integrated sediment discharge rating curve. He developed the integrated rating curves for two sites on Mississippi river in USA using artificial network by considering various combinations of input data. Comparing the results of ANN modelling with conventional method he reported that ANN are much superior to conventional method of regression analysis.

Sudheer and Jain (2003) analysed the same data as that of Jain and Chalisgaonkar (2000) with same input variables, to assess the performance of radial basis function (RBF) neural network for modelling the rating curves. Using Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) they compared the results of RBF model with back propagation multilayer perceptron model (BP-MLP) of Jain and Chalisgaonkar (2000). Generalization capabilities of RBF model were found to be better than BP-MLP neural network especially in case of high flows and looped rating curves.

Moyeed and Clarke (2005) used Bayesian methods to fit the rating curve for two very large and five small watersheds as they allow incorporation of prior information of nature of rating curves. Calculating the posterior distribution of rating curve parameters by employing Markov Chain Monte Carlo (MCMC) methods they demonstrated log-normal of discharge fits better for large watersheds. However, if the priors for the parameters are uninformative as is the usual case for stage discharge rating curves use of such approach may not lead to reliable results.

Bhattacharya and Solomatine (2005) established stage discharge relationship for Swarupgunj site on river Bhagirathi, India using model tree M5 and ANN using data set for a period of 1990-98. They used average mutual information (AMI) for investigating dependency between variables and related lag effect in order to select a proper combination of inputs for the model. AMI of stage with itself exhibited a high information content about current discharge. Piecewise linear equations were developed for estimating the discharge by dividing the observed data into subsets with the help of decision trees. Initial two-third data was used for training and rest was used for validation. The discharge estimated by back propagation ANN and model tree M5 approximately showed same degree of accuracy in estimation of discharge and were more accurate than the conventional method.

Sivapragasam and Muttil (2005) proposed the use of Support Vector Machine (SVM) for extrapolating the rating curve. Considering the data sets of three rivers in USA they extrapolated the developed rating curves using logarithmic plot, polynomial of degree two, polynomial of degree three, backpropagation ANN and SVM. Based on the comparative analysis of these method SVM was found to fit the observed data best.

Peterson-Øverleir (2006) outlined the limitations of modification in Jone's formula for practical use as these modifications made the approach data intensive. He proposed a method to track the hysteresis effect in rating curves based on Jone's formula and non-linear regression which just require stage-discharge data and its duration of measurement as an input. Computing the rate of change of stage by finite difference approximation he successfully traced the hysteresis curves of Chattahoochee River at Georgia, Ohio River at Wheeling and Tennessee River at Scottsboro, in USA.

Habib and Meselhe (2006) modelled the stage discharge relationship for low gradient tidal stream characterized by multiple loops using ANN and non-parametric optimization technique Loess. After preliminary analysis of data set of Coulee site on Vermilion River in Louisiana for a period of October 2002 to November 2004 1250 pairs of stage discharge observation were used for the study. Multilayer feedforward back propagation neural network was employed to estimate the discharge. Various combinations of input variables were used to develop the model, however, input data included only local water level. The inclusion of surrounding water level such as upstream water level and downstream water level improved the prediction capability of developed models significantly. For

the validation of developed models twelve significant runoff events occurring over the observational period were separated using holdout technique rather than conventional split sample technique as data driven model are usually unable to validate the results beyond the range of data used in training. Based on the comparative analysis on the basis of RMSE, coefficient of efficiency and modified coefficient of efficiency ANN was found to be superior to Loess optimization technique. They further concluded that adding more complexity to model structure cannot compensate the need of including physically essential variables which account for hydraulic behaviour of low gradient streams.

Lohani et al. (2006) modelled the rating curve using the Takagi-Sugeno (TS) fuzzy inference. Data sets of five Indian gauging sites as well as a hypothetical looped rating curve were used for the study. The FIS of fuzzy model was generated using subtractive clustering. For each site six combination of input that included current stage, antecedent discharge and antecedent stage were tried to achieve higher accuracy in discharge estimation. Optimum fuzzy model was achieved by trial and error procedure. Comparative analysis of estimated discharge by TS fuzzy, back propagation ANN and conventional rating curves showed TS fuzzy as the most reliable approach among the three approaches.

