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Estimation of water's surface elevation in compound channels with converging and diverging floodplains using soft computing techniques

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ABSTRACT

In this research, water's surface elevation in compound channels with converging and diverging floodplains using soft computing models including the Multi-Layer Perceptron Neural Network (MLPNN), Group Method of Data Handling (GMDH), Neuro-Fuzzy Group Method of Data Handling (NF-GMDH) and Support Vector Machine (SVM) was modeled and predicted. For this purpose, laboratory data published in this field were used. Parameters including convergence angle (with a positive sign) and divergence angle (with a negative sign), relative depth, and relative distance were used as input variables. The results showed that all the used models have appropriate performance. However, the best performance was related to the SVM model with statistical indicators $R^2 = 0.998$ and $RMSE = 0.008$ in the testing stage. The use of the adaptive fuzzy approach in developing the GMDH model led to a remarkable increase in accuracy so that its statistical indicators in the testing stage reached $R^2 = 0.985$ and $RMSE = 0.203$. It was found that the best performance of the activation and kernel functions in the development of the MLPNN model and the SVM is related to the sigmoid and radial tangent functions.

Key words: artificial neural network, non-prismatic floodplains, relative depth of flow, support vector machine, water surface

HIGHLIGHTS

- Water's surface elevation in compound channels with converging and diverging floodplains using Multi-Layer Perceptron Neural Network (MLPNN).
- Water's surface elevation in compound channels with converging and diverging floodplains using Group Method of Data Handling (GMDH).
- Water's surface elevation in compound channels with converging and diverging floodplains using Neuro-Fuzzy Group Method of Data Handling (NF-GMDH).
- Water's surface elevation in compound channels with converging and diverging floodplains using Support Vector Machine (SVM).

NOTATIONS

WSE	water's surface elevation
GMDH	Group Method of Data Handling
NF-GMDH	Neuro-Fuzzy Group Method of Data Handling
SVM	Support Vector Machine
MLPNN	Multi-Layer Perceptron Neural Network
SVR	Support Vector Regression
H	water depth in the main channel
h	water depth in the floodplain
D_r	relative depth of the flow
θ	angle of divergence and convergence of the section
x/L	relative distance from the start of divergence and convergence of the section
R^2	coefficient of determination
$RMSE$	root mean square error
SI	scattering index
DDR	developed discrepancy ratio

INTRODUCTION

Floods are natural phenomena that cause countless damages to industrial facilities, agricultural lands, and urban communities. When floods occur, the water level in the main channel of rivers increases and enters the surrounding floodplains. In this condition, the cross-section of the passing stream is out of the normal state and becomes a compound section. The compound section refers to the main channel and floodplains. Due to the relatively high roughness of floodplains compared with the main channel, the flow velocity in the main channel is higher than in floodplains. This difference in velocity generates longitudinal and vertical eddies at the border of the main channel and the floodplain(s), resulting in the loss of flow energy (Parsaie *et al.* 2017a). These eddies are responsible for the momentum transfer between the main channel and the floodplain (Devi & Khatua 2016). Besides these turbulent structures, there are also secondary currents with a longitudinal axis (Shiono & Knight 1991). Secondary currents are created as a result of turbulence inhomogeneities in the channel bottom and side walls (Kang & Choi 2005) and increase due to the development of the mixing layer at the interface between the main channel and the floodplain. Thus, the hydraulics of compound open channels are much more complicated than for single open channels. The complexity of the flow in a non-prismatic compound open channel (non-uniform flow) is many times higher than in a prismatic compound open channel. Tang & Knight (2009) studied the effect of the roughness of a prismatic floodplain on discharge capacity, bedform geometry, flow resistance, and sediment transport in the main channel.

Non-prismatic compound channels according to the geometrical changes of the floodplains are categorized into three: converging, diverging, and diagonal. A channel is called a converging compound channel when both floodplains move toward the main channel and a diverging compound channel is when the floodplains move away from the main channel. When one of the floodplains moves away from the main channel and the other approaches the main channel, it is known as a diagonal compound channel (Das *et al.* 2017). Bousmar *et al.* (2006) investigated the flow hydraulics in non-prismatic compound channels. They declared that the velocity gradient at the border of the main channel and floodplains of a non-prismatic compound channel is more than that of a prismatic compound channel. Rezaei & Knight (2009) stated the conventional Shiono and Knight's method (SKM) cannot successfully model the hydraulic behavior of flow in compound channels with non-prismatic floodplains. Parsaie *et al.* (2017a) conducted a study to investigate the effects of the roughness of floodplains and the divergence angle of floodplains.

Nowadays, with the advancing of soft computing methods in hydraulic and river engineering, researchers have been motivated to investigate the performance of these methods in solving various river engineering problems. In this regard, various soft computing models were used to estimate the hydraulic properties of compound channels, for example, flow discharge, shear stress, and Manning's coefficient in prismatic and non-prismatic compound channels (meander and prismatic and non-prismatic floodplains). Najafzadeh & Zahiri (2015) predicted the discharge in prismatic compound channels using the Group Method of Data Handling (GMDH) model trained by two optimization algorithms. Azamathulla & Zahiri (2012), Zahiri & Azamathulla (2014), Parsaie & Haghiabi (2017), and Parsaie *et al.* (2017b) predicted discharge in compound open channels using Support Vector Machine (SVM), GMDH, Adaptive Neuro-Fuzzy Inference System (ANFIS), Multi-Layer Perceptron Neural Network (MLPNN), and Multivariate Adaptive Regression Splines (MARS) techniques. Flow discharge in non-prismatic compound channels was successfully estimated by SVM, GMDH, ANFIS, MLPNN, and MARS methods using soft computing models (Das *et al.* 2020, 2021; Yonesi *et al.* 2022).

Estimating the water's surface elevation at the time of a flood is one of the most important challenges in flood management and control. Das & Khatua (2019) obtained the water's surface elevation in compound channels with a converging floodplain using computational methods. They performed several statistical error analyses for the obtained results and concluded that their computational model was in good agreement with the laboratory results of other researchers. Naik *et al.* (2022) investigated the water's surface elevation in non-prismatic compound channels with converging floodplains using the Gene Expression Programming (GEP) model and their findings showed that the water's surface elevation obtained from GEP has a good correlation with experimental data and data from other studies data ($R^2 = 0.99$ and $RMSE = 0.028$ for training data and $R^2 = 0.99$ and $RMSE = 0.027$ for test data). Nowadays, modeling flow in rivers based on the concept of compound channels is one of the modern methods of flood simulation. Estimation of water's surface elevation in floods is one of the most important outputs of modeling to determine the extent of floodplains and flooded areas. Considering that the compound channel has much hydraulic complexity, the necessity of research and efforts to estimate the discharge and the water's surface elevation in these sections is still valid. In this research, the estimation of the water's surface elevation in compound channels has been conducted using soft computing techniques including SVM, GMDH, ANFIS, MLPNN, and MARS methods. In this research, due to the double complexity of hydraulic flow in non-prismatic compound channels and also the inefficiency of numerical models such as the SKM model, the use of soft computing models can be a way to estimate hydraulic properties in such channels.

