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Hybrid model of support vector regression and fruitfly optimization algorithm for predicting ski-jump spillway scour geometry

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ABSTRACT

Accurate prediction of the scour hole depth and dimensions downstream of ski-jump spillways has been an important issue among hydraulic researchers for decades. In recent years, computing methods such as Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Inference Systems (ANFISs) and Support Vector Regression (SVR) have shown a powerful performance in the prediction of scour characteristics owing to their flexibility and learning nature. In the present paper, a new hybrid approach has been proposed for the first time in order to improve the estimation power of the SVR tool for scour hole geometry prediction below ski-jump spillways. The principal characteristics of the scour hole pattern in the equilibrium phase have been predicted using SVR optimized with Fruitfly Optimization Algorithms (FOAs). The hybrid model is compared with the corresponding simple SVR model. To evaluate the proposed hybrid model further, it is also compared with other machine learning and empirical methods, such as ANNs, ANFISs and regression equations. The results show that the proposed SVR-FOA method performs well, improves remarkably on Support Vector Machines (SVMs) results, estimates scour hole geometrical parameters more accurately than the simple SVR model, and can be applied as an alternative reliable scheme for estimations on which simple SVR and other methods demonstrate shortcomings. The proposed hybrid method improves the precision level for scour depth prediction by about 8% compared with simple SVM in terms of the correlation coefficient.

Introduction

The local scour process due to the downstream jet of ski-jump spillways is a serious concern and precise prediction of the scour hole depth and dimensions is essential for the protection of dams and their adjacent structures. The scour can cause instability and failure of the dam structure in the area. Many hydraulic, hydrological and geotechnical factors influencing the scour mechanism make it a very complex phenomenon. For decades, numerous investigators have made prototypes and conducted experimental studies to formulate the scour below ski-jump spillways based on regression approaches. The earlier of these studies developed equations to predict the scour hole depth formed as a result of impinging jets, such as Schoklitch (1935), Veronese (1937), Martins (1975), Mason and Arumugam (1985), and Yildiz and Uzucek (1994). The majority of them considered

their equations as a function of two or three parameters, namely discharge intensity (q), head difference between tail water and reservoir levels (H), and bed sediment size (d). However, the results from these formulae show inconsistencies owing to the complexity of the phenomenon and the deficiencies of traditional approaches such as regression.

The literature indicates that artificial-intelligence (AI)-based methods are proficient in simulating complex systems because of their nonlinear nature. They are used successfully in water resources engineering—see for example Fotovatikhah et al. (2018), Shende and Chau (2019), and Yaseen et al. (2019). Reported work on the application of such soft computing methods for scour prediction can also be found in the literature, such as Bateni et al. (2007), who estimated scour depth around bridge piers using Artificial Neural Networks

(ANNs) and neuro-fuzzy approaches, Azamathulla and Ghani (2011), who estimated scour depth at culvert outlets using an Adaptive Neuro-Fuzzy Inference System (ANFIS), Bateni and Jeng (2007), who estimated pile group scour using a neuro-fuzzy approach. Azmathullah et al. (2005) applied ANNs successfully to predict the location of scour hole depth; their results showed the supremacy of ANNs in comparison with statistical regression equations. Azamathulla, Deo, et al. (2008) presented a study concerning the estimation of scour depth below a ski-jump spillway in prototype dams through the use of different neural networks and an ANFIS. Azamathulla, Ghani, et al. (2008) utilized Genetic Programming (GP) for estimating the scour depth downstream of a ski-jump spillway. Naini (2011) and Naini et al. (2011) used the ANN and ANFIS techniques, respectively, for predicting the scour hole geometrical pattern below a ski-jump spillway. The results showed that the AI tools turn out to produce more accurate results than the conventional regression equations.

The literature shows that Support Vector Regression (SVR) has also been applied in various studies of water resources and hydraulic engineering. Kargar et al. (2020) used machine learning models including Support Vector Machines (SVMs), Gaussian process regression, M5 Model trees (M5P), random forests and regression to estimate the longitudinal dispersion coefficient using data sets gathered from 60 natural rivers. They concluded that both M5P and SVM were satisfactory but that M5P was superior. Ghazanfari Hashemi and Shahidi (2012) utilized SVM and ANN techniques to estimate pile groups scour, the results indicating that SVMs produce superior estimations of scour depth. Parsaie et al. (2019) estimated the scour depth below a river pipeline by an SVM, comparing the results with those of ANNs and ANFISs, the SVM results being more accurate.

SVMs can be a promising method in practical and field cases as it needs fewer parameters for good estimation than ANNs (Goyal & Ojha, 2011), and also it is less time consuming and less sensitive to variations of the parameters (Ghazanfari Hashemi & Shahidi, 2012).

In case of ski-jump scour, Goyal and Ojha (2011) estimated the scour downstream of a ski-jump bucket by SVM and M5 models. The results were compared with ANNs and it was found that SVMs and M5 perform well in comparison with ANNs and regression models. However, sensitivity analysis of SVMs with a raw data set showed SVMs' performance to be more satisfactory when they have a lower number of inputs, and increasing the number of input parameters decreases the precision of the estimation of the output parameters.

Ayoubloo et al. (2015) applied various models for scour depth prediction below ski-jump spillways including Classification And Regression Trees (CARTs), SVMs, and M5, and it was found that CARTs emerged as the most promising approach.

Current research shows that using simple SVMs with the application of all input parameters (five inputs) for ski-jump scour prediction is not as appropriate as using other soft computing techniques such as ANNs and ANFISs. Hence, to win through this drawback of SVMs, the need for an optimized SVM was felt. This paper suggests that integration of SVMs with Fruitfly Optimization Algorithms (FOAs) could resolve this issue to some degree as far as ski-jump scour estimation is concerned.

SVMs require hyperparameter tuning: parameters such as C, γ, and ε should be selected in a way such that the model produces the optimal output with the lowest error. This is usually obtained through a trial-and-error procedure. This research, accordingly, aims to combine SVMs with a novel nature-inspired optimization scheme.

Integrating the latter single AI tools with optimization algorithms can develop a more powerful tool for modeling and predicting scour hole features in hydraulic structures. Najafzadeh et al. (2014) utilized the Group Method of Data Handling (GMDH) developed via Particle Swarm Optimization (PSO), GP, and back propagation for estimating the scour below ski-jump buckets, the results indicating that GMDH-BP outperformed other techniques. Hassanzadeh et al. (2019) predicted bridge pier scour depth using an ANFIS optimized with three different optimization algorithms, the results confirming the higher performance of the new methods. Azimi et al. (2019) used Genetic Algorithms (GAs) and Singular Value Decomposition (SVD) for optimizing ANFIS parameters to predict the scour depth around abutments; they concluded that the ANFIS-GA/SVD model was superior to other simple AI methods. Mahmodian et al. (2019) combined ANFISs and differential evolution algorithms as an optimization scheme for predicting the scour around submerged pipes. It was found that the hybrid models performed with higher accuracy.

Some of the successful applications of FOAs in engineering problems are available in the literature, such as Li et al. (2013), who proposed a hybrid model for forecasting power load coupling using Generalized Regression Neural Networks (GRNNs). The results they obtained indicated that the proposed model outperformed simple GRNN modeling. Samadianfard et al. (2019) integrated Support Vector Regression (SVR) with an FOA for river flow forecasting. They stated that the SVR-FOA hybrid model performed better compared with the M5 and SVR models.

To the best of the authors' knowledge, employing an FOA with SVR has not been investigated for ski-jump scour prediction yet. So the key objective of the current

research is to evaluate the performance of the SVR-FOA hybrid model in predicting the scour hole geometrical characteristics below ski-jump spillways including six scour parameters and to assess if the combination of SVR with an FOA improves on simple SVR results. The results of dimensionless SVR-FOA models are compared with those of SVR and other techniques.

For developing the computational models in this study, data obtained from experimental studies are used. The data include three less considered features of the scour hole (the landmarks denoting the starting and ending of scour, as well as the scour hole length). To assess the performance of the prediction models, several evaluation criteria are used.

Material and methods

Support vector regression

The SVM method was presented by Vapnik (1995). SVM, as a known method, was used for both classification and regression problems, and regression-based SVM is usually called SVR. It is constructed so as to minimize the structural risk for solving complex problems (Samadianfard et al., 2019).

Suppose we have training data $\{(x_1, y_1), \ldots, (x_\ell, y_\ell)\} \subset X \times \mathbb{R}$, where X is the space of the input forms (e.g. $X = \mathbb{R}^d$). In ε–SV regression, the goal is finding $f(x)$ that has at most a deviation ε from the obtained targets y_i and is as flat as possible. First we describe the linear function f, which takes the form (Smola & Scholkopf, 2004)

$$f(x) = \langle \mathcal{W}, x \rangle + b \quad \text{with } \mathcal{W} \in X, \ b \in \mathbb{R}, \quad (1)$$

in which $\langle \cdot, \cdot \rangle$ is the dot product in X. We have to minimize the norm, i.e. $||\mathcal{W}||^2 = \langle \mathcal{W}, \mathcal{W} \rangle$, to ensure that we seek a small $\mathcal{W}$. So it can be written as

$$\text{minimize} \quad \frac{1}{2}||\mathcal{W}||^2$$

$$\text{subject to} \quad \begin{cases} y_i - \langle \mathcal{W}, x_i \rangle - b \leq \varepsilon \\ \langle \mathcal{W}, x_i \rangle + b - y_i \leq \varepsilon. \end{cases} \quad (2)$$

It is assumed that the function f actually exists approximating all pairs (x_i, y_i) with accuracy. Sometimes, this is not the case and we might want to permit some errors. Therefore, the slack variables ξ_i, ξ_i^* may be introduced for overcoming infeasible constraints of the optimization problem

$$\text{minimize} \quad \frac{1}{2}||\mathcal{W}||^2 + C\sum_{i=1}^{\ell}(\xi_i + \xi_i^*)$$

$$\text{subject to} \quad \begin{cases} y_i - \langle \mathcal{W}, x_i \rangle - b \leq \varepsilon + \xi_i \\ \langle \mathcal{W}, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0. \end{cases} \quad (3)$$

The balance between the flatness of f and the amount up to which deviations larger than ε are tolerated is determined by the constant $C > 0$. So the ε-insensitive loss function $|\xi|_\varepsilon$ can be defined as follows:

$$|\xi|_\varepsilon := \begin{cases} 0 & \text{if } |\xi| \leq \varepsilon \\ |\xi| - \varepsilon & \text{otherwise.} \end{cases} \quad (4)$$

The final nonlinear regression function is given as (Cimen, 2008)

$$f(x) = \sum_{i=1}^{N}(\alpha_i^* - \alpha_i)K(x, x_i) + B, \quad (5)$$

where α_i, α_i^* denote the Lagrange multipliers, $K(x, x_i)$ is the kernel function, and B is a bias term. In the current research, the Gaussian Radial Basis Function (GRBF) has been selected for computations based on trial-and-error procedures, as follows:

$$K(x, x_i) = \exp\left(\frac{||x - x_i||^2}{2\sigma^2}\right). \quad (6)$$

The optimum parameters of the GRBF kernel have to be found; moreover, the size of the error and the regularization parameter C have to be determined. In this study, the default values of C and ε for SVR models are 1 and 0.001, respectively. Further details on SVM can be found in Smola and Scholkopf (2004) and Vapnik (1995).

