



# Application of an evolutionary technique (PSO–SVM) and ANFIS in clear-water scour depth prediction around bridge piers

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## Abstract

The mechanism of the local scour around bridge pier is so complicated that it is hard to predict the scour accurately using a traditional method frequently by considering all the governing variables and boundary conditions. The present study aims to investigate the application of different hybrid soft computing algorithms, such as particle swarm optimization (PSO)-tuned support vector machine (SVM) and a hybrid artificial neural network-based fuzzy inference system to predict the scour depth around different shapes of the pier using experimental data. The important independent input parameters used in developing the soft computing models are sediment particle size, a velocity of the flow and the time taken in the prediction of the scour depth around the bridge pier. Different pier shapes used in the present study are circular, round-nosed, rectangular and sharp-nosed piers. The accuracy and efficiency of the two hybrid models are analyzed and compared with reference to experimental results using model performance indices (MPI) such as correlation coefficient (CC), normalized root-mean-squared error (NRMSE), normalized mean bias (NMB) and Nash–Sutcliffe efficiency (NSE). The ANFIS model with Gbell membership and the PSO–SVM model with polynomial kernel function yield good results in terms of MPI. The performance of PSO–SVM with polynomial kernel function with CC of 0.949, NRMSE of 7.47, NMB of  $-0.009$  and NSE of 0.90 reveals that the hybrid ANFIS model with Gbell membership function yields slightly better than that of the PSO–SVM model with CC of 0.950, NRMSE of 6.92, NMB of  $-0.002$  and NSE of 0.91 for the optimum bridge pier with circular shape, whereas the performance of PSO–SVM model is better than that of ANFIS model for optimum bridge piers with rectangular and sharp nose shape. The PSO–SVM model can be adopted as accurate and efficient alternative approach in predicting scour depth of the pier.

**Keywords** Bridge pier · Scour depth · PSO–SVM · ANFIS

## 1 Introduction

Bridges play an essential role in the society since they enable quick access across a river or any water body. Bridges facilitate transportation of goods and people and hence play a leading role in the development of a province. The failure of bridges is a severe problem because of the high investment costs, safety problems in the event of a

failure and adverse effects on the economy of the region. The scour related to bridge hydraulics, its relation to flood hydrology and hydraulic processes received much attention in the past decade.

“Men who overlook water under the bridge will find bridge under water” to the provisions in the existing codes of practice for determination of design scour depth require immediate review [1]. This situation highlights the important effect of flowing water on the stability of the bridge and in particular, its impact on a bridge pier. The mechanism of flow around a pier structure is so complicated to the point that it is hard to set up a general observational model to give exact estimates for scouring. The bridge scour is the removal of sediments such as sand and rocks from around bridge abutments or piers. During the flow of water through an opening of a bridge with

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acceptable velocity, in general, the elevation will be changed. The significance of this change in elevation is more important near the abutments and piers.

The scour means lowering of the riverbed level by erosion, such that there is a tendency to expose the foundations of a bridge. There are three main types of scouring effects on the performance of safety of bridges, namely general scour, contraction scour and local scour. However, all types mentioned above of scouring generate from different causes, it is essential to determine the scour due to each cause individually and they should be linearly added to their contribution in predicting the maximum scour depth for bridge pier design. Among them, the local scour is the most critical one in scour-related safety issues of bridges. The typical local scour mechanism is shown in Fig. 1. There are two types of scour conditions such as clear-water and live-bed scour. The clear-water scour occurs when there is no movement of bed material in the flow upstream of the crossing. This condition of scour is just because of the obstructions (piers, abutments) in the flow. The rate of sediment supply to the scour hole is equal to zero for clear-water scour condition and the depth of scour hole continues to grow until the equilibrium scour depth is reached.