MATERIALS AND METHODS

The aim of this research is to model and predict the water's surface elevation in compound open channels with diverging and converging floodplains using the soft computing models of MLPNN, GMDH, Neuro-Fuzzy Group Method of Data Handling (NF-GMDH), and SVM. Since soft computing techniques are data-driven models, it is necessary to collect relevant data from the results of the experimental studies. Therefore, firstly the experimental studies are introduced from which the results have been used. In this regard, the data related to the water's surface elevation in the converging channels were collected from Bousmar (2002) and the data related to the water's surface elevation in diverging channels were collected from Bousmar *et al.* (2006). In the following, the aforementioned soft computing models are introduced.

Experimental setup

Converging floodplains

Bousmar (2002) conducted experimental studies in a 10-m-long and 1.2-m-wide flume at the Hydraulics Laboratory of the Catholic University of Leuven, Belgium. The bed slope of the main channel was 0.99×10^{-3}. In this flume, a symmetrical compound channel was built, consisting of the main channel with a width of 400 mm and a depth of 50 mm and two floodplains with a width of 400 mm and a height of 50 mm. The Manning roughness coefficient was 0.0107. He investigated two convergence angles of 3.8° and 11.3° considering two convergence lengths of 6 and 2 m. The discharge in this channel was measured by an electromagnetic flow meter capable of measuring the discharge between 2 and 28 L/s. The level of the water's surface elevation along the compound channel was also measured in the channel axis of the main channel using an automatic needle depth gauge.

Diverging floodplains

Bousmar *et al.* (2006) conducted their experiments in a flume with a length of 10 m and a width of 1.2 m and a floor slope of 0.99×10^{-3}. In this flume, a symmetrical compound channel was built, consisting of a main channel with a width of 400 mm and a depth of 50 mm and two floodplains with a width of 400 mm and a height of 50 mm. They considered three types of floodplains: a prismatic floodplain with a 200 mm width and two diverging floodplains with widths of 0–400 mm, with two divergence angles of 3.8° and 5.7° with divergence lengths of 6 and 4 m, respectively. The 3D and plan views of the compound channel with converging and diverging floodplains are shown in Figure 1.

The specifications of the tests performed to measure the water's surface elevation separately for the compound channels with converging and diverging floodplains are summarized and presented in Table 1. In this table, the variety of tests in terms of channel shape, discharge, and different relative depths are presented. Each of the tests is named; for example, DV4/0.3/16 represents the experiment on a compound channel with diverging floodplains with a divergence length of 4 m, a relative depth of 0.3, and a discharge of 16 L/s. in this study, the water's surface elevation is estimated using the three variables of relative depth (D_r), divergence or convergence angle (θ), and relative distance (x/L). These parameters are summarized in Equation (1); x/L starts from the beginning of the divergence and convergence of the section.

$$WSE = f\left(D_r, \theta, \frac{x}{L}\right) \quad (1)$$

where D_r is defined as in Equation (2):

$$D_r = \frac{H - h}{h} \quad (2)$$

where H is the water depth in the main channel and h is the water depth in the floodplain.

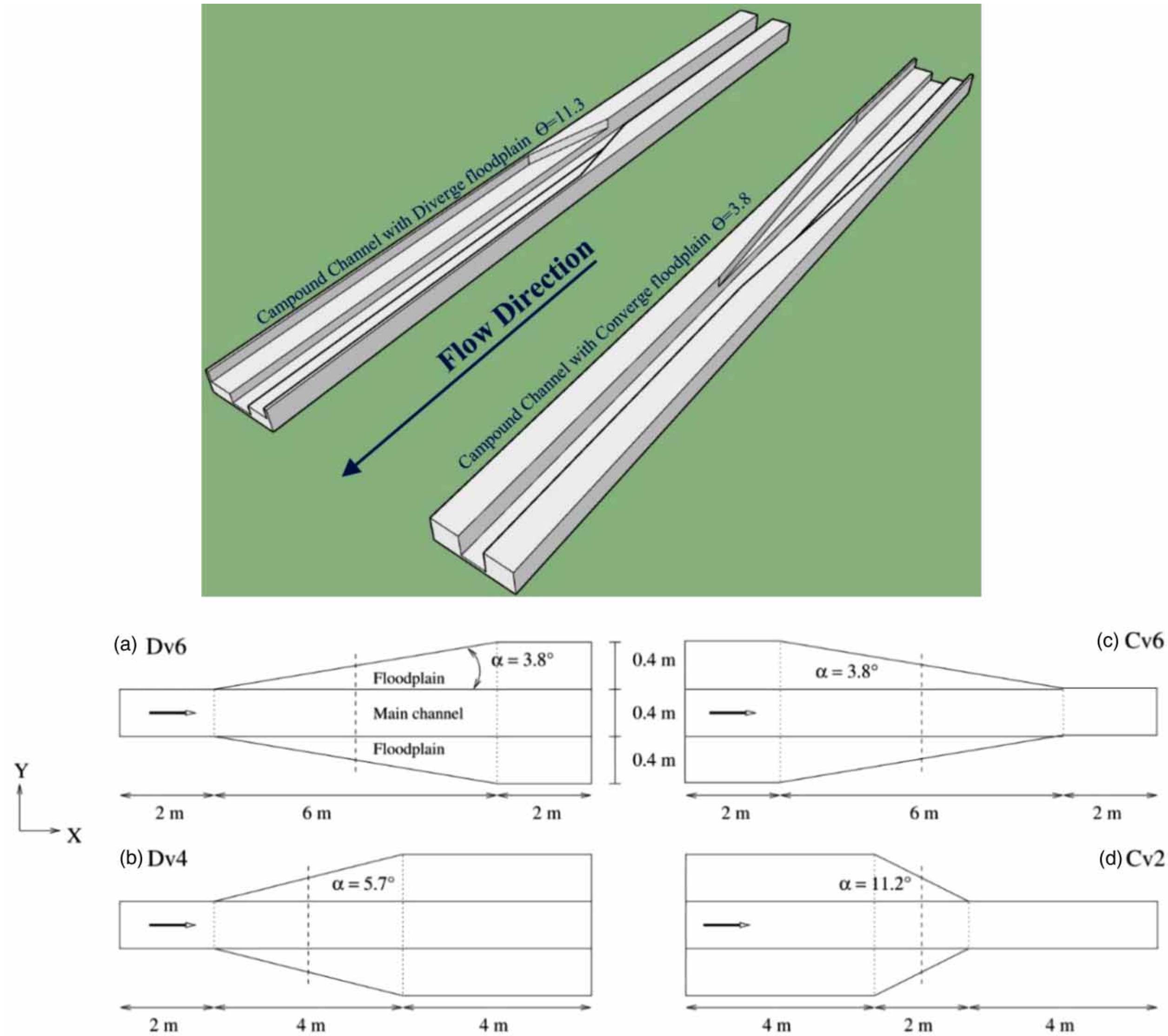

Figure 1 | 3D view and top view of geometries: diverging geometries (a) Dv6 and (b) Dv4, and converging geometries (c) Cv6 and (d) Cv2 (Proust *et al.* 2009).