### The Fruitfly Optimization Algorithm (FOA)

The FOA is a swarm optimization tool introduced by Pan (2012). The FOA is based on fruitfly behavior for food finding as follows: firstly, the osphresis organ helps the fruitfly to smell the source of its food, then it moves near the location and vision is utilized to find the food. After that, further flies fly towards that direction and flock at the location. Figure 1 illustrates the iterative process of food finding. The algorithm is described in several steps as follows (Pan, 2012; Shan et al., 2013):

Step 1: The main parameters of the FOA should be initialized. So, the random flight direction and distance zone of the fruitfly (FR) should be initialized first:

$$X\_axis = rand(LR)$$

$$Y\_axis = rand(LR). \quad (7)$$

Step 2: The random direction and distance for the search for food using osphresis by an individual fruitfly is defined:

$$X_i = X\_axis + RandomValue$$

$$Y_i = Y\_axis + RandomValue. \quad (8)$$
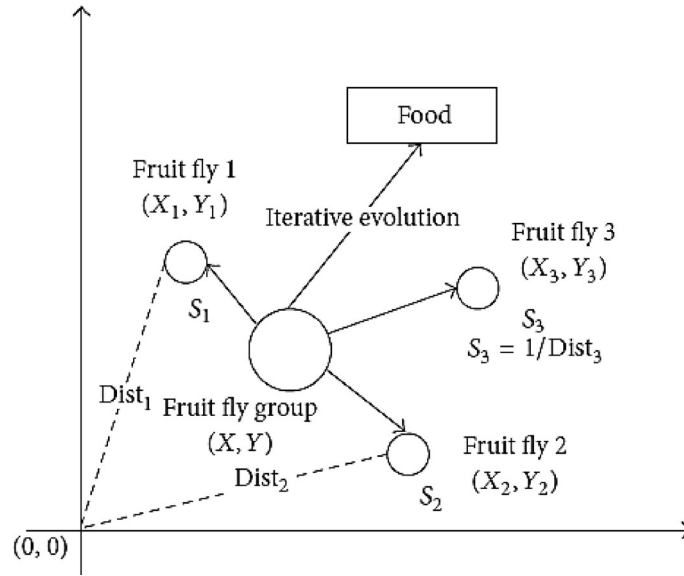
Figure 1. The iterative progression of food finding by a fruitfly swarm.

Step 3: The distance to the origin (*Dist*) is estimated, then the smell concentration judgment value (*S*) is calculated:

$$Dist_i = \sqrt{X_i^2 + Y_i^2}$$

$$S_i = \frac{1}{Dist_i}. \tag{9}$$

Step 4: The smell concentration judgment value (*S*) is substituted into the smell concentration judgment function for finding the smell concentration (*Smell_i*) at the individual location of the fruitfly:

$$Smell_i = Function(S_i). \tag{10}$$

Step 5: The fruitfly with maximum smell concentration among the swarm is determined:

$$(bestSmell\ bestIndex) = \max(Smell). \tag{11}$$

Step 6: Using the best smell concentration value and *x*-, *y*-coordinates, the fruitfly swarm flies towards the location:

$$Smellbest = bestSmell$$

$$X\_axis = X(bestindex)$$

$$Y\_axis = Y(bestindex). \tag{12}$$

Step 7: The procedures of steps 2–5 may be repeated as an iterative optimization procedure until the smell concentration converges to a constant value.

The flowchart of the process applied in this study is shown in Figure 2 adapted from Shan et al. (2013).

Artificial neural networks

ANNs accord with our understanding of the biological behavior of interconnected brain nodes known as neurons. ANNs create a relationship between input and output layers through hidden layer(s) by a learning process. The networks can be trained using data. During the training process, weighted connections between layers become updated so that the error between computed and observed values are minimized. In this research, the most conventional network, i.e. the Feed Forward Back Propagation (FFBP) network is utilized. A feed forward network with one hidden layer has the power to map any input to an output, provided that it has enough neurons in the hidden layer.

The simplest FFBP network is made up of an input, an output, and a hidden layer. The network was developed using the coding method in MATLAB® software. To train the network, a back propagation process with a Bayesian regularization (BR) algorithm was used that updates the weights and biases with Levenberg–Marquardt optimization. The main advantage of the BR method over other training methods is generalization improvement and the lack of a requirement for the validation data set to be set aside. The optimum neural network was selected via a trial-and-error method in which the error between the observed and computed values was minimum. Various numbers of neurons in hidden layers and different transfer functions were examined for this purpose. The training process ended up with an optimum network having five tansig-functioned neurons in the hidden layer and a linear function in the output layer neurons. A five-input model receiving the $F_0, H/d_w, d_{50}/d_w, R/d_w, \Phi$
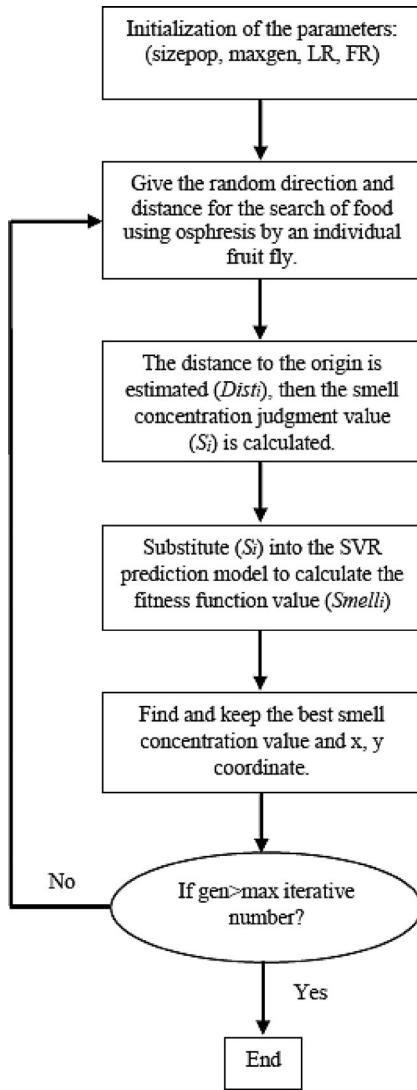
Figure 2. The Fruitfly Optimization Algorithm (FOA) method flowchart.

parameters and producing d_s/d_w, l_s/d_w, l_2/d_w, l_1/d_w, L_s/d_w, and w_s/d_w outputs at once was developed. Further details on ANNs can be found in Haykin (1994).

Adaptive neuro-fuzzy inference systems (ANFISs)

The adaptive neuro-fuzzy inference system is an improved modeling approach that can capture the action of complex systems. The ANFIS was first introduced by Jang (1993). It is a hybrid model that integrates the learning procedures of neural networks with those of fuzzy inference systems. Its learning algorithm updates the membership functions of a Sugeno fuzzy inference system using the input–output data. The ANFIS is a fuzzy inference system that profits from the back propagation structure of the neural network. It uses fuzzy IF–THEN rules to map inputs to outputs. An example of a fuzzy
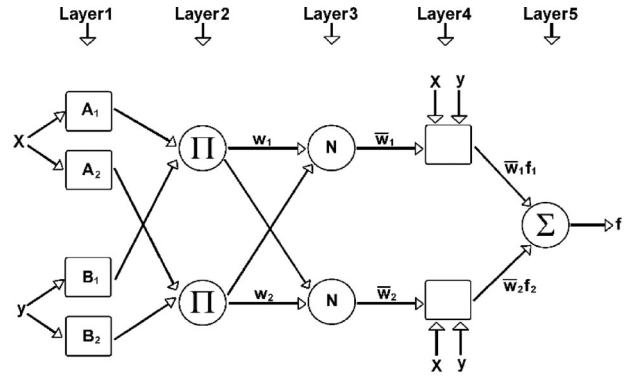
Figure 3. Basic ANFIS architecture.

rule can be expressed as 'IF the discharge intensity is high and the total head is high THEN the scour is large'. An ANFIS can tune membership function parameters by using a hybrid learning algorithm that combines the least squares method and back propagation gradient descent. Figure 1 shows the ANFIS structure: it is a five layer model with interconnected nodes. Some of the nodes are tuned through the learning process. As stated from Jang et al. (1997), a first-order Sugeno model with two fuzzy rules (Figure 3) can be described as

$$\text{Rule 1}: \text{ If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1 x + q_1 y + r_1, \tag{13}$$

$$\text{Rule 2}: \text{ If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2 x + q_2 y + r_2, \tag{14}$$

in which x and y are the inputs and A_1, A_2, B_1, B_2 are membership functions (such as 'cold' or 'warm'). Each layer has nodes with the same functions, so the process can be stated as follows.

Each node output is represented as $O_{l,i}$.

Layer 1: each node has a function that can be tuned as follows:

$$O_{1,i} = \mu_{Ai}(x) = \frac{1}{1 + |x - c_i/a_i|^{2b_i}}, \tag{15}$$

in which $\mu_{Ai}(x)$ is a bell function with a range between [0,1]; a_i, b_i, and c_i are modifiable parameters.

Layer 2: each node is a constant node, which produces the output as the product of all the inputs:

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y). \tag{16}$$

Layer 3: each node is constant and calculates the ratio of the ith output to the sum of all outputs (normalized output) as follows:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}. \tag{17}$$
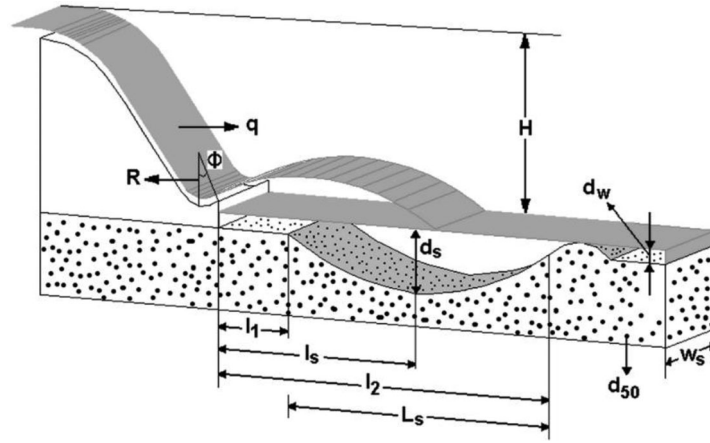
Figure 4. Scour hole characteristics below ski-jump spillway.

Layer 4: each node can be tuned by the following formula:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \qquad (18)$$

in which p_i, q_i and r_i are modifiable parameters.

Layer 5: the node is constant that estimates the total output by summing all inputs:

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \qquad (19)$$

There are two approaches for clustering data: subtractive clustering and fuzzy c-means. In subtractive clustering, the influence range is determined, but in fuzzy c-means clustering, the number of clusters is specified.