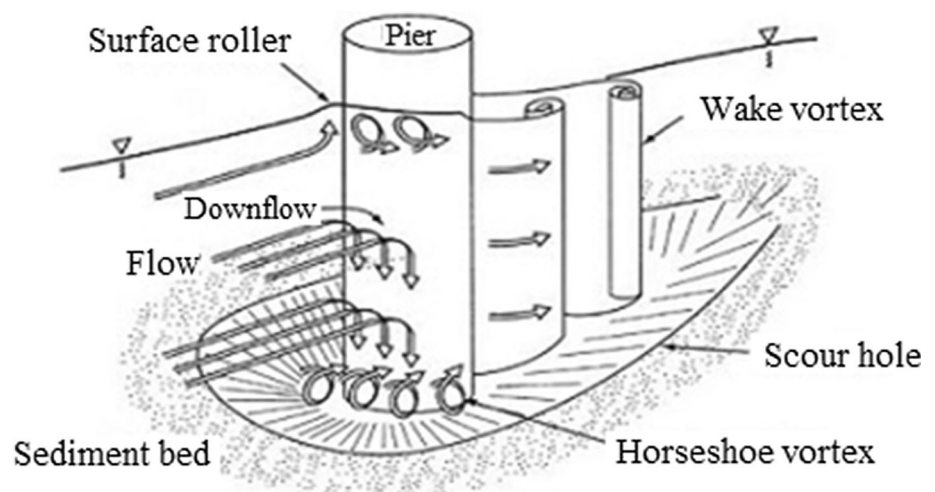
Defining interdependency among variables which are influencing the depth of pier scour in recent years is understood using laboratory research as a primary tool. Various studies have been performed in the laboratory tests to study the scour phenomenon around a bridge pier. Those experimental data were further used for numerical modeling and soft computing applications. Recently, researchers have studied on applications of soft computing techniques in considering the scouring phenomenon as their focal point. The different soft computing techniques such as an

artificial neural network (ANN), fuzzy logic, linear regression, genetic programming (GP), group method of data handling (GMDH), model tree approach have been used to predict the scour depth around the bridge pier.

ANN model was developed by Bateni et al. [3], Lee et al. [4] and Kaya [5] to predict the scour depth around the bridge pier by using experimental data. Flow depth, mean velocity, critical flow velocity, median grain diameter and pier diameter are used as input parameters. They applied backpropagation and Bayesian neural network in their study and concluded that the ANN models give good correlation with experimental results. Uyamuz et al. [6] and Wang et al. [7] used the fuzzy logic model and fuzzy group decision-making approach to study the scour at the downstream of vertical gate and bridge risk assessment. Guven et al. [8] presented the linear genetic programming (LGP), which was an extension of GP, as an alternative tool in the prediction of scour depth around a circular pile due to waves in medium dense silt and sand bed. Group method of data handling (GMDH) network used by Najafzadeh et al. [9] to predict abutments scour depth of bridges which have been embedded in two types of montmorillonite and kaolinite clay soils. The GMDH network has been developed using backpropagation technique to the modeling of abutment scour depth. Pal et al. [10] investigated the potential of M5 model tree, a tree-based regression approach to predict the local scour around bridge piers using field data set and results are compared with the empirical equations.

Some researchers used other soft computing techniques such as adaptive network-based fuzzy inference system (ANFIS) and support vector machine (SVM) to solve the scour-related problems. Goel et al. [11] used the SVM model to predict the maximum depth of scour on grade-

**Fig. 1** Mechanism of scour at a circular pier *Source* [2]



control structures like sluice gates, weirs and check dams. Keshavarzi et al. [12] used ANFIS to model the local scouring depth and pattern scouring around concave and convex arch-shaped circular bed sills. The laboratory data were used to develop and validate the model, and the ANFIS models produced good performances with experimental results. Azamathulla et al. [13] described the use of ANFIS to estimate the scour depth at culvert outlets.