Soft computing methods

The neural network model is one of the most efficient prediction models in the field of modeling hydraulic problems. The correctness of this model has been proven by different researchers in different fields of water engineering (Singh *et al.* 2021). Each of the different types of neural networks has better capabilities than the other types in a particular field. However, for function approximation, MLPNNs are the most suitable. The structure of the MLPNN includes the input layer (to introduce input variables), hidden layers, the number of neurons in hidden layers, the training method, and the output layer. All the mentioned items are effective in evaluating the performance of the developed MLPNN model. In back-propagation networks, there is a specific rule for selecting hidden layers and also the number of neurons in the hidden layer. Choosing the number of neurons in the hidden layer and also the number of hidden layers changes according to the type of problem. In modeling a complex phenomenon, due to the severe changes of the data, the disturbance ruling on the data, the use of the MLPNN model due to its ability of high flexibility with an architecture consistent with experience and trial and error is taken into consideration. Usually, the sigmoidal activation function is considered in MLPNN and it is trained by the Levenberg–Marquardt technique because it has more power and velocity than the gradient method. Creating a suitable network

Table 1 | Specification of experiments

Row	Channel type	Test name	θ	Q (L/s)
1	Converge	CV2/0.2/10	11.2	10
2	Converge	CV2/0.3/12	11.2	12
3	Converge	CV2/0.5/16	11.2	16
4	Converge	CV6/0.2/10	3.8	10
5	Converge	CV6/0.3/12	3.8	12
6	Converge	CV6/0.5/16	3.8	16
10	Diverge	DV4/0.2/12	5.7	12
11	Diverge	DV4/0.3/16	5.7	16
12	Diverge	DV4/0.5/20	5.7	20
13	Diverge	DV6/0.2/12	3.8	12
14	Diverge	DV6/0.3/16	3.8	16
15	Diverge	DV6/0.5/20	3.8	20

structure for a problem is done in three steps: structure stabilization, network training, and network control. Figure 2 shows the structure of the neural network model developed in this research.

Group method of data handling

The GMDH model is one of the MLPNNs, which has an introduction layer (for input-variable introduction), hidden layer(s), and an output layer. The use of optimizer and approximation combinations in the structure of this GMDH creates more accurate results in predicting the physical behavior of phenomena. In this network, the relationship between the input and output parameters of each system can be expressed by the series of Volterra, which is similar to the discretized Kolmogorov–Gabor polynomial, as the following formula (Ivakhnenko 1971):

$$y = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} a_{ijk} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} a_{ijk} x_i x_j x_k + \cdots \quad (3)$$

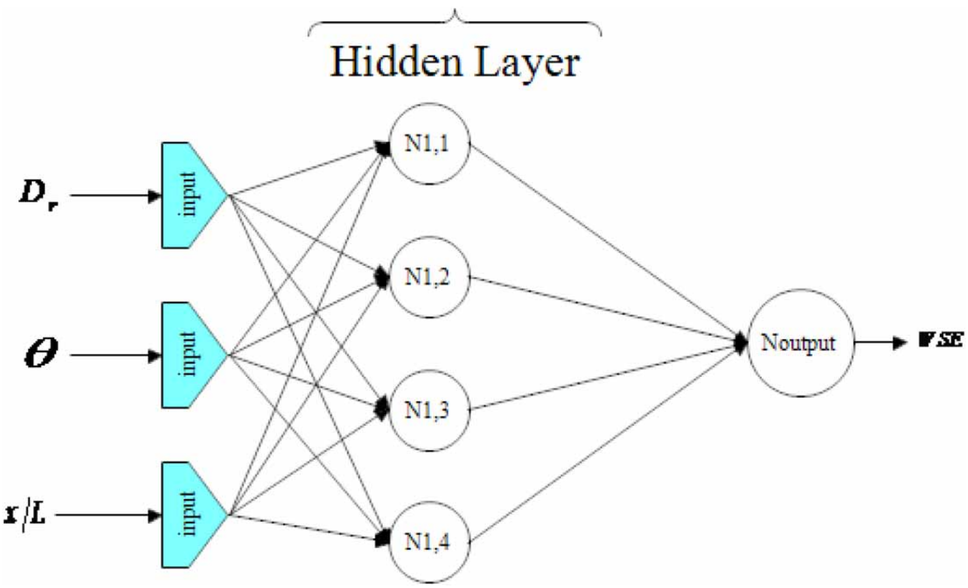

Figure 2 | Schematic view of the structure of a multi-layer neural network.

In this formula, $x_0, x_1, x_2, \cdots, x_m$ are input vectors, and $a_0, a_1, a_2, \cdots, a_m$ are the vectors of weight coefficients. In the GMDH structure, each neuron has at least two inputs. The relationship between the input and output variables in each neuron can be expressed using the activation function, which can be a linear or nonlinear polynomial. In the basic structure of the GMDH model, it is expressed as the following formula of quadratic polynomials with two input variables:

$$y = w_0 + w_1x_1 + w_2x_2 + w_3x_1^2 + w_4x_2^2 + w_5x_1x_2 \tag{4}$$

where $w_0, w_1, \cdots, w_5$ are polynomial coefficients. To build the GMDH network, first, pairs of input variables should be considered. After that, the weight coefficients of each neuron are calculated in each neuron using the least squares method. In each layer, the following error criterion is used to select the best neurons:

$$E = \frac{1}{n}\sum_{i=1}^{n}(y_{\mathrm{obs}_i} - y_{\mathrm{prd}_i})^2 \tag{5}$$

where y_{obs_i} and y_{prd_i} are observed and calculated values, respectively. E, n represent the error in each neuron and the number of observation data.