The method for generating a Fuzzy Inference System (FIS) in this research is subtractive clustering. The rules produced with this fuzzy inference system are thus minimized.

To develop the ANFIS models presented in this work, the MATLAB® Fuzzy Logic Toolbox is used. ANFIS model structures with first-order Sugeno and Gaussian membership functions are developed. Models consisting of the combination of non-dimensional parameters are built to predict scours' geometrical characteristics downstream of ski-jump spillways. To develop each ANFIS model and to reach the appropriate architecture, different values for the range of influence are selected in a trial-and-error approach until the highest Correlation Coefficient (CC) is achieved in the testing data set. To adjust the parameters of membership functions, the models are trained using the hybrid learning algorithm. For more detailed information on ANFIS models, readers may refer to Jang (1993) and Jang et al. (1997).

Dimensional analysis and data set used

In the current paper, the dimensionless parameters are applied for building the structure of intelligent models. As can be seen from Figure 4, the scour hole's geometrical dimensions are formed according to the erosive jet downstream of a flip bucket spillway, i.e. the maximum scour depth from the water surface (d_s), the location of the maximum scour depth from the bucket-lip (l_s), the scour hole length ($L_s = l_2 - l_1$), the location of the ending point of the scour hole (l_2), the location of the starting point of scour hole (l_1), and the scour hole width (w_s) may be considered as functions of other influential parameters, namely the head difference between the tail water and the reservoir (H), the unit discharge (q), the tail water (d_w), the bucket radius (R), the bucket lip angle (Φ), the median sediment size (d_{50}), the densities of sediment (ρ_s) and water (ρ_w), and the acceleration due to gravity (g), which is expressed as

$$d_s, l_s, l_1, l_2, L_s, w_s = f(q, H, R, \Phi, d_w, d_{50}, g, \rho_w, \rho_s). \quad (20)$$

By applying the Π theorem of Buckingham, dimensionless parameters are obtained and scour features are normalized with the tail water depth as

$$\frac{d_s}{d_w}, \frac{l_s}{d_w}, \frac{l_1}{d_w}, \frac{l_2}{d_w}, \frac{L_s}{d_w}, \frac{w_s}{d_w}$$
$$= f\left(F_0, \frac{H}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \Phi\right), \qquad (21)$$

in which the dimensionless parameter $F_0 = [q/(g d_w^3)^{1/2}]$ is the Froude number. The constant ratio ρ_s/ρ_w is eliminated from the input set. The above functional relationship (Equation 21) is used in the development of the dimensionless SVR and SVR-FOA models.

The data pertaining to two experimental studies are utilized. The data set contains 96 data gathered from

Asadi Saryazdi (1997) and Momeni Vesalian (2006), respectively, to estimate the geometrical characteristics of the scour hole. Table 1 displays the utilized data in the current study.

Three significant parameters considered in this study are the starting point and the ending point of the scour hole (l_1, l_2) and the length of the scour hole (L_s), previously considered by Naini (2011) and Naini et al. (2011) in ANN and ANFIS simulations, respectively.

The data are divided into two separated data sets, the first is called the training data set and includes 70% of the entire samples that were randomly selected and used to construct and calibrate the models, the second is

called the testing data set and includes the remaining 30% used for validation of the calibrated models. Table 2 shows the statistics of the dimensionless data employed for the modeling.

Nonlinear regression equations

In order to evaluate the efficiency of the soft computing models, a comparison is made with nonlinear regression equations. Regression equations were derived using the same 70% dimensionless data selected randomly and used for training of the AI models. Considering the functional relations produced in the dimensional analysis section (Equation 21), the following set of equations were obtained for prediction of the scour hole geometrical characteristics:

$$\frac{d_s}{d_w} = 3.959(F_o)^{0.771}\left(\frac{H}{d_w}\right)^{0.044}\left(\frac{R}{d_w}\right)^{0.02}\left(\frac{d_{50}}{d_w}\right)^{0.01}(\Phi)^{-0.01} \quad (22)$$

$$\frac{l_s}{d_w} = 1.756(F_o)^{0.288}\left(\frac{H}{d_w}\right)^{0.496}\left(\frac{R}{d_w}\right)^{0.075}\left(\frac{d_{50}}{d_w}\right)^{0.01}(\Phi)^{-1.532} \quad (23)$$

$$\frac{l_2}{d_w} = 8.456(F_o)^{0.392}\left(\frac{H}{d_w}\right)^{0.491}\left(\frac{R}{d_w}\right)^{0.01}\left(\frac{d_{50}}{d_w}\right)^{0.01}(\Phi)^{0.01} \quad (24)$$

$$\frac{l_1}{d_w} = 0.414(F_o)^{0.012}\left(\frac{H}{d_w}\right)^{0.81}\left(\frac{R}{d_w}\right)^{-0.009}\left(\frac{d_{50}}{d_w}\right)^{-0.002}(\Phi)^{-1.382} \quad (25)$$

$$\frac{L_s}{d_w} = 13.467(F_o)^{0.691}\left(\frac{H}{d_w}\right)^{0.135}\left(\frac{R}{d_w}\right)^{0.01}\left(\frac{d_{50}}{d_w}\right)^{0.02}(\Phi)^{0.01} \quad (26)$$

$$\frac{w_s}{d_w} = 32142.161(F_o)^{0.01}\left(\frac{H}{d_w}\right)^{0.874}\left(\frac{R}{d_w}\right)^{0.006}\left(\frac{d_{50}}{d_w}\right)^{0.132}(\Phi)^{14.16}. \quad (27)$$

In addition, in order to evaluate the developed models in the present study, regression equations from the previous research done by Azmathullah et al. (2005) were used in estimation of the corresponding scour hole features:

$$\frac{d_s}{d_w} = 6.914(F_o)^{0.694}\left(\frac{H}{d_w}\right)^{0.0815}\left(\frac{R}{d_w}\right)^{-0.223}\left(\frac{d_{50}}{d_w}\right)^{0.196}(\Phi)^{0.196} \quad (28)$$

$$\frac{l_s}{d_w} = 9.85(F_o)^{0.42}\left(\frac{H}{d_w}\right)^{0.28}\left(\frac{R}{d_w}\right)^{0.043}\left(\frac{d_{50}}{d_w}\right)^{0.037}(\Phi)^{0.34661} \quad (29)$$

$$\frac{w_s}{d_w} = 5.42(F_o)^{-0.015}\left(\frac{H}{d_w}\right)^{0.55107}\left(\frac{R}{d_w}\right)^{0.1396}\left(\frac{d_{50}}{d_w}\right)^{0.242}(\Phi)^{-0.16}. \quad (30)$$

The above equations were validated using the remaining 30% data used as the testing data set. The performance results of Equations (22)–(30) are given in Table 3.

Evaluation criteria

In the present paper, the performance of the soft computing models and empirical regression schemes are measured in terms of six different error criteria, namely the CC, Scatter Index (SI), Willmott's Index of agreement (WI), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), which are denoted as follows.

I: CC expressed as

$$CC = \frac{\left(\sum_{i=1}^n O_i P_i - \frac{1}{n}\sum_{i=1}^n O_i \sum_{i=1}^n P_i\right)}{\left(\sum_{i=1}^n O_i^2 - \frac{1}{n}\left(\sum_{i=1}^n O_i\right)^2\right)\left(\sum_{i=1}^n P_i^2 - \frac{1}{n}\left(\sum_{i=1}^n P_i\right)^2\right)}. \quad (31)$$

II: SI follows as

$$SI = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^n (P_i - O_i)^2}}{\overline{O}}. \quad (32)$$

III: WI expressed as

$$WI = 1 - \left[\frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n \left(\left|P_i - \overline{O}_i\right| + \left|O_i - \overline{O}_i\right|\right)^2}\right]. \quad (33)$$

IV: MAPE expressed as

$$MAPE = \frac{1}{n}\sum_{i=1}^n \left|\frac{O_i - P_i}{O_i}\right| \times 100. \quad (34)$$

V: RMSE expressed as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^n (O_i - P_i)^2}. \quad (35)$$

VI: MAE expressed as

$$MAE = \frac{1}{n}\sum_{i=1}^n |O_i - P_i|, \quad (36)$$

where P_i and O_i are the predicted and observed ith values, respectively.

Taylor diagrams are also used to facilitate assessment of the SVR and SVR-FOA models. They

Table 1. Ranges of raw database used.

Data source	No. of samples	Discharge intensity, q ($m^3/s/m$)	Total head, H (m)	Bed sediment size, d_{50} (m)	Bucket radius, R (m)	Tail water depth d_w (m)	Lip angle, Φ (rad)	Scour depth, d_s (m)	Max scour location, l_s (m)	Starting location, l_1 (m)	Ending location, l_2 (m)	Scour length, L_s (m)	Scour width, w_s (m)
Momeni Vesalian (2006)	32	0.0196–0.0758	1.129–1.404	0.00018–0.006	0.1	0.06–0.265	0.451	0.19–0.44	1.375–2.025	0.8–1.4	1.625–2.8	0.425–1.8	0.26
Asadi Saryazdi (1997)	64	0.0204–0.0471	0.2791–0.3827	0.008	0.1–0.2	0.0286–0.1	0.524	0.0562–0.3587	0.42–0.82	0.1–0.34	0.66–1.6	0.35–1.35	0.65

Table 2. Statistical characteristics of the utilized data.

Skewness	Coefficient of variation	Standard deviation	Maximum	Minimum	Mean	Variable
1.441	0.950	0.779	3.110	0.052	0.819	Fo
0.738	0.513	4.060	21.267	2.791	7.914	H/dw
1.025	0.767	1.828	6.993	0.377	2.382	R/dw
0.538	0.771	0.092	0.280	0.001	0.119	d50/dw
−0.707	0.067	0.033	0.524	0.451	0.500	Φ
1.521	0.733	2.662	12.542	0.562	3.633	ds/dw
0.821	0.504	6.578	28.750	4.550	13.062	ls/dw
1.122	0.581	11.661	55.944	6.600	20.075	l2/dw
1.164	0.501	2.876	17.500	1.456	5.739	l1/dw
1.317	0.722	10.346	47.203	1.837	14.336	Ls/dw
0.607	0.778	7.443	22.727	0.981	9.569	ws/dw

Table 3. General computation results for the soft computing and regression models.

