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Improving the performance of multi-layer perceptron and radial basis function models with a decision tree model to predict flow variables in a sharp 90° bend

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ABSTRACT

The use of artificial intelligence methods in different hydraulic sciences has become conventional in recent years. In this study, two artificial neural networks (ANN), namely multilayer perceptron (MLP) and radial basis function (RBF) models were modified with decision trees (DT) and designed as two new hybrid models, namely DT-MLP and DT-RBF. The performance of the proposed hybrid (DT-MLP and DT-RBF) and simple (MLP and RBF) models was compared for velocity and water surface prediction in sharp 90° bends. The experimental data for 5 different hydraulic conditions in a sharp 90° bend were used to train and test the models. In velocity prediction, the mean absolute error (*MAE*), root mean square error (*RMSE*) and relative error (δ) values decreased with the DT-MLP model compared to the MLP model by 16%, 9% and 0.17% and the values of DT-RBF reduced by 11%, 7% and 0.11% compared to the RBF model, respectively. For water surface prediction, the *MAE*, *RMSE* and δ errors decreased with the DT-MLP model by 5.2%, 5.5% and 0.095% compared with MLP and with the DT-RBF model the errors decreased by 20%, 23% and 0.5% compared with RBF, respectively. Using the new proposed hybrid algorithms based on decision trees enhanced the simple MLP and RBF models' performance.

1. Introduction

Due to the centrifugal force in bends, the longitudinal pressure gradient creates spirals and secondary flows in curved channels and naturally meandering rivers. These flows lead to changes in flow pattern [1,2]. Changes in the distribution of velocity and surface water profiles are caused by the complex nature of three-dimensional flow [3,4]. Therefore, recognizing the flow patterns in bends is necessary when studying the behavior of rivers. One of the main factors in bends is the ratio of channel curvature radius to channel width (R_c/b), which determines the bend type (sharp or mild). In sharp bends ($R_c/b \leq 3$), flow patterns are more complex than in mildly curved bends ($R_c/b > 3$) [5]. Fundamental experimental studies on bends have been conducted by Shukry [6]. Several experimental studies have also been conducted on the distribution of velocity and water surface profiles [7–15].

Ye and McCorquodale [10] and DeMarchis and Napoli [16] extensively studied the velocity distribution and displacement at maximum velocity in mild and sharp bends using three-dimensional numerical models. Jung and Yoon [17], Booij [18] and Lu et al. [19] investigated the velocity patterns and secondary flows in 180° bends using three-dimensional models, while Zhou et al. [20] and Wang et al. [21] considered two-dimensional models. Ramamurthy et al. [22] and Gholami et al. [15] used a three-dimensional numerical model to evaluate the flow patterns and water surface profiles in 90° sharp bends. Bonakdari et al. [23] studied these in 90° mild bends. The velocity at the inner wall of a sharp channel bends is greater than the outlet cross section in a mild bend. Bonakdari et al. [24] also investigated the effect of curvature on velocity patterns in a channel with a circular cross section using a Computational Fluid Dynamics (CFD) model. Zhang and Shen [25] analyzed flow along a meander path. They stated that the water surface profile remains higher at the outer wall than at the inner wall in every channel section. The velocity profile results showed higher velocity values at the inner wall than the outer wall, which gradually decrease towards the outer wall.

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In recent decades, artificial intelligence methods have been increasingly applied in various engineering sciences (e.g. flow resistance [26]; friction factor prediction in channels [27]; discharge of triangular side weirs in curved channels [28]; lateral outflow over side weirs [29]; velocity prediction in curved channels [30]). Neural networks are one type of artificial intelligence, although ANNs come in various forms for predicting different subjects [31–37]. MLP and RBF models are the most widely used in hydraulic science [38–40]. The two methods have many applications for predicting velocity values in a variety of channels. Yang and Chang [41] used an MLP neural network to predict the velocity field and fluid discharge value in combined open-channel flow. The results indicated acceptable MLP model accuracy. Zaji and Bonakdari [42] compared ANN and CDF model performance in predicting the velocity values in open channel junctions. The results showed that the ANN model outperformed the CDF model in predicting velocity at different points and fluid discharge rates. Zaji and Bonakdari [43] employed MLP and Genetic Programming (GP) to predict the velocity values in an open channel junction. The study results showed that the MLP can model the longitudinal velocity field with a small training dataset highly accurately. Sun et al. [44] used ANN modeling to evaluate the velocity distribution in open channel junctions. They examined different random model parameter initializations by designing a training strategy and assessing the models' accuracy. The aim of the studies mentioned above was to evaluate the efficiency of neural network models in comparison with other models. These methods have also been applied to curved channels. However, there is no report concerning accuracy in predicting flow hydraulics. Sahu et al. [45] used ANN modeling to study and predict the velocity values in a curved open channel. The aim of their study was to evaluate the model's ability to predict the velocity fields and the results indicated high model accuracy. Bonakdari et al. [23] studied and compared the application of MLP and GA models in predicting the flow velocity values in a 90° mild bend. Baghalian et al. [46] compared ANN and CFD models, and studied analytical equations for predicting the velocity field. High ANN and CFD accuracy was noted. Gholami et al. [47] compared ANN and CFD model performance in predicting flow variables in a 90° sharp bend. The results demonstrated high ANN model accuracy, but due to the lack of a clear relationship the proposed model was not able to predict flow variables at different fluid discharge rates. Moreover, Gholami et al. [48] examined the application of a Gene Expression Programming (GEP) model in predicting velocity and water depth variables in a 90° bend. The accuracy of the presented model in predicting the variables was good, but in addition to the lack of an equation to predict velocity and water depth, the model was unable to detect different fluid discharge values more rapidly. Bhattacharya et al. [49] utilized machine learning methods, ANNs and decision trees to model the bed and total load using measured data. According to their results, the machine learning methods led to increased modeling accuracy compared with existing methods. Senthil Kumar et al. [50] applied different methods including ANNs with back propagation (BP), RBF and decision trees (DT), such as REP trees and M5, and fuzzy logic (FL) to predict suspended sediment concentration. According to their results, the M5 tree model was more accurate than the other methods. This model presents decision makers with a better outlook compared with the rest of the models and offers engineers explicit expressions for practical use.