Development of the NF-GMDH model

To develop the GMDH model and convert it into the NF-GMDH model, the following simplified fuzzy rule is used. If x_1 is equal to F_{x_1} and x_2 is equal to F_{x_2}, then the output y is equal to W_k. In the above fuzzy rule, x_1 and x_2 are the input variables and the Gaussian function is used according to F_{x_j}, which is related to the kth fuzzy rule of the xth input values and is written in the form of the following formula (Najafzadeh & Azamathulla 2015; Najafzadeh & Tafarojnoruz 2016; Najafzadeh *et al.* 2017; Najafzadeh & Mahmoudi-Rad 2019):

$$F_{kj}(x_j) = \exp\left(-\frac{(x_j - a_{kj})^2}{b_{kj}}\right) \tag{6}$$

In the above equation, a_{kj} and b_{kj} are constant values for each fuzzy rule. Also, the output vector of each neuron of the NF-GMDH model is defined as the following equation:

$$y = \sum_{k=1}^{k} u_k \times w_k \tag{7}$$

where w_k is the real value for the kth fuzzy rule and u_k is the Gaussian function defined as in the following equation:

$$u_k = \Pi_j F_{kj}(x_j) \tag{8}$$

In the NF-GMDH model, each partial descriptor (neuron) has two input variables and one output variable, and the output of each neuron is considered an input variable in the next layer. Finally, the final output is obtained using the average of the outputs of the last layer. The relationship between the neurons of the current layer and the neurons of the previous layer is expressed as Equation (9):

$$y^{pm} = f(y^{p-1,m-1}, y^{p-1,m}) = \sum_{k=1}^{k} u_k^{pm} \times w_k^{pm} \tag{9}$$

where u_k^{pm} is the product of the membership functions formed in each neuron, which is obtained from the following formula:

$$u_k^{pm} = \exp\left\{-\frac{(y^{p-1,m-1} - a_{k,1}^{pm})^2}{b_{k,1}^{p,m}} - \frac{(y^{p-1,m} - a_{k,2}^{pm})^2}{b_{k,1}^{p,m}}\right\} \tag{10}$$

Also, the final output vector in the NF-GMDH model is calculated as the average of the output layers of the previous layer, through the following equation:

$$y = \frac{1}{M}\sum_{m=1}^{M} y^{pm} \tag{11}$$

In the NF-GMDH network, there are two fuzzy rules in each neuron and a total of six unknown coefficients, which include four Gaussian parameters and two weighting coefficients. Six unknown parameters in each neuron were obtained using optimizer algorithms.

SVM model

The SVM model is an efficient learning system based on the theory of constrained optimization, which uses the inductive principle of structural error minimization and leads to a general optimal solution. This model was first presented by Vapnik (1999). The SVM model has been divided into two main groups: (a) the Support Vector Classification model and (b) the Support Vector Regression (SVR) model. The SVM classification model is used to solve data classification problems that are placed in different classes, and the SVM regression model is used to solve forecasting problems (Azamathulla *et al.* 2016).

As stated, the SVM is based on minimizing the risk structure, which is taken from the theory of statistical training. Vapnik (1999) used an error function for the application of support vector machines in regression problems, which ignores the errors that are in an ε-insensitive area defined at a certain distance from the real values. This function is defined as Equation (12):

$$L(y, f(x, \alpha)) = |y - f(x, \alpha)|_{\varepsilon} = \begin{cases} 0 & \text{for} \quad |y - f(x-\alpha)| \le \varepsilon \\ |y - f(x-\alpha)| - \varepsilon & \text{if} \quad |y - f(x-\alpha)| > \varepsilon \end{cases} \tag{12}$$

This error function does not consider values less than ε. The problem of approximating is considered for a set of data below.

$$D = \{(x^1, y^1), \ldots (x^i, y^i)\}, \quad (x \in R^n, \ y \in R) \tag{13}$$

The regression function is estimated by the following function.

$$f(x) = \langle w, x \rangle + b \tag{14}$$

That $\langle\rangle$ is an internal multiplication. The optimal regression function is expressed by the minimum of the following function:

$$\Phi(\omega, \xi) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}(\xi_i^- + \xi_i^+)$$
$$\text{subject to} \begin{cases} y_i - (\langle \omega, x_i \rangle + b) \le \varepsilon + \xi_i \\ (\langle \omega, x_i \rangle + b) - b \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{15}$$

where C is a predetermined value and ε is the error function that determines the upper and lower limits of the system output. If the data are linearly separated, ξ_i^- and ξ_i^+ train an optimal level that separates the data without error and with the maximum distance between the plane and the nearest training points (support vectors). If training data are defined as $[x_i, y_i]$ and input vector $x_i \in R^n$, the data are linearly separable, and the equation is as follows:

$$y = f(x) = \text{sign}\left[\sum_{i=1}^{N} y_i a_i \langle x_i, x \rangle + b\right] \tag{16}$$

where y is the output of the equation and y_i is the class value of the experimental sample x_i. The $x = (x_1, x_2, \ldots, x_n)$ vector represents input data and the $x_i,\ i = 1, 2, \ldots, N$ vectors are the support vectors. If the data are not linearly separable, it is possible to move the samples to a higher space by applying pre-processing. In this case, Equation (16) changes to Equation (17):

$$y = f(x) = \text{sign}\left[\sum_{i=1}^{N} y_i a_i K(x, x_i) + b\right] \tag{17}$$

The x function is a kernel function that produces inner multiplications to create machines with different types of nonlinear levels in the data space. Different kernels are used to support the vector machine regression model, which is linear, quadratic, Gaussian, and polynomial. The radial Gaussian kernel function (RBF) usually performs better for prediction. The equation of this kernel function is as follows:

$$K(x, y) = \exp\left(-\frac{\|x_i - y_j\|}{2\sigma^2}\right) \tag{18}$$

In building an efficient SVM model, model parameters must be accurately calculated using an optimization method. These parameters are kernel function type, kernel function parameter σ^2, tuning parameter C, and accuracy parameter ε corresponding to the maximum error in the ε-insensitive area.

Evaluation criteria

To evaluate and compare the developed models, statistical error indicators including coefficient of determination (R^2), root mean square error ($RMSE$), scattering index (SI), and developed discrepancy ratio (DDR) were selected. The calculation formula of each of the mentioned indices is presented in Equations (19)–(22), respectively:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - y_i)^2} \tag{20}$$

$$SI = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - y_i)^2}}{\bar{x}} \tag{21}$$

$$DDR = \left(\frac{x_i}{y_i}\right) - 1 \tag{22}$$

In these formulas, n is the number of data, x_i is the predicted results by numerical simulation, y is the result obtained from laboratory investigations, and $\bar{x}$ is the average value of the results obtained from laboratory measurements, and is obtained from Equation (23):

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{23}$$

RESULTS AND DISCUSSION

In this part, the results of the development of the soft computing models of MLPNN, GMDH, NF-GMDH, and SVM to estimate the water's surface elevation in compound open channels with converging and diverging floodplains are presented. First, the MLPNN model is developed. The development of the MLPNN model, as mentioned in the Materials and Methods section, is a multi-step process based on trial and error; however, it is helpful to use the experiences of other researchers. The design of the MLPNN model structure includes determining the number of hidden layers, the number of neurons in each hidden layer, and the activation function and training algorithm. In this research, the recommendations of Parsaie *et al.* (2018) have been used to design the structure of the MLPNN. According to their suggestion, first, a hidden layer that has some neurons equal to the number of input features should be considered. Then, various types of well-known (suitable) transfer functions should be used and evaluated. During the development of the MLPNN model, activation functions including the logarithm of the sigmoid (logsig), the tangent of the sigmoid (tansig), and the radial basis function (RBF) were evaluated, and their results are presented in Table 2. As can be seen from this table, the best performance is for the log-sigmoid and RBF. However, both transfer functions were selected as superior functions. The structure of the MLPNN model is shown in Figure 2. As is clear from this figure, the developed model has a hidden layer with four neurons.