Model	Statistical parameters					
	CC	SI	WI	MAPE	RMSE	MAE
SVR-1	0.892	0.477	0.826	29.0	1.704	1.074
SVR-FOA-1	0.971	0.220	0.976	14.3	0.784	0.508
SVR-2	0.958	0.262	0.888	22.3	3.418	2.677
SVR-FOA-2	0.990	0.080	0.994	7.8	1.043	0.888
SVR-3	0.946	0.332	0.867	25.2	6.637	4.949
SVR-FOA-3	0.990	0.084	0.995	6.5	1.678	1.193
SVR-4	0.876	0.351	0.817	29.5	2.008	1.361
SVR-FOA-4	0.941	0.196	0.963	19.1	1.122	0.815
SVR-5	0.930	0.415	0.871	30.5	5.931	3.966
SVR-FOA-5	0.980	0.164	0.987	14.0	2.344	1.709
SVR-6	0.982	0.217	0.978	18.3	1.874	1.350
SVR-FOA-6	0.993	0.094	0.997	17.6	0.808	0.664
ANN-1	0.992	0.104	0.996	9.9	0.371	0.301
ANN-2	0.991	0.073	0.995	5.6	0.957	0.703
ANN-3	0.991	0.099	0.994	6.4	1.989	1.302
ANN-4	0.961	0.156	0.980	18.8	0.890	0.705
ANN-5	0.994	0.104	0.996	9.9	1.487	1.065
ANN-6	0.999	0.014	0.999	3	0.119	0.081
ANFIS-1	0.995	0.078	0.997	7.7	0.280	0.210
ANFIS-2	0.991	0.073	0.995	6.0	0.946	0.667
ANFIS-3	0.991	0.084	0.995	6.1	1.684	1.217
ANFIS-4	0.951	0.173	0.974	18.5	0.992	0.735
ANFIS-5	0.992	0.123	0.994	9.6	1.761	1.284
ANFIS-6	0.999	0.001	0.999	0.2	0.011	0.008
Reg-1	0.956	0.237	0.976	24.3	0.845	0.625
Reg-2	0.991	0.078	0.994	7.3	1.021	0.787
Reg-3	0.979	0.133	0.987	10.3	2.660	1.915
Reg-4	0.939	0.193	0.966	20.9	1.104	0.834
Reg-5	0.978	0.169	0.987	13.6	2.413	1.755
Reg-6	0.997	0.237	0.983	11.9	2.048	1.165
Azmathullah et al. (2005) (ds/dw)	0.947	0.321	0.947	25.5	1.145	0.823
Azmathullah et al. (2005) (ls/dw)	0.899	0.288	0.919	19.4	3.758	2.442
Azmathullah et al. (2005) (ws/dw)	0.953	0.521	0.885	110.6	4.499	2.550

are used to express the degree of correspondence between observed and model values according to the RMSE, the CC, and the standard deviation (Taylor, 2001).

Results and discussion

In this section, the SVR and SVR-FOA results are compared with each other and those of the machine learning and regression methods (ANN, ANFIS and regression equations) in a testing data set employing the same input combinations for all the models. Table 5 shows the name of established AI models developed to estimate the scour

hole parameters and Table 4 displays the specific parameters for each soft computing method.

Comparison of SVR-FOA with SVR

Comparing the results of the models in terms of the statistical measures shown in Table 3, it can be understood that the SVR-FOA hybrid models remarkably outperform the simple SVR models. For instance, in the case of scour hole depth (ds/dw) prediction, the CC value has increased from 0.892 with SVR-1 to 0.971 with the SVR-FOA-1 model, which shows a considerable growth (by about 8%). WI also shows a similar trend, increasing

Table 4. Parameters of the soft computing models.

Model	Model parameters		
	C	γ	ε
SVR-1	1.0000	0.0100	0.0010
SVR-FOA-1	1.4029	0.0599	0.0464
SVR-2	1.0000	0.0100	0.0010
SVR-FOA-2	1.7257	0.0863	0.2222
SVR-3	1.0000	0.0100	0.0010
SVR-FOA-3	1.7026	0.1148	0.0682
SVR-4	1.0000	0.0100	0.0010
SVR-FOA-4	2.7597	0.0428	0.0705
SVR-5	1.0000	0.0100	0.0010
SVR-FOA-5	1.8537	0.0559	0.0915
SVR-6	1.0000	0.0100	0.0010
SVR-FOA-6	1.5677	0.0667	0.0648
	Number of member-ship functions	Range of influence	
ANFIS-1	5	0.5	
ANFIS-2	3	0.5	
ANFIS-3	3	0.7	
ANFIS-4	2	0.8	
ANFIS-5	5	0.5	
ANFIS-6	4	0.5	
	Architecture	transfer function	
ANN	5-5-6	Tansig–Purelin	

Table 5. The names of soft computing models.

Output parameter	SVR	SVR-FOA	ANN	ANFIS
ds/dw	SVR-1	SVR-FOA-1	ANN-1	ANFIS-1
ls/dw	SVR-2	SVR-FOA-2	ANN-2	ANFIS-2
l2/dw	SVR-3	SVR-FOA-3	ANN-3	ANFIS-3
l1/dw	SVR-4	SVR-FOA-4	ANN-4	ANFIS-4
Ls/dw	SVR-5	SVR-FOA-5	ANN-5	ANFIS-5
ws/dw	SVR-6	SVR-FOA-6	ANN-6	ANFIS-6

from 0.826 to 0.976. WI is a measure of the degree of model estimation error and varies between zero and one, with a perfect estimation being indicated by one, moreover, the expected error percentage in terms of the SI shows a lower value (0.220) in the case of SVR-FOA-1 than SVR-1 (0.477). MAPE is also lower in the case of SVR-FOA-1 (14.3) and we can see that the lower errors of RMSE = 0.784 and MAE = 0.508 in the case of SVR-FOA-1 denote the superiority of the new method.

SVR-FOA-2 shows better estimation than SVR-2 in the prediction of (ls/dw), about 3.2% increase in CC is observed, and the WI improves by about 10% from 0.888 to 0.994, the SI decreases from 0.262 to 0.080 and MAPE decreases from 22.3 to 7.8 (14.5%). The errors in the case of SVR-2 (RMSE = 3.418 and MAE = 2.677) are higher compared to SVR-FOA-2 (RMSE = 1.043 and MAE = 0.888).

For l2/dw, SVR-FOA-3 improves the CC and WI criteria to 4.4% and 12.8%, respectively, and decreases the MAPE from 25.2 to 6.5 (18.7%). A decrease is also observed in terms of RMSE (from 6.637 to 1.678) and MAE (from 4.949 to 1.193) for the hybrid tool.

In the case of the location of the maximum scour (ls/dw) and the ending point of the scour hole (l2/dw), as can be seen from Table 3, the statistical results for CC, SI, and WI are very much the same for the SVR-FOA-2 and SVR-FOA-3 models, respectively. But they differ from each other in their errors (MAPE, RMSE, and MAE).

From a comparative point of view, both the SVR-FOA-2 and SVR-FOA-3 schemes, in terms of scour hole longitudinal characteristics, outperform their counterparts, i.e. SVR-2 and SVR-3, respectively.

In terms of the prediction of the starting point of the scour hole from the bucket (l1/dw), the hybrid method performs with higher accuracy. A growth of 6.5% is observed in the CC using SVR-FOA-4, the MAPE also decreases by about 10.4% from 29.5 to 19.1. A drop is also seen in RMSE (from 2 to 1.122) and MAE (from 1.361 to 0.815) values, respectively. From Table 3, it can be said that the l1/dw parameter is the most difficult parameter to estimate compared with the other five scour hole features in all of the applied models, with the lowest CC and WI.

In estimation of the scour hole length (Ls), the accuracy is also improved using SVR-FOA-5 by about 5% in terms of the CC criterion, and the WI improves to 11.6%, while the MAPE decreases from 30.5 to 14 (16.5%) and the SI decreases from 0.415 to 0.164. The RMSE and MAE values decrease to about 3.587 and 2.257, respectively.

In the case of the scour hole width (ws), both SVR-FOA-6 and SVR-6 performed well with CC = 0.993 and CC = 0.982, respectively, but the SVR-FOA-6 scheme is slightly better w.r.t. the statistics with lower errors.

Comparing the CC and WI statistics in Table 3, it is noted that the difference between them is lower in the case of the SVR-FOA schemes than in the case of the SVR models. For instance, the maximum difference between the CC and WI in the case of SVR-FOA pertains to SVR-FOA-4 (about 2.2), while the maximum difference between the CC and WI in the case of SVR is 7.9, which pertains to SVR-3.