Lohani et al. (2007) introduced the concept of developing stage-discharge-sediment concentration relationship using fuzzy logic. Considering the daily gauge and discharge data of the Jamtara and Manot gauging sites of river Narmada, India Lohani et al. (2007) demonstrated the superiority of fuzzy logic based approach over conventional rating approach as well as ANN approach. Following a similar approach considering the data sets of two stations (Chester and Thebes) on river Mississippi and Conococheague creek in USA Jain (2008) investigated the generalisation capabilities of compound neural networks (CNN) by developing the integrated stage discharge suspended sediment rating curves. On the basis of coefficient of correlation and sum of square of error statistics he concluded that CNN consisting of two network can model the rating curve more accurately than single artificial neural network.

Reitan and Peterson-Øverleir (2008) proposed an efficient MCMC based Bayesian approach to fit the standard power law rating curve model to overcome the limitation of finite probability of negative discharge associated with the GLM model considered by Moyeed and Clarke (2005).

Guven and Aytek (2009) introduced the concept of GEP (Gene Expression programming) to establish the stage discharge relationship for two stations on American rivers. They utilized the data sets of Berne and Philadelphia sites on Schuylkill River in USA for a period of October 1, 2000 to September 30, 2006. First five-year data were set to train the models and the last year data were used for validation purpose at either station. Two genes per chromosome with head length of eight were employed to model the stage discharge relationship using GEP. Several combinations of input variables which included stage, discharge with 1 day and 2-day lag, stage with 1 day and 2-day lag were used to model the rating curves at both sites. However, stage and discharge with no lag was found as the best input for accurate estimation of discharge. Rating curves developed by GEP outperformed the simple rating curves as well as those developed by linear multiple regression (LMR) approach.

Ghimire and Reddy (2010) used genetic algorithm (GA) and model tree (MT) to develop the stage discharge relationship and compared their results with Gene Expression Programming (GEP), multilinear regression (MLR) and classical stage discharge curves. They used the same data sets as that of Guven and Aytek (2009). First five-year data were set to train the models and the last year data were used for validation purpose at either station. Parameters such as population size and mutation rate for GA resulting in minimization of fitness function were found by trial and error. To develop rating curves using model tree five and seven logic sets were used for Berne and Philadelphia sites respectively. A comparative analysis based on coefficient of determination and root mean square error demonstrated both GA and MT outperformed GEP, MLR and classical rating curve. Among MT and GA results of GA were found to be more promising.

Lee et al. (2010) outlined the limitations of using log transformed linear regression method for developing the rating curve and proposed the use of maximum likelihood estimation method to capture heteroscedasticity in the stage-discharge data. Developing the rating curves for six gauging sites in Geum River basin they concluded that use of maximum likelihood estimation method results in more accurate estimation of discharge.

Bisht et al. (2010) used feed forward back propagation multilayer perceptron artificial neural network to model the stage discharge relationship for Dhawalaishwaram barrage site of river Godavari in India. They developed twenty models with ten each for single and double hidden layers. Comparing the results on the basis of correlation coefficient and coefficient of efficiency best fit model out of twenty model developed was chosen. Best fit model had two hidden layer and outperformed the multilinear regression approach.

Goel and Pal (2011) employed Support Vector Machine (SVM) to develop the stage discharge relationship for two Indian River sites and hypothetical looped rating curve. Data set of Jenapur site on Brahman river and Tikarapara site on Mahanadi were used to assess the performance of SVM and back propagation neural network. Radial basis and Polynomial basis kernel were implemented to the rating using SVM. Various input combinations which included stage, antecedent stage, and antecedent discharge were employed to develop the relationship for estimation of discharge using ANN a three-layer network with single hidden layer was used for both the data set. The results for SVM for the first data set were comparable to ANN, while for the second data set SVM performed better than ANN. Further, a hypothetical data set (168 pairs of stage-discharge) depicting hysteresis effect was analysed using SVM. Looped rating curve was successfully traced by SVM when the data set was divided into rising and falling stage data set. Aggarwal et al. (2012) again employed SVM, ANN and persistence model for forecasting stage-discharge for Tikarapara site on Mahanadi for a period of 1-day, 7-day and 1-year. SVM provided the best forecast for stage as well as the discharge.