The performance of the developed MLPNN model in the training and testing phases is shown in Figure 3. The MLPNN statistical error indices of the MLPNN model in the training stage are $R^2 = 0.971$ and $RMSE = 0.282$, and in the testing stage they are $R^2 = 0.971$ and $RMSE = 0.276$. The *SI* of this model in the training and testing stages is 0.035 and 0.034.

In the following, the results obtained from the development of the GMDH model to estimate the water's surface elevation in compound channels with converging and diverging floodplains are presented. The structure of the developed GMDH model is shown in Figure 4.

Considering that there are only three variables in the inputs and considering the development criteria of the GMDH model, only three neurons can be produced in the first layer. According to the development rules of the GMDH model, not all these neurons (in the first hidden layer) can participate in forming the next (second) hidden layer, therefore, two neurons were

Table 2 | The performance of transfer functions investigated in the development of the MLPNN model

Name	R^2	*RMSE*	*SI*
tan-sigmoid	0.990	0.158	0.035
log-sigmoid	0.996	0.091	0.035
RBF	0.997	0.091	0.091

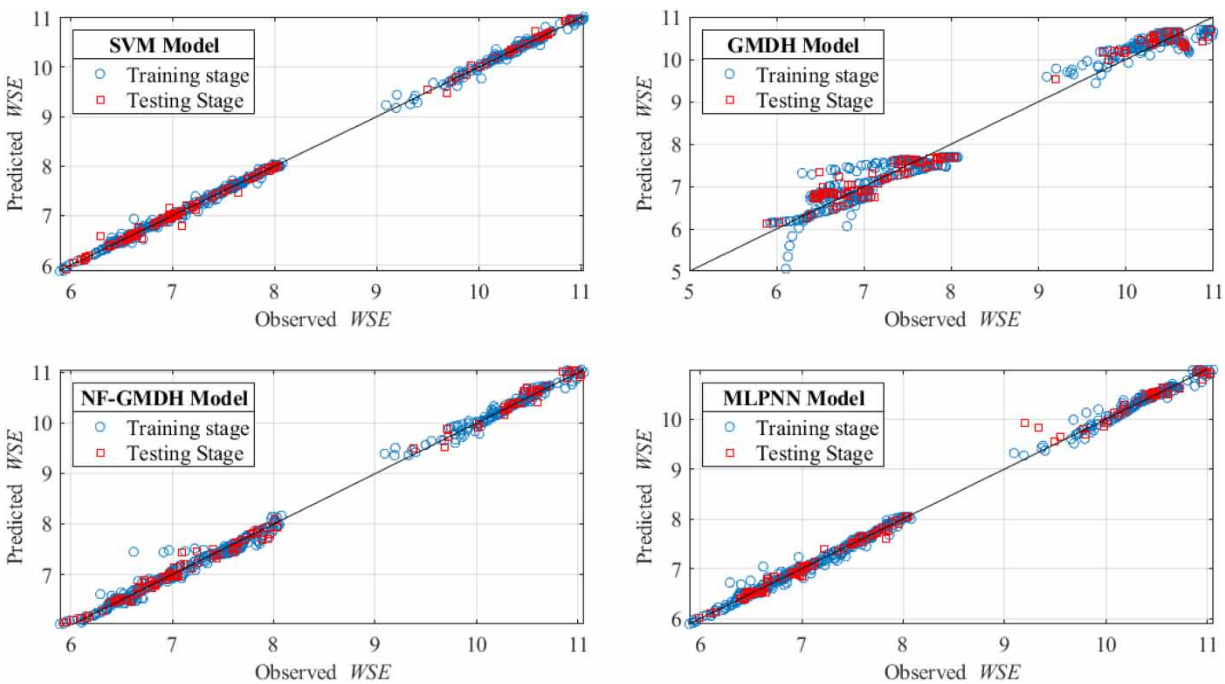

Figure 3 | The results of the developed models in estimating the water level in the compound channels with converging and diverging floodplains.

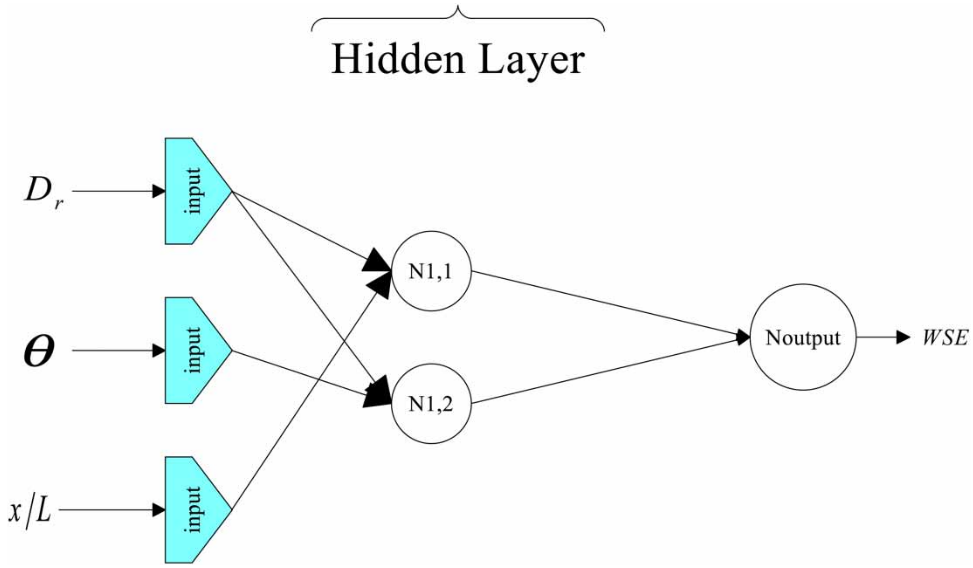

Figure 4 | The structure of the GMDH network developed to estimate the water level in compound channels with converging and diverging floodplains.

selected. In the forming of the next hidden layer, since there were only two neurons in the second hidden layer, only one neuron can be prepared, which also plays the role of the output neuron. The statistical error indicators of the GMDH model in the training stages are $R^2 = 0.965$ and $RMSE = 0.309$, and in the testing stage they are $R^2 = 0.964$ and $RMSE = 0.310$. The results of the developed GMDH model in different stages of development (training and testing) are presented in Figure 3. The *SI* of this model's performance in the training and testing stages is 0.038. Comparing the statistical indices of the GMDH model with the MLPNN model in different development stages shows that the accuracy of the GMDH model is partially lower, although the *SI* of its results is significantly higher. As is clear from Figure 3, this model has more scatter than the MLPNN model. However, its statistical indicators are slightly less accurate. In the following, the results obtained from the application of adaptive fuzzy concepts in the development of the GMDH model are presented. The structure of the developed NF-GMDH model is shown in Figure 5.