For assessing the behavior of the models graphically, the scatter plots of the observed values versus the estimated ones for the SVR and SVR-FOA models are also given in Figures 5–10. As can be understood from these figures, the SVR-FOA scatter plots demonstrate that the points are much more distributed around the best fit line (45°), denoting their higher precision in the estimation of the scour hole parameters. While for the SVR scatter plots, the points are less distributed around the ideal fit line, signifying their lower accuracy in scour parameters estimation. A common fact that can be observed in Figures 5–10 is that almost all the six SVR models (SVR-1–6) overestimate the scour value from the lowest values to the nearly middle values and underestimate
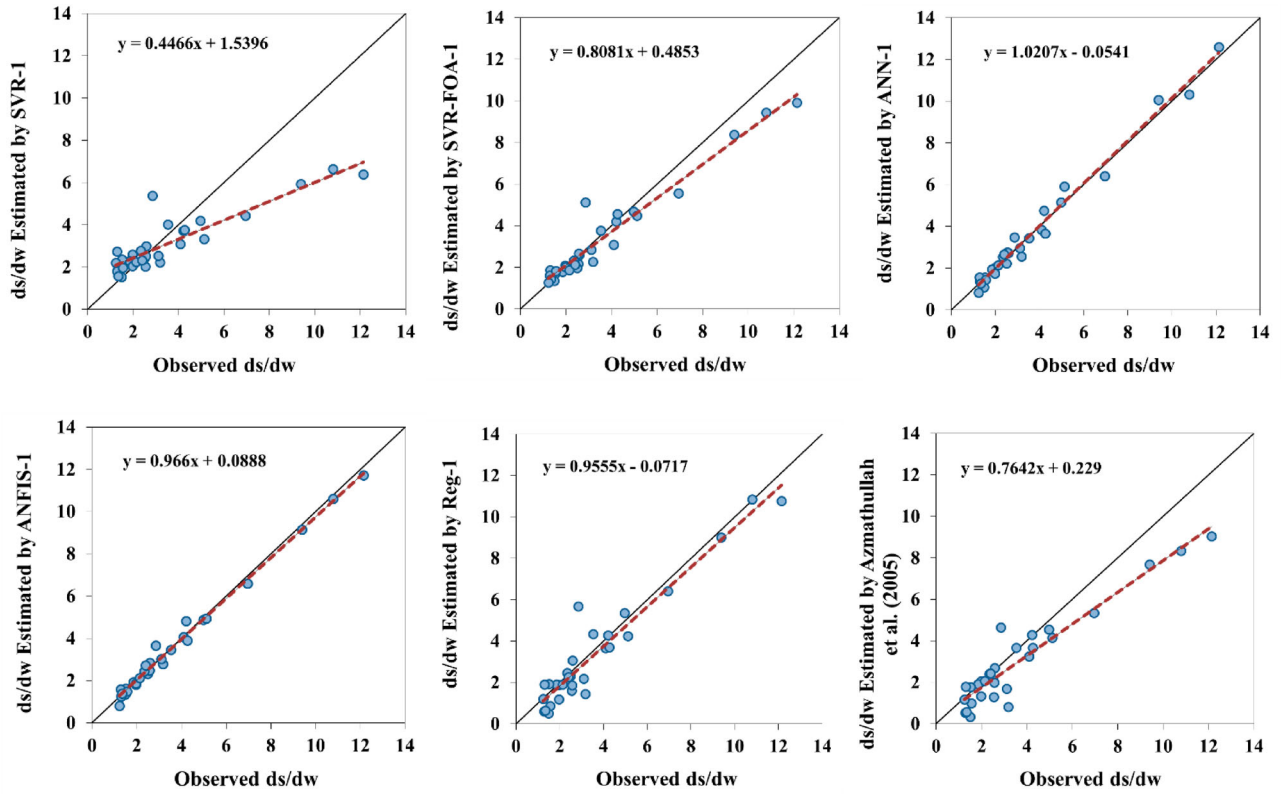
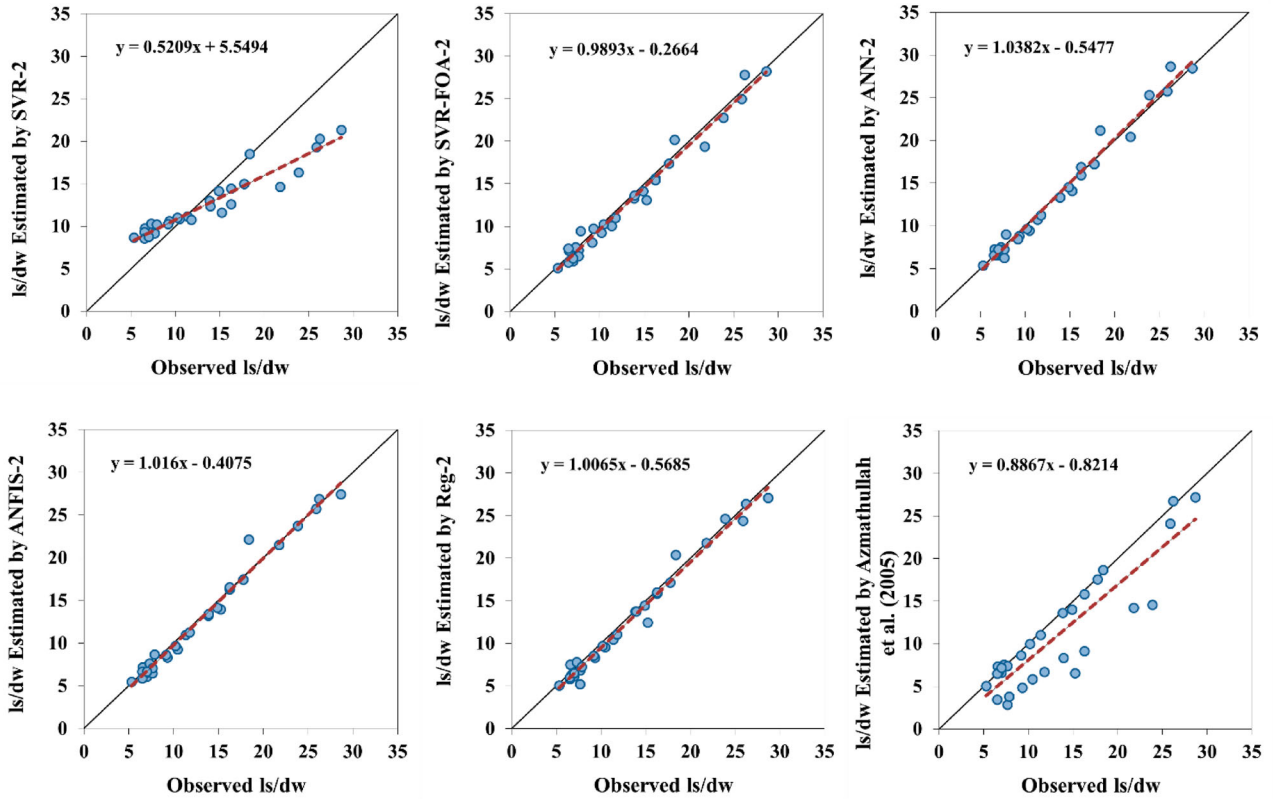**Figure 5.** Scatter plots of observed versus estimated values of ds/dw for various models.

Figure 6. Scatter plots of observed versus estimated values of ls/dw for various models.
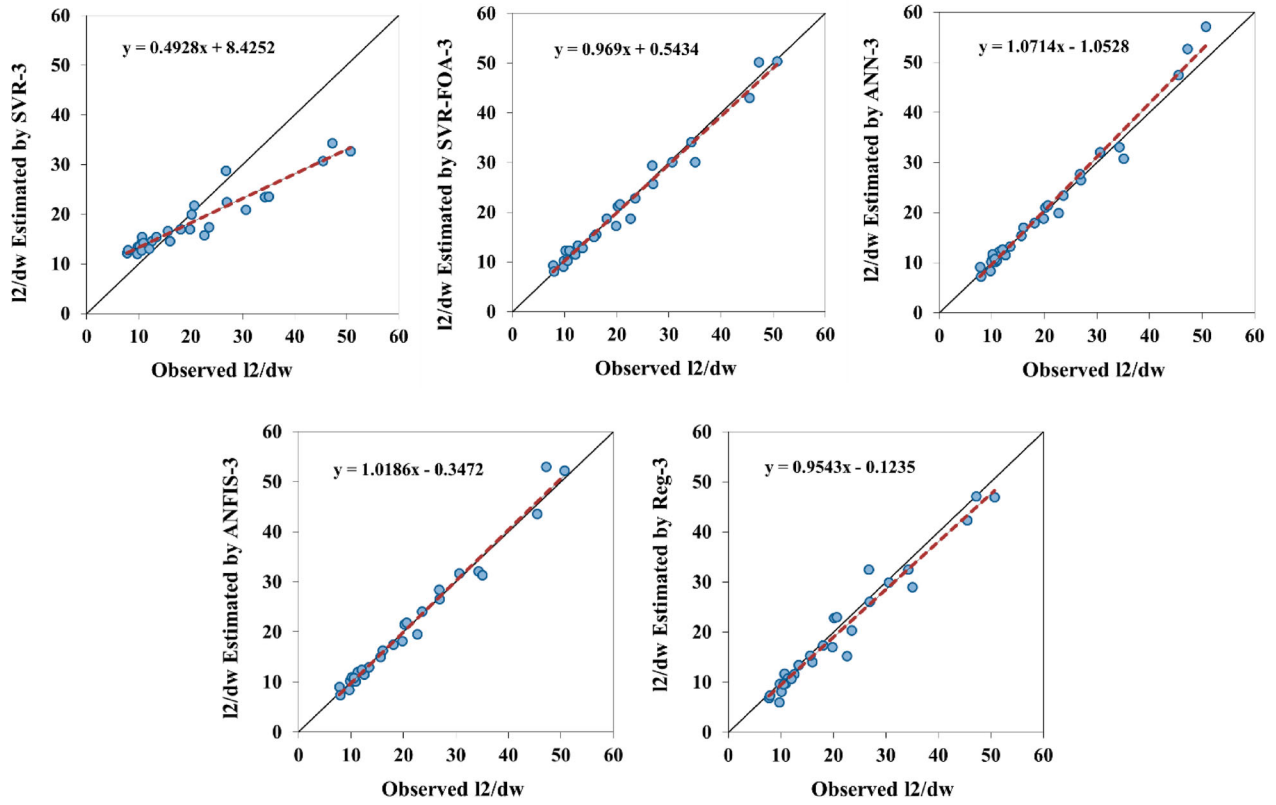
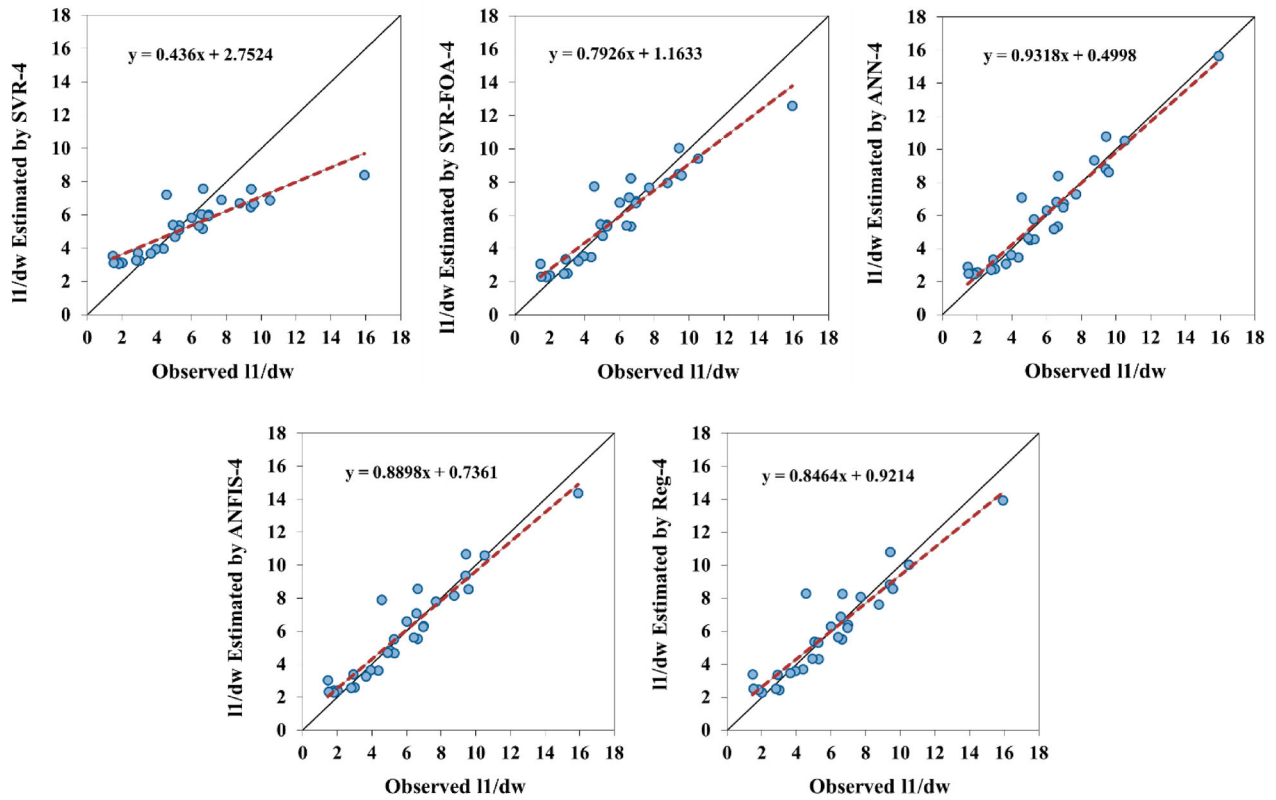**Figure 7.** Scatter plots of observed versus estimated values of l2/dw for various models.