Azamathulla et al. (2011) developed the relationship between stage and discharge for Temerloh station on Pahang River using Gene Expression Programming (GEP). Time series of daily stage and discharge data for year 2007 was used for training and 2004 data series was tested. Data series of 2007 was employed for training to capture a wider range of stage discharge data as flood occurred in the river during that period. GP yielded a cubic equation to express the dependency of discharge on stage while GEP yielded a quadratic equation to express the same. Comparing their results for regression method, simple rating curve, radial basis function Artificial Neural Network (ANN), Gene Programming (GP) and Gene Expression Programming (GEP) on the basis of root mean square error and coefficient of determination they reported GEP as the best approach for establishing stage discharge relationship.

Ajmera and Goyal (2012) compared the performance of model tree M5, ANN (with three different algorithms) and the conventional rating curve for data set of Peachtree creek on river Chattahoochee, USA. Weekly, daily, hourly and 15-minutes data for a period of October 1, 2006 to January 12, 2006 was put to analysis. Neural network was trained using three different algorithms namely back propagation gradient descent learning (BPGDX) algorithm, conjugate gradient Polak-Riberie update (CGP) algorithm and Levenberg-Marquardt (LM) algorithm. For all the algorithms, single hidden layer having two nodes with sigmoid transfer function were used to model the rating curves. Comparative analysis based on coefficient of correlation, RMSE and mean absolute error (MAE) revealed that LM algorithm was the best algorithm for training ANN's for modelling rating curves. Further, the discharge estimation by model tree M5P were observed to be much better than those of ANN and conventional rating curves.

Wolfs and Willems (2014) discussed possible factors resulting in looped rating curves and developed stage discharge curves affected by hysteresis using time varying models, model tree and artificial neural network. Data set for Marke and Dender, two Belgian rivers were considered by them for the study. Five events with hourly data of one month or less were used for either site, out of which two events were combined for calibration and other three events were utilized for validation of developed models. For the development of ANN model stage and stage gradient data was fed as an input for the feedforward multilayer perceptron neural network with single hidden layer. The optimal number of neuron in the hidden layer were selected by trail-error procedure. They also developed a simple rating curve using interior-reflective Newton method and modified this simple rating curve by introducing a time varying (TV) state dependent parameter (SDP) using fixed interval smoothing (FIS) technique. SDP modified simple rating curve produced better results than ANN model for the validation data-sets. The results of model tree M5 were slightly better than SDP modified rating curve. However, high transparency and estimation of discharge using only current stage data without any other additional measurement was the main advantage of developing SDP modified rating curves.

Mir and Dubeau (2014) proposed the use of curvilinear asymptotes rather than straight ones for least square fitting of stage discharge relationship. They used five modified sigmoid models characterized by curvilinear asymptotes to model the stage discharge relationship for data sets of six gauging sites in USA. Major advantages of these models was reported that they may possess several inflection points and are flexible. Constrained least square function "Isquonlin" based on interior reflective Newton method was used to model the stage discharge relationship with randomly selected initial starting rating curve parameters. Out of the five models that were developed estimation of discharge by exponential model led to the least uncertainty for most of the cases, yet, it cannot be generalized as best model for a river would depend on prevailing hydrologic, hydraulic and morphological conditions.

Atiaa (2015) modelled rating curve using data driven techniques and emphasized on the importance of antecedent discharges as an input for developing reliable rating curve. Data set of Hay station on Gharraf River in southern Iraq for a period of April 2006 to May 2006 was used to model the rating curve using ANN, Takagi-Sugeno (TS) fuzzy inference and model tree. For the development multilayer backpropagation ANN model data set was normalized and the number of neuron in the hidden layer were determined by trial and error procedure. A comparative analysis of the three approaches based on RMSE and coefficient of determination shows that model tree M5 gives the best fit curve. However, the results of TS fuzzy inference were also quite reliable for modelling the rating curves.