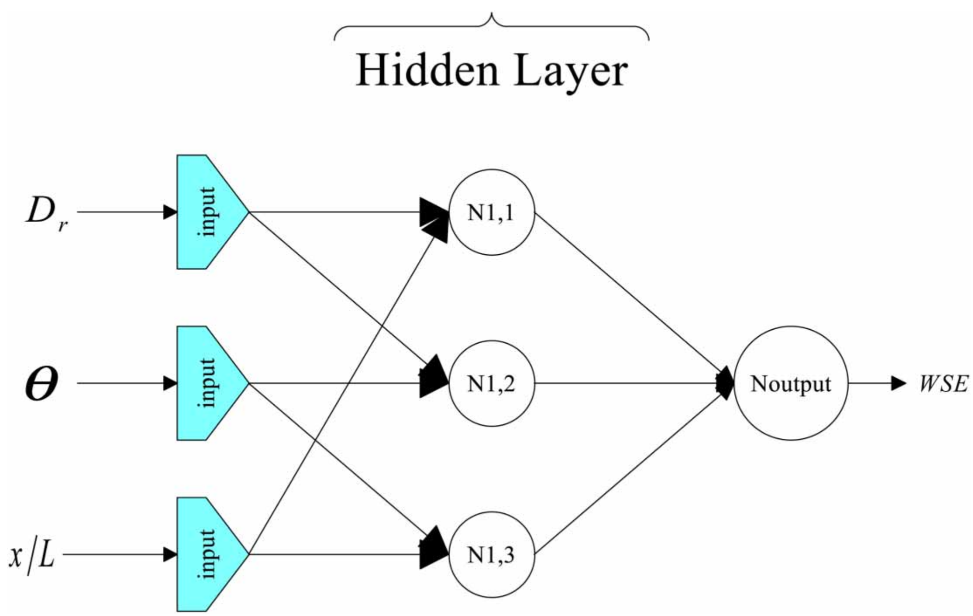

Figure 5 | An NF-GMDH model structure to estimate the water level in the compound channels with converging and diverging floodplains.

As is clear from this figure, the NF-GMDH model has two hidden layers in which there are three neurons in both layers. The statistical error indicators of the NF-GMDH model in the training stage are $R^2 = 0.996$ and $RMSE = 0.097$, and in the testing stage they are $R^2 = 0.997$ and $RMSE = 0.097$. The SI of the NF-GMDH model in the training and testing stages is 0.012 and 0.011, respectively. The performance of the NF-GMDH model in the development stages is shown in Figure 3. Examining and comparing the performance of the NF-GMDH model with the previous models (GMDH and MLPNN) shows that the accuracy of the NF-GMDH model has increased significantly compared with the GMDH model, and compared with the MLPNN model, they have almost the same statistical indicators.

In the following, the results obtained from the development of the SVM model are presented. To develop the SVM model, the performance of different types of kernel functions has been examined and the results are presented in Table 3. This table shows that the best performance is related to the radial kernel function. The structure of the developed SVM model is shown in Figure 6.

The statistical indicators of the developed SVM model in the training phase are $R^2 = 0.999$ and $RMSE = 0.053$, and in the testing stage, they are $R^2 = 0.997$ and $RMSE = 0.051$. The SI of the developed SVM model is equal to 0.007 in the training stage, and 0.006 in the testing stage. Comparing the performance of this model with the previous models (MLPNN, GMDH, and NF-GMDH) shows that the accuracy of this model is significantly better than the GMDH model and comparable to the MLPNN and NF-GMDH models.

Table 3 | Performance of transfer functions investigated in SVM model development

Name	R^2	$RMSE$	SI
Polynomial	0.940	0.085	0.022
RBF	0.996	0.065	0.007
Sigmoid	0.997	0.053	0.009

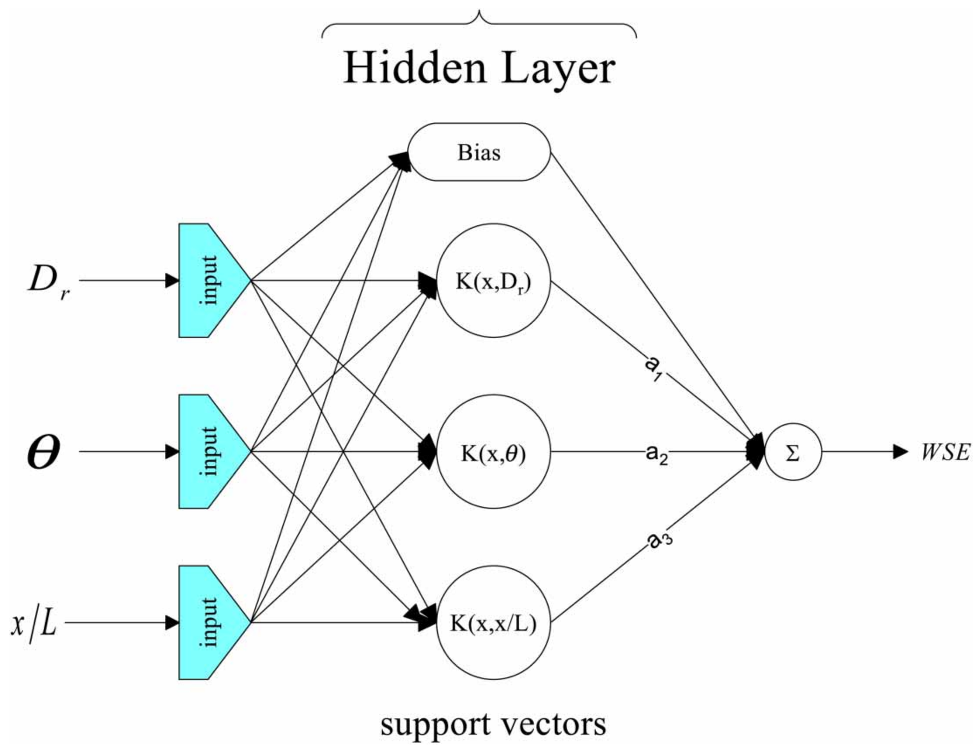

Figure 6 | The structure of the SVM network developed to estimate the water level in the compound channels with converging and diverging floodplains.