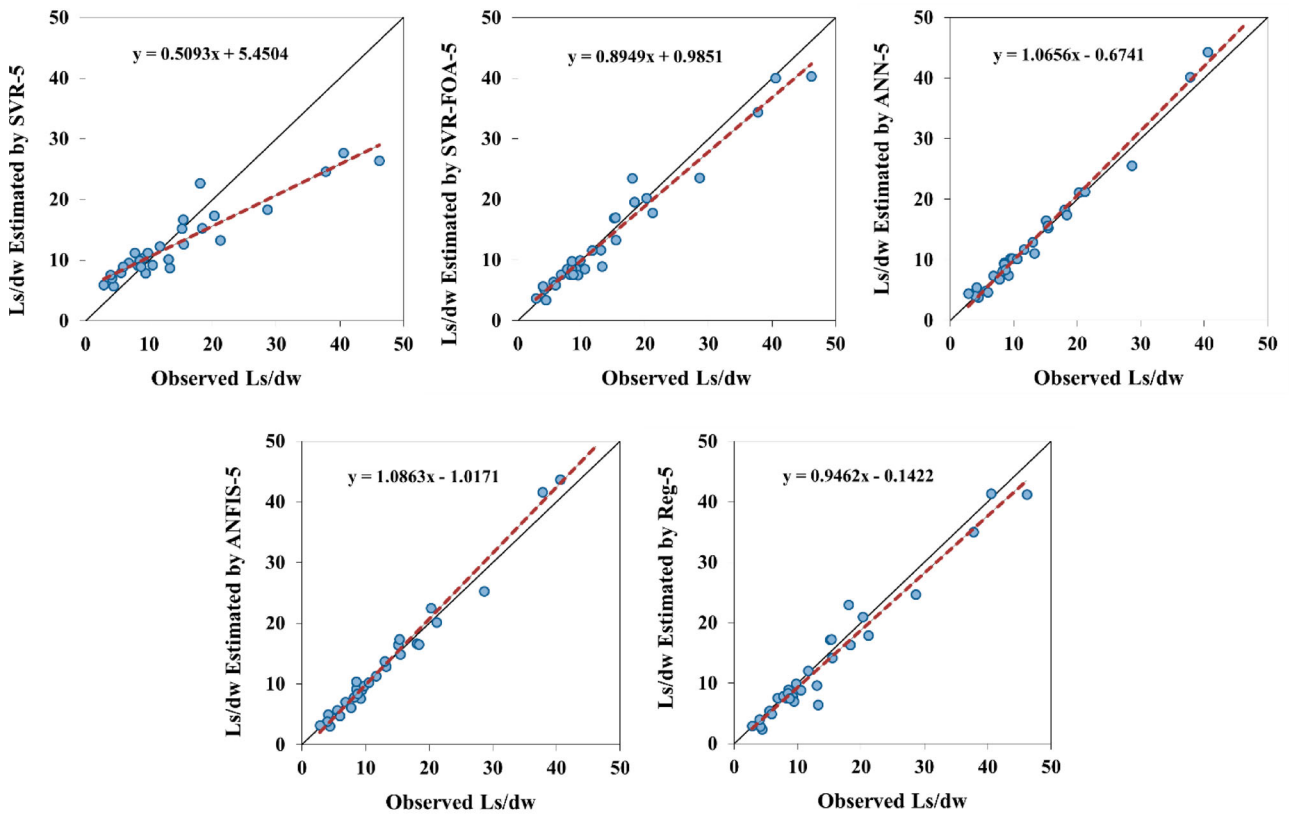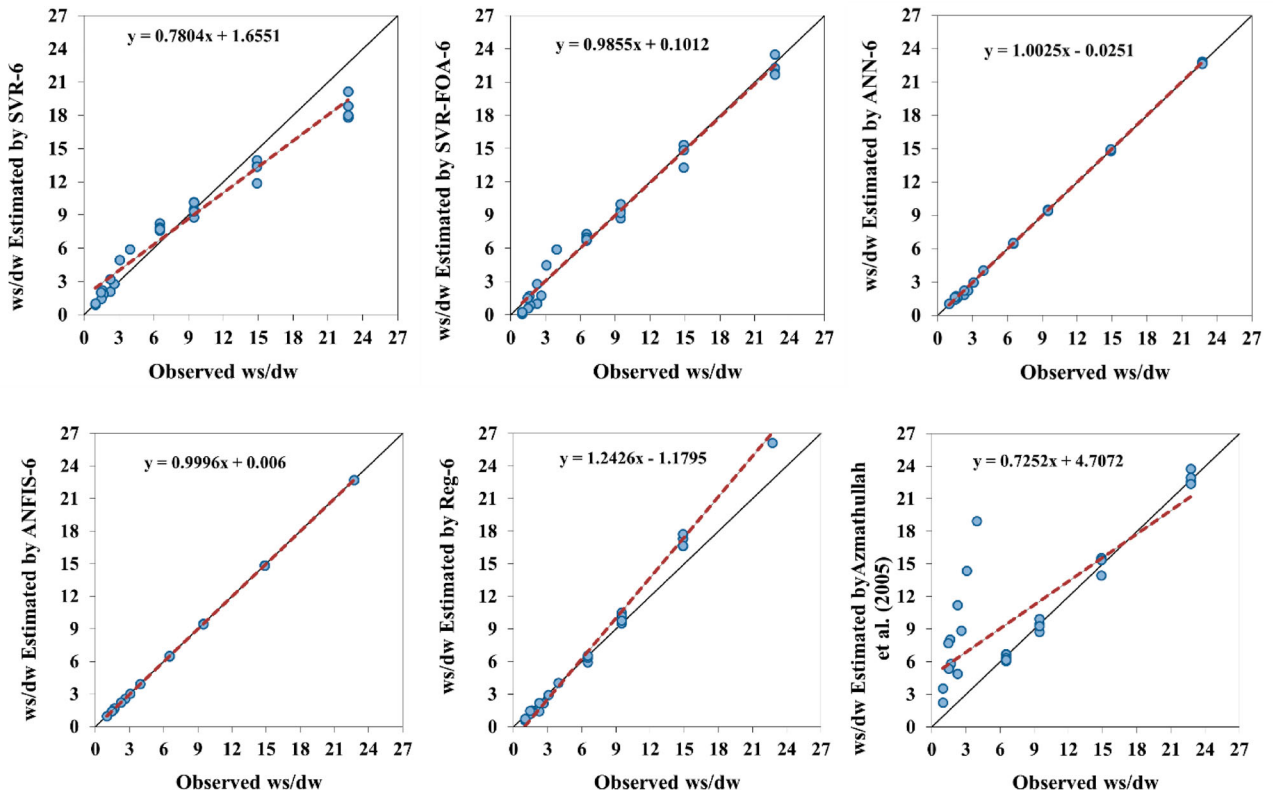**Figure 8.** Scatter plots of observed versus estimated values of l1/dw for various models.

Figure 9. Scatter plots of observed versus estimated values of Ls/dw for various models.

Figure 10. Scatter plots of observed versus estimated values of ws/dw for various models.

the scour from the middle values to the highest values, while, in the SVR-FOA plots (SVR-FOA-1–6), the points are distributed with more balanced values.

Figure 11 illustrates the comparison between the observed and estimated values of the SVR and SVR-FOA models. The green marks (for SVR-FOA-1–6) in the vicinity of the black marks (target values) indicate the higher accuracy of the proposed hybrid approach in prediction of the scour hole features, while the purple marks (SVR-1–6) are placed at a greater distance relative to the target values, denoting SVR's lower accuracy. In addition, the overestimation and underestimation mentioned earlier in the SVR-1 to SVR-6 models can also be seen in Figure 11.

Furthermore, from Figure 12 it is apparent that SVR-FOA (the red closed circles) is a more accurate scheme in predicting the scour hole characteristics due to its lower distance from the observed green closed circles.

Comparison with other techniques (ANN, ANFIS and regression equations)

Scour hole depth. As can be seen from Table 3, in general ANNs and ANFISs perform well and give very similar predictions for the scour parameters as shown by the error criteria statistics. As can be seen from Table 3, for predicting ds/dw, ANN-1 has a higher CC (0.992) and WI (0.996) than SVR-FOA-1 (CC = 0.971, WI = 0.976), the errors are also lower for ANN-1 (MAPE = 9.9, RMSE = 0.371, and MAE = 0.301). The accuracy of ANFIS-1 (CC = 0.995, WI = 0.997, RMSE = 0.28, and MAE = 0.21) is better than that of ANN-1 and SVR-FOA-1 in predicting the scour hole depth. It is obvious that the accuracy of SVR-FOA-1 (CC = 0.971) is higher than those of Reg-1 (CC = 0.956, RMSE = 0.845, and MAE = 0.625) and Azmathullah et al. (2005) (CC = 0.947, RMSE = 1.145, and MAE = 0.823) due to the lower errors. In contrast to SVR-FOA-1, SVR-1 yields lower accuracy (CC = 0.892, RMSE = 0.1704, and MAPE = 29) in comparison with the regression equations, which can also be seen in Figure 5, in which the trend line deviates more from the ideal fit line. From the scatter plots of Figure 5, the superiority of ANFIS-1 can be seen, and the fact that the two regression equations underestimate most of the data.

Maximum scour location

In the case of the maximum scour location (ls/dw), SVR-FOA-2 provides higher precision than the scour depth prediction model (SVR-FOA-1). The results show that SVR-FOA-2 (with CC = 0.990, RMSE = 1.043, and MAE = 0.888) performs well and has approximately the same level of accuracy as ANN-2 (CC

= 0.991, RMSE = 0.957, and MAE = 0.703) and ANFIS-2 (CC = 0.991, RMSE = 0.946, and MAE = 0.667). The accuracy of Reg-2 is also as high as the prominent soft computing methods with CC = 0.991, RMSE = 1.021, and MAE = 0.787 (Figure 6). The formulae of Azmathullah et al. (2005) underestimate some of the data (see Figure 6) for ls/dw, with CC = 0.899 and RMSE = 1.021. The SVR-2 predictions (CC = 0.958, RMSE = 22.3) are relatively better than those of SVR-1. However, in predicting ls/dw, it only performs better than the equation of Azmathullah et al. (2005).

Ending point of the scour hole

In predicting l2/dw, the accuracy of SVR-FOA-3 is approximately at the same level as ANN-3 and ANFIS-3, but some of its error criteria (RMSE = 1.678, MAE = 1.193, and SI = 0.084) are lower than those of ANN-3 (RMSE = 1.989, MAE = 1.302, and SI = 0.099) and ANFIS-3 (RMSE = 1.684, MAE = 1.217). From Figure 7, it is obvious that SVR-FOA-3 has fewer scattered points around the best fit line and the trend line is close to it. But the trend line in the ANN-3 plot deviates slightly from the ideal line. The Reg-3 equation estimates l2/dw with CC = 0.979, RMSE = 2.66, and MAE = 1.915, which outperforms SVR-3 with CC = 0.946 and RMSE = 4.949, but it underestimates most of the data and is below SVR-FOA-3, ANN-3 and ANFIS-3 from the aspect of the accuracy level. Therefore, SVR-FOA-3 seems to be evaluated as the most accurate model for l2/dw prediction.