Muzzamil et al. (2015) proposed the use of simple spreadsheet based nonlinear optimization technique known as Generalized Reduced Gradient (GRG) to establish the stage-discharge relationship for a gauging site at Lakhwar

dam site on river Yamuna, India (Zakwan ,2016). The data set they used for the study pertains to a period before the construction of the dam. Comparing the results of GRG technique with the classical rating curve approach they reported GRG technique more reliable than the classical rating curve approach based on graphical and regression approach.

Londhe and Panse-Aglave (2015) compared ANN, MT and nonlinear regression method for modelling stage discharge curve. ANN and MT performed equally well for estimation of discharge however, MT appear to be more transparent than ANN. Ghorbani et al. (2016) compared the performance of SVM, ANN, MLR and simple rating curve (RC) reporting SVM to be best among them for estimating the discharge.

Maghrebi and Ahmadi (2017) proposed an innovative approach for modelling discharge rating curve using isovel contours with the corresponding hydro-geometric parameters of the cross sections and dimensional analysis to interrelate the discharges at two different stages. Although the approach appears to be promising but it requires estimate of cross-sectional area, wetted perimeter, the width of the free surface and isovel contours, availability of data these quantities impose limitation on application of this approach.

EMERGING ISSUES

Several researchers have reported ANN, SVM and fuzzy logic for modelling discharge rating curves, however, it is not easy to train complex ANN periodically (Aytek and Kisi, 2008). ANNs, fuzzy logic and model trees may involve discharge from previous time step as an input in estimating discharge for current stage which may lead to propagation of errors (Aytek and Kisi, 2008). Further, they do not yield the functional form of stage discharge relationship. Information is shared between all chromosomes in the mating pool using a GA, on the other hand in particle swarm optimization (PSO), information is only given out from the best particle to other members of the population. Therefore, the evolution only looks for the best solutions and, as a result, locates near optima significantly faster than GA (Kingston 2008b). Application of GA or PSO, although yields the functional form of stage-discharge relationship but they are more suitable for complex nonlinear programming problems (Haupt and Haupt (2004)) and as such for continuous convex analytical optimization functions gradient based method may reach optimal solutions very quickly (Haupt and Haupt (2004)). GRG technique as proposed by Muzzammil et al. (2015) could prove to be an excellent tool to yield functional form of stage-discharge relation after further investigations of its reliability to estimate rating curve parameters for a large number of gauging sites.

RESEARCH PERSPECTIVES

Most of the researchers have adopted and compared various black box Machine learning approaches involving current stage, stage with time lag, and discharge with time lag as an input to model the stage-discharge relationships however, the use of discharge with time lag may lead to propagation of error. Among the machine learning approaches most of the researchers favoured the application of SVM. Another approach of application of MT appear to be promising one from the literature review. However, Ghimire and Reddy (2010) suggested that GA has a slight edge over the MT in estimating discharge for the two data sets of American rivers. Comparison of MT and GA must be extended to a large number of data sets to arrive at conclusive evidence. The PSO algorithm has fewer parameters to adjust than the GA making this algorithm simpler and faster to reach optimal solution (Kingston et al. 2008b). At the same time reliability of GRG technique applied by Muzzammil et al. (2015) must be assessed as it appears to be the simplest approach to develop the stage discharge rating curves. Application of modern optimization such as ant colony algorithm, particle swarm optimization (PSO), and pattern search (PS), hybrid genetic algorithm (Deep and Das (2008)) to develop stage-discharge relationships and comparison of these techniques with the GA and GRG could be appreciated in the near future.

Several researchers have compared the modelling techniques which yield functional form relationship with those which do not yield functional form of relationship (black box models), although, such comparison is useful, but a comparative analysis of techniques yielding functional form of relationship for a large number of data sets could provide a clear view as to which approach is to be adopted for reliable modelling of stage discharge relationship.

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