In many previous studies, only the application of simple methods such as RBF and MLP has been assessed in terms of variable prediction, which is not something new. These methods are applicable only in existing situations and cannot predict flow parameters accurately when the hydraulic conditions and channel points change. As a result, a method that can improve the performance of these models is still necessary. Moreover, because they simply have no ability to detect input and output parameters based on values, the previously mentioned models cannot establish a correlation between the output and input parameters. Therefore, a model that makes correlations between the key parameters of velocity and water depth with geometric and hydraulic parameters is required. For this reason, in the present study it is endeavored to provide a model that is able to create a relationship between input and output values. Using combined methods (simple methods in combination with decision trees) increases the accuracy of simple models. In addition, the methods that involve classification are able to predict flow variables for any preferred discharge and different points of the channel using the class relationships provided.

In this study, two hybrid MLP and RBF models based on decision trees are designed to improve the performance of the simple models and predict flow variables in a 90° sharp bend. Two variables, namely velocity and water surface are predicted using MLP, RBF, DT-MLP and DT-RBF models to compare their performance. Extensive experimental studies have been conducted by the authors at five different discharge rates: 5, 7.8, 13.6, 19.1 and 25.3 lit/s [51,52]. In the current study, 520 velocity and 506 water depth data were used to train and test the networks respectively. In each model, the inputs were different channel point coordinates in two directions (X and Y) and fluid discharge (Q). The outputs were the velocity and water depth corresponding to the points, respectively. The results demonstrate the proposed hybrid DT algorithms reduced the simple models' (MLP and RBF) errors in estimating the velocity and water depth parameters in a 90° bend.

Table 1
Hydraulic properties in the experiments.

No. of Test	Normal depth Y (cm)	Discharge Q (Lit/s)	Velocity (m/s)	Froude number	Reynolds number
1	4.5	5	0.273	0.42	12460
2	6	7.8	0.321	0.42	18460
3	9	13.6	0.374	0.40	28940
4	12	19.1	0.394	0.36	36860
5	15	25.3	0.419	0.34	44705

2. Experimental model

The experimental data for velocity and water depth employed in this study were measured in the hydraulic laboratory at University of Mashhad, Iran [51]. The flume consisted of three parts: the entrance to a straight channel (3.6 m long), a curved channel with a sharp central angle of 90° ($R_c/b = 1.5 < 3$) and a straight exit channel (1.8 m long). The channel cross section was a 40.3×40.3 cm (width and height) square. The channel bed and walls were fixed and made of Plexiglas. Five different discharge rates at water depths of 4.5, 6, 9, 12 and 15 cm were conveyed into the flume by changing the size of the valve opening to the main reservoir. At the channel entrance, a pump conveyed the flow into the entrance reservoir (reservoir 1). A sharp-crested triangular weir was used to measure the discharge in the main reservoir. This channel was designed in such a way that the rectangular weir would adjust the water depth at the downstream end of the channel. The water level was adjusted by the triangular weir in the main reservoir, and when changing the outlet weir height the water depth across the channel remained fixed. After adjusting the discharge and channel water depth, velocity measurements were taken. A one-dimensional propeller velocity meter measured the velocity with 2 cm/s precision and the water depth was measured by a micrometer (mechanical bathometer) with 0.1 mm accuracy [53]. The velocity meter was placed by vernier ruler in the transverse direction with 0.5 mm accuracy and by analog caliper in the depth direction with 0.1 mm accuracy. The hydraulic flow characteristics from the laboratory are given in Table 1 and the geometric characteristics of the studied channel are shown in Fig. 1. The experimental setup is presented in