Starting point of the scour hole

In predicting the l1/dw parameter, all the models dealt deficiently with producing a good prediction compared with the other scour characteristics. ANN-4 estimates this parameter with better precision (CC = 0.961, RMSE = 0.890, and MAE = 0.705) than SVR-FOA-4 (CC = 0.941, RMSE = 1.122, and MAE = 0.815) and ANFIS-4 (CC = 0.951, RMSE = 0.992, and MAE = 0.735). This superiority of ANN-4 can be observed in Figure 8, which shows that the trend line deviates less from the best fit line. The Reg-4 equation with CC = 0.939 and MAPE = 20.9 outperforms SVR-4 (CC = 0.876 and MAPE = 29.5) in predicting l1/dw. The lower accuracy of SVR-4 in estimating l1/dw can be seen in Figures 8 and 11.

Scour hole length. In the case of scour hole length (ds/dw), ANN-5 outperforms the other techniques with CC = 0.994, RMSE = 1.487, and MAE = 1.065. The second best model is ANFIS-5 with CC = 0.992, RMSE = 1.761, and MAE = 1.284. SVR-FOA-5 stands in third place with CC = 0.98, RMSE = 2.344, and MAE = 1.709. The REG-5 results are similar to those of
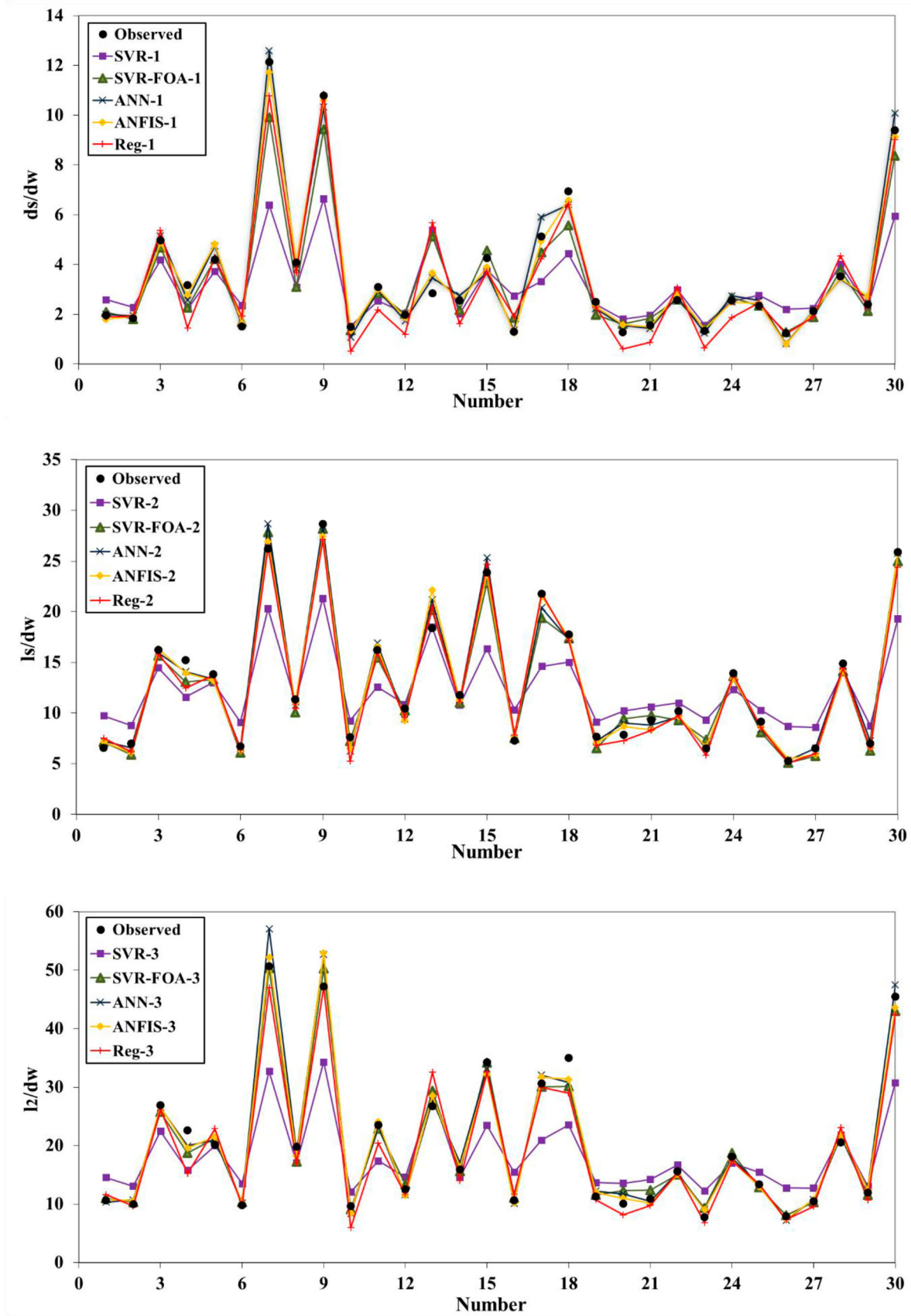
Figure 11. Plots of observed and estimated values of studied parameters with machine learning and regression models.
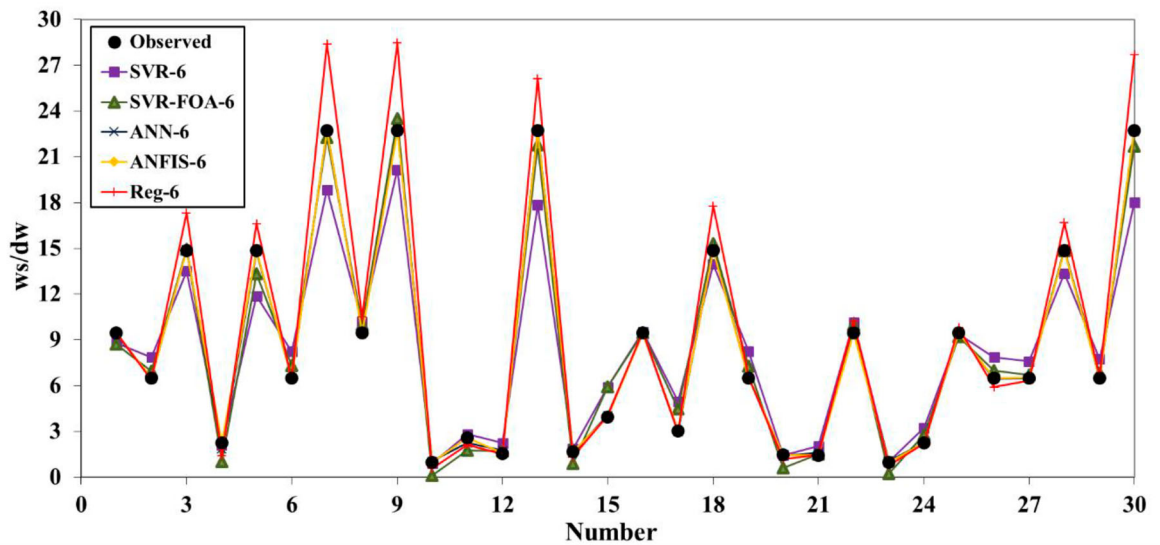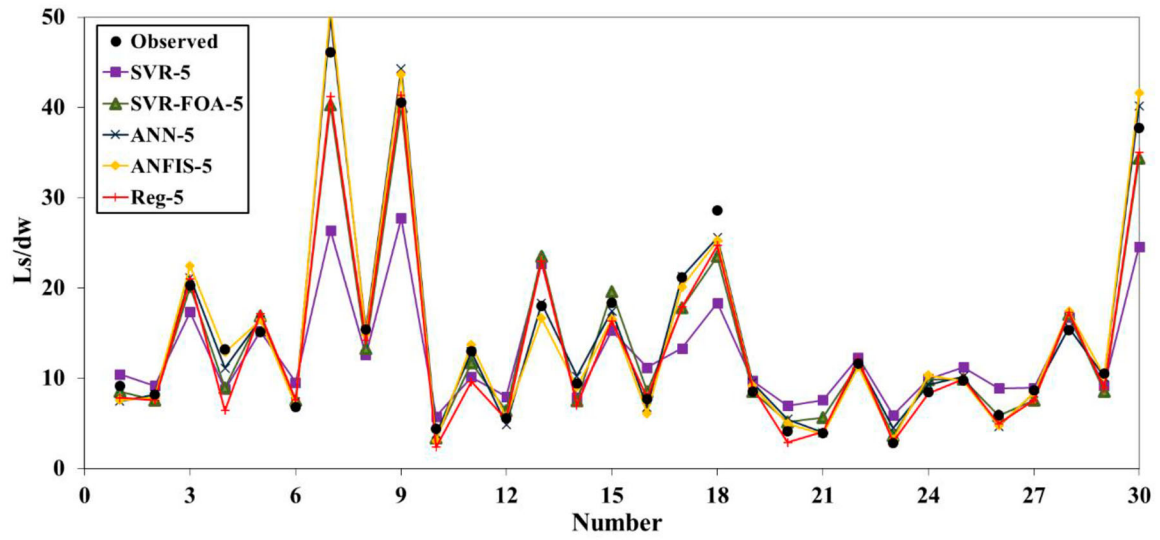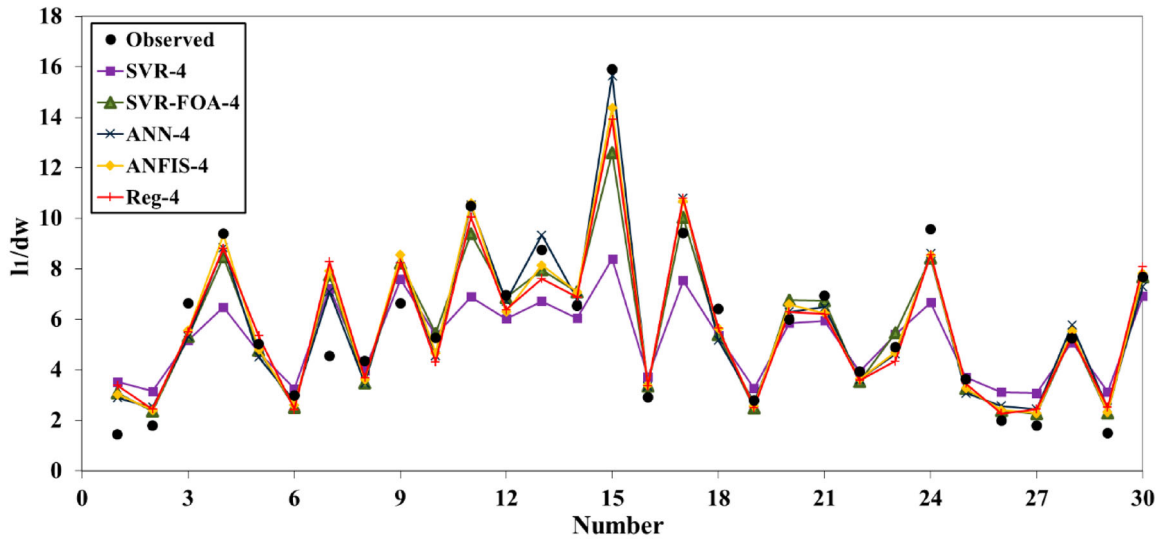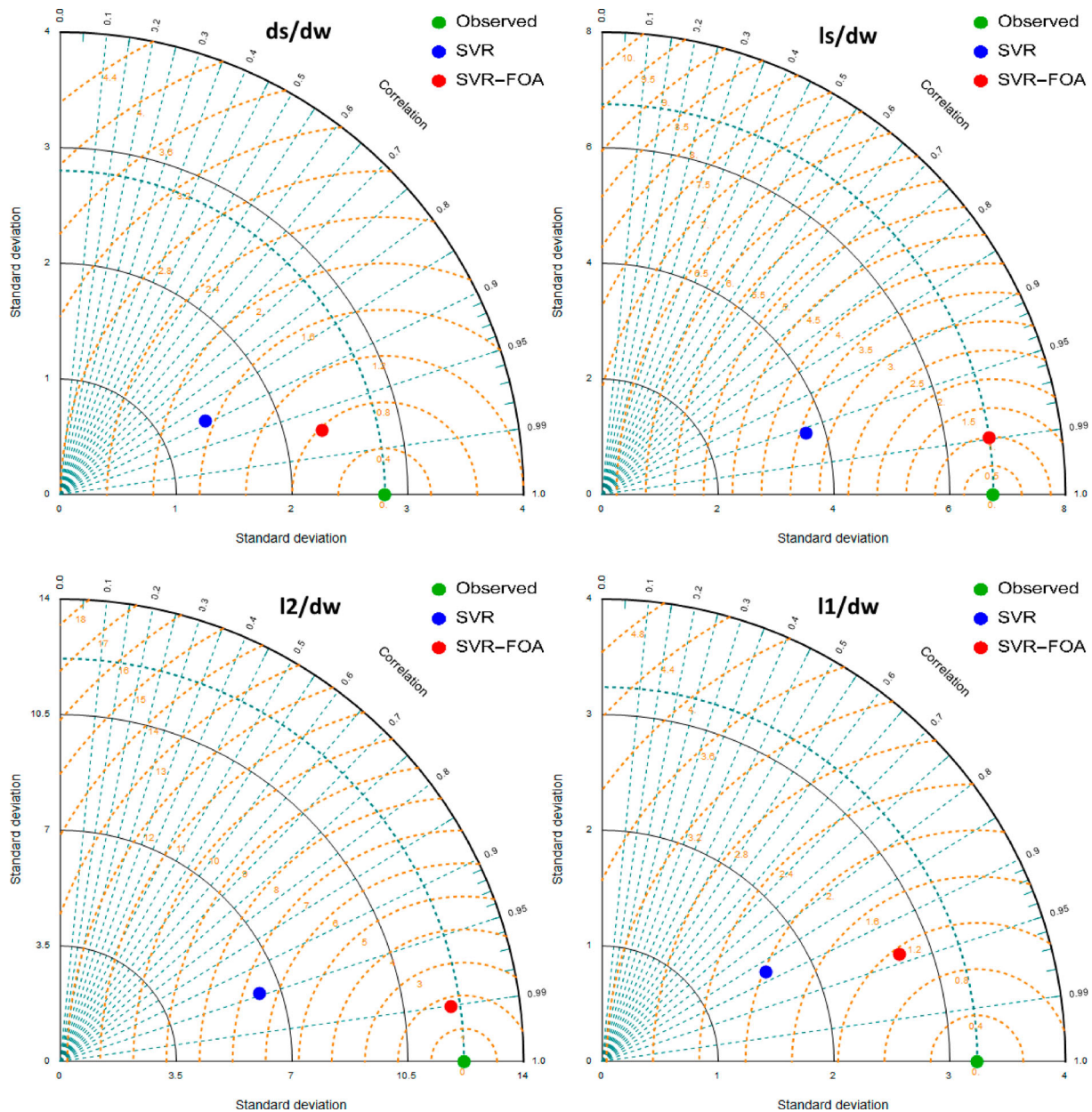
Figure 11. Continued.

SVR-FOA-5 with a slightly lower accuracy. SVR-5 performs weakly compared with the other methods, with CC = 0.930 and RMSE = 5.931. This weakness can be seen graphically in Figures 9 and 11.

Scour hole width. For estimation of the scour width (ws/dw), all the models show quite good performance; however, ANFIS-6 presents better results (CC = 0.999, SI = 0.001, and RMSE = 0.011) than those of ANN-6 (CC = 0.999, SI = 0.014, and RMSE = 0.119) and SVR-FOA-6 (CC = 0.993, SI = 0.094, and RMSE = 0.808). The Reg-6 equation estimates ws/dw with CC = 0.997, RMSE = 2.048, and MAE = 1.165. The formulae of Azmathullah et al. (2005) predict the scour width with

CC = 0.953, RMSE = 4.499, and MAE = 2.550, and a more scattered plot is observed in its predictions.

The results obviously indicate how applying a new optimization algorithm like the FOA improves further on the primitive results of the lower accuracy single SVM. The SVR-FOA may even demonstrate a higher performance with different numbers of input parameters in comparison with the other soft computing techniques. The current research employs a higher number of non-dimensional inputs than was previously performed by Azmathullah et al. (2005) and Naini et al. (2011). It can be concluded that the SVM model may have been optimized in the worst-case scenario as it has lower accuracy in comparison with the traditional regression equations

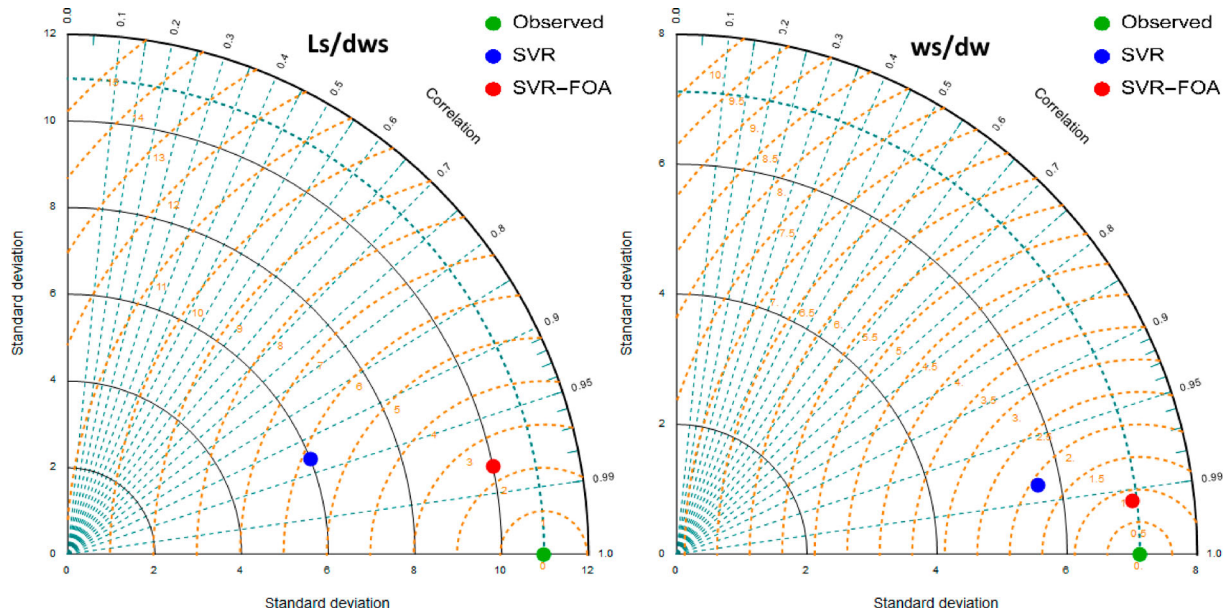**Figure 12.** Taylor diagrams of the predicted parameters of the scour hole (%).

Figure 12. Continued.

both from this research and the literature (Azmathullah et al., 2005). The sensitivity analysis implemented on ANNs and ANFISs in previous studies (Azmathullah et al., 2005; Naini et al., 2011) indicated that, by employing all the input parameters (five inputs) in the models, a better mapping is formed between the input and output spaces, and the results improve, and the uncertainty decreases. Therefore, all those influential input parameters were utilized in the current research modeling. However, as illustrated by Goyal and Ojha (2011) in their research on scour estimation with the SVM and M5 models, SVM performed better with lower numbers of raw inputs than ANNs. Additional research could be done to identify the most influential parameters for the single SVM scour model in the non-dimensional case; it could then be put into the optimization process performed by one of the recognized algorithms like the FOA. In that case, the accuracy might improve even further than with the other techniques. It is concluded that, although ANNs and ANFISs perform slightly better, the SVR-FOA method is potentially more robust and practical in the field of engineering.

Conclusion

In this study, the applicability of support vector regression coupled with the fruitfly optimization algorithm (SVR-FOA) was evaluated for estimating the geometrical characteristics of the ski-jump scour hole below spillways, such as the maximum depth of the scour hole, the maximum scour depth location, the starting and ending points of scour hole, as well as the scour hole length

and width. The data set was made available through two different experimental studies. The results were compared with other soft computing techniques (SVR, ANN and ANFIS) and the conventional regression models. A comparative analysis was implemented using quantitative criteria and graphical diagrams. The results indicate that the developed SVR-FOA hybrid model is a robust approach and performs well in comparison with SVR, ANNs and ANFISs and can be used successfully for predicting scour hole dimensions downstream of a ski-jump. It was observed that, by using the SVR-FOA, the accuracy of predicting scour depth improves by about 8% in terms of the CC, and the error (MAPE) decreases to 14.7%. There is also an improvement in the estimation of the l1/dw and l2/dw parameters to 6.5 and 4.5%, respectively, and a 5% improvement in Ls/dw in comparison with simple SVR models. It is concluded that the SVR-FOA combination is a promising approach which should be further used and studied in a wide range of hydraulic structures dealing with the scour problem and also water resources issues. The FOA method can be applied as a booster in fields where using single SVM is associated with deficiency and drawbacks, for instance when the number of inputs is higher. According to a study by Goyal and Ojha (2011), SVM seems to be more practical and suitable in the field of design, needing a lower number of inputs to estimate the scour parameters more accurately than ANNs. A sensitivity analysis would also help to recognize the most useful combination of input parameters for the SVR-FOA, but this is beyond the scope of this paper and can be accomplished in future studies. The results of this research may be limited to laboratory

scale, but as a suggestion the method could be applied to field data. Additional future research is needed to assess if this new nature-inspired algorithm is any better than previous optimization algorithms.

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