To more accurately check the performance of the models developed, the *DDR* statistical index was calculated for the results of all models in the training and testing stages (Figures 7 and 8). If the *DDR* index is greater than zero, it indicates that the results of a model are greater than the observed data and the model provides a higher estimation property. Likewise, if the index is less than zero, the model has a lower estimation property. Figure 7 shows the distribution of the *DDR* index versus x/L. Examining this figure shows that in the case of the SVM model, by increasing the relative distance x/L, the values

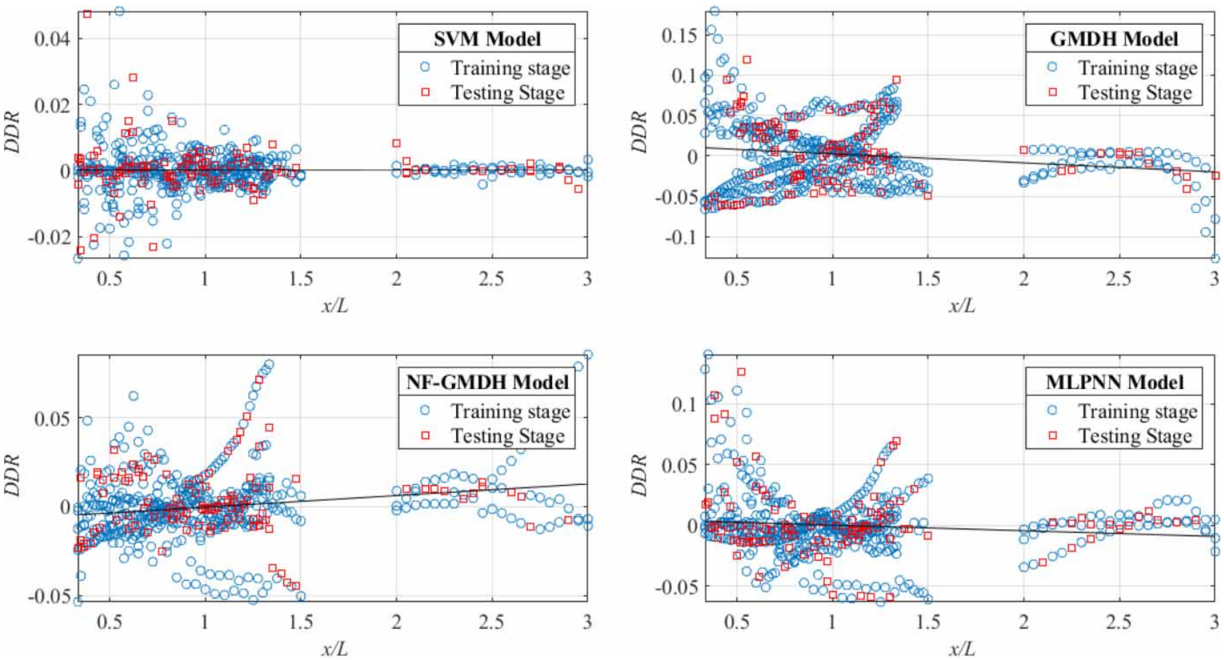

Figure 7 | Changes in the *DDR* index versus relative distance.

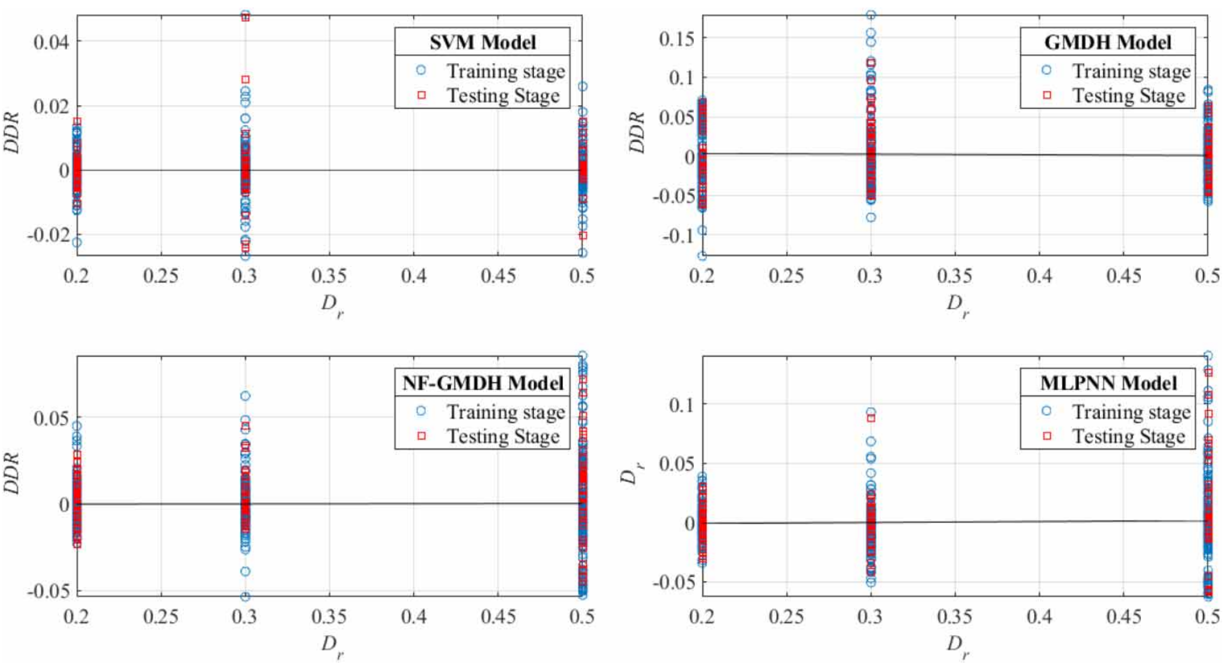

Figure 8 | Changes in the *DDR* index versus relative depth.

of the *DDR* index have decreased significantly, and this means that the accuracy of the model increases. Almost the same trend is observed for the MLPNN model. This trend is not observed for the other models. *DDR* values are also plotted against D_r and shown in Figure 8. This figure does not show a specific trend of the *DDR* with the increase of D_r.

In the following, to compare the performance of the models more precisely, Taylor's diagram was drawn for both the training and testing stages and is shown in Figures 9 and 10. Taylor's diagram uses both correlation and standard deviation parameters to check and scale soft computing models. Examining Figure 9 shows that in the training stage, the performance of the SVM, NF-GMDH, and MLPNN models match the observed values very well and are very close to each other.

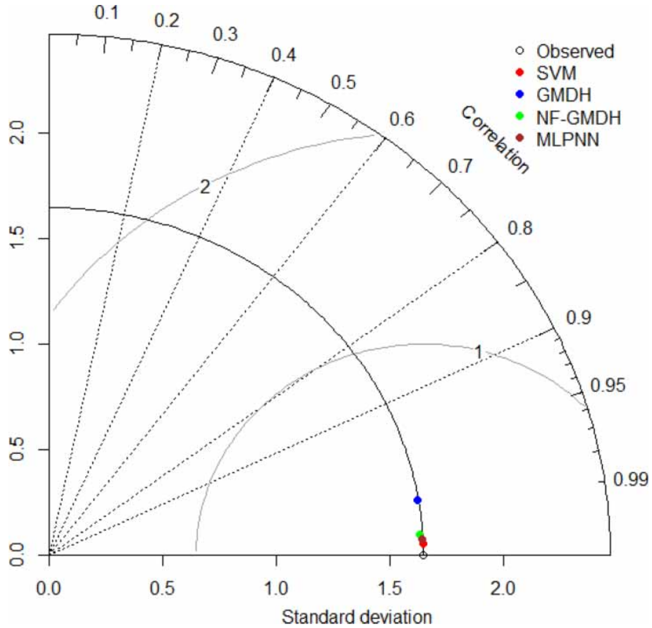

Figure 9 | Taylor diagram of the performance of the developed models in the training stage.