In the present days, the researchers are focusing on the hybridization by combining individual's models with other optimization techniques to improve the prediction accuracy. There are numbers of optimization techniques such as, particle swarm optimization (PSO), ant colony optimization (ACO), honey bee search, from the literature; it was found that swarm intelligence-based algorithms which are today's one of the powerful tools of optimization techniques. Basser et al. [14] proposed a new approach ANFIS-PSO to determine optimal parameters of a protective spur dike to mitigate scouring depth amount around existing main spur dikes. Najafzadeh et al. [15] introduced a new application of GMDH in the prediction of scour depth around a vertical pier. Two models of the GMDH network were developed using genetic programming and a back propagation algorithm. Hasanipanah et al. [16] presented a new hybrid model of artificial neural network (ANN) optimized by particle swarm optimization (PSO) for the prediction of maximum surface settlement. Cus et al. [17] presented a hybrid multi-objective optimization technique, based on ant colony optimization algorithm (ACO), to optimize the machining parameters in turning processes.

The main novelty of the present study is considering PSO–SVM as an evolutionary hybrid technique, where SVM is tuned by PSO to achieve the improved performance efficiency and accuracy of the SVM model. Based on the literature study, it is observed that there are hardly any applications of hybrid SVM models to study the prediction of the scour depth for the different shape piers. Hence, in the present paper, the performance of PSO–SVM technique in predicting scour depths is investigated. Here, swarm intelligence part, i.e., PSO is used for optimization of SVM and kernel parameters. Performance of PSO–SVM models is compared with that of SVM and ANFIS models.

## 2 Data analysis

The experimental study on scour depth around bridge piers was carried out by Goswami Pankaj [18]. The laboratory data sets are collected in a 1000 mm wide, 1300 mm depth and 19.25 m length of flume dimensions. The bed material used in the study is sand gravel of  $d_{50} = 4.2$  mm and uniformly graded sand of  $d_{50} = 0.42$  mm. The model was

run for clear-water scour condition with velocities of 0.215, 0.278, 0.226 m/s for sand gravel and 0.184, 0.278, 0.351 m/s for uniformly graded sand. The data are collected from 0 to 6 h with 1 h interval. The pier of circular, rectangular, round-nosed and sharp-nosed shapes is used in the experiment.

Three input parameters, namely sediment size ( $d_{50}$ ), velocity ( $U$ ) and time ( $t$ ) are used to predict the scour depth. The experimental data were collected for different pier shapes such as circular, rectangular, round-nosed and sharp-nosed pier. The whole data set is divided randomly into training data (50%) and testing data (50%). The statistical parameters such as most extreme (maximum), least (minimum), mean, standard deviation and kurtosis for every one of the factors for different pier shapes are listed in Table 1. The negative value for kurtosis indicates that the distribution of data has lighter tails and flatter peaks. The training and testing data are applied to the models, and the predicted scour values are compared to the measured values.

## 3 Methodology

### 3.1 Adaptive network-based fuzzy inference system (ANFIS)

The principle involved behind ANFIS technique says that it is an artificial intelligence (AI) tool which has a set of networks for adaption presented by Jang and Sun [19] and a benefit of the tool is exploited to support in forecasting and to predict desired outputs. This AI tool can be viewed as a structure with the system of neural network induced feedforward, in which every layer is taken as neuro-fuzzy structure (NFS) element. It imitates the fuzzy rule of Sugeno and part by part of the rule is a direct fusion of given input and a constant. Finally, end prediction of the method is the weighted average of each rule's outcome.

ANFIS is also known as neuro-adaptive learning technique because of the synthesis of Neural Network with fuzzy inference system (FIS), developed by Jang [20]. It maps inputs and outputs with respective membership functions (MF) and related parameters of both input, and output and then it can be used to interpret the inputs/output mapping.

The concept of a hybrid technique is adopted here because FIS alone lacks learning capability from the examples. The ANN can overcome this. ANFIS uses the gradient descent method (GDM) and least square method (LSM) and then combined with feedforward backpropagation (FFBP) technique. In which, FIS is used to measure the input and