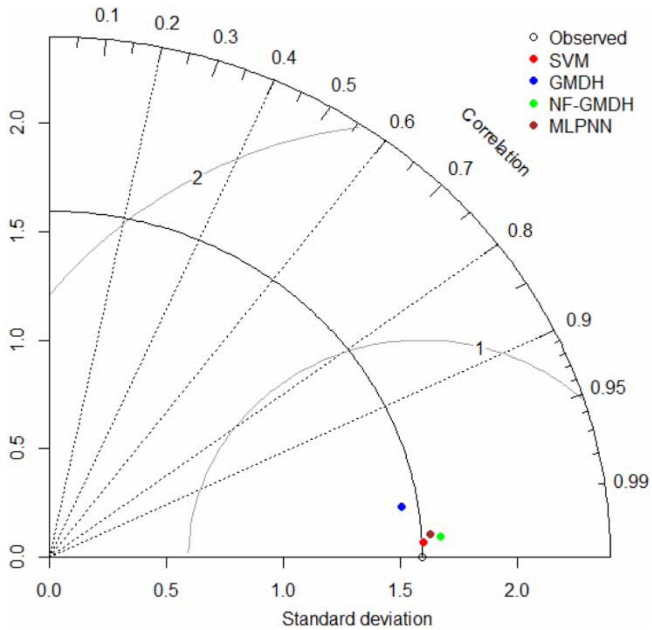

Figure 10 | Taylor diagram of the performance of the developed models in the testing stage.

However, the results of the GMDH model are far from the observed data and weaker than the other soft calculation models. This analysis is almost true for the testing stage as well.

In the following, the performance of the models developed to estimate the water's surface elevation in the compound channels with converging and diverging floodplains studied by Bousmar *et al.* (2006) has been evaluated. For this purpose, the water's surface elevation in the compound channel with one in three values of D_r with diverging floodplain with two divergence angles and the converging floodplain with two convergence angles were simulated. The simulation results and estimation of the water's surface elevation for one of the simulations (11.3° angles of convergence and divergence) are shown in Figures 11 and 12. As is clear from these figures, the developed models have appropriate accuracy in estimating the water's surface elevation in the compound channel with converging or diverging floodplains.

Comparison with previous findings

This section presents the results of the development of data mining models including the SVM model and the NF-GMDH data model compared with other soft computing models proposed by research workers. Kaushik & Kumar (2023)

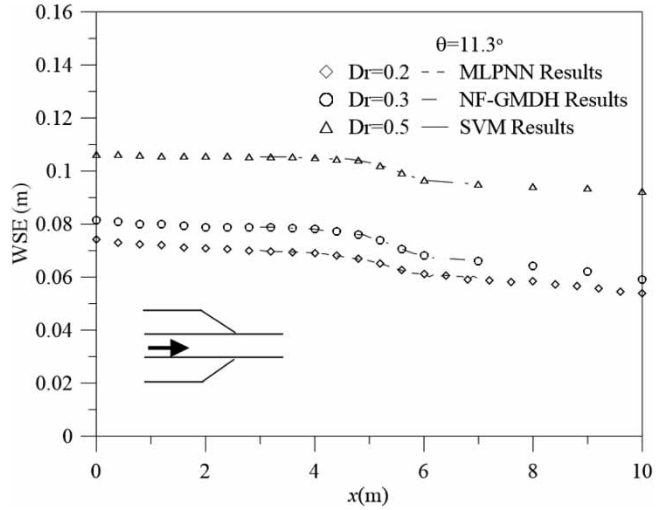

Figure 11 | The performance of SVM, MLPNN, and NF-GMDH models in estimating the water level in the compound channel with a converging floodplain.

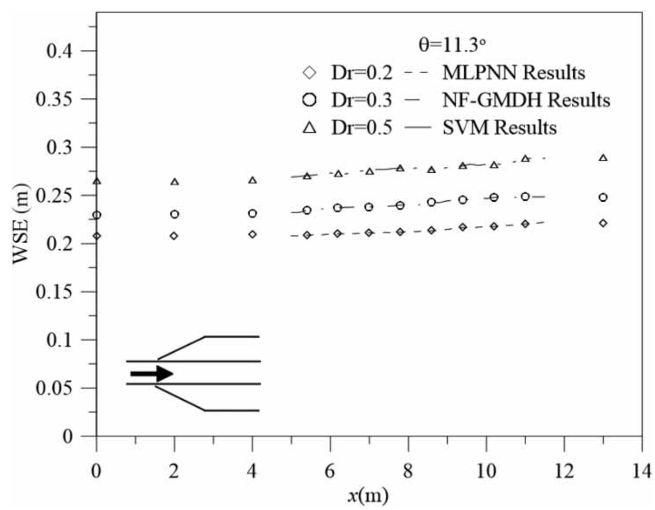

Figure 12 | The performance of SVM, MLPNN, and NF-GMDH models in estimating the water level in the compound channel with a diverging floodplain.

investigated the water's surface elevation in non-prismatic compound channels using machine learning techniques, including GEP, artificial neural networks (ANNs), and SVMs. They also presented a new equation using the GEP model to predict the water's surface elevation. Their results showed that the ANN model predicted the water's surface elevation more accurately among the used models, so that $R^2 = 0.999$ and $RMSE = 0.003$, while in the current research, the best performance was related to the SVM model with statistical indices of $R^2 = 0.998$ and $RMSE = 0.008$ in the test phase. The use of the adaptive fuzzy approach in the development of the GMDH model resulted in a remarkable increase in the accuracy of this model, the statistical indicators reaching values of $R^2 = 0.985$ and $RMSE = 0.203$ in the testing stage. Another advantage of the current research that makes it unique is finding effective parameters in predicting the water's surface elevation in compound channels, which was discussed in detail in the Results and Discussion section.

CONCLUSION

In this research, the water's surface elevation in compound channels with converging and diverging floodplains was modeled and estimated using the soft computing models of MLPNN, GMDH, NF-GMDH, and SVM. For this purpose, data related to the angle of convergence and divergence, relative depth, and longitudinal distance were used for both these types of floodplain. The results showed that all the soft computing models have good accuracy in estimating the water's surface elevation in such compound channels. However, the best performance and accuracy were related to the SVM. It was found that the use of adaptive fuzzy logic in the development of the GMDH model significantly increases the accuracy of the GMDH. The sensitivity analysis of the developed models, along with the structure of the GMDH model, showed that the relative depth parameter and the relative distance, respectively, have the most effect in modeling and estimating the water's surface elevation in compound channels with converging and diverging floodplains.

DATA AVAILABILITY STATEMENT

All relevant data are available from https://dial.uclouvain.be/downloader/downloader.php?pid=boreal:4996&datastream=PDF_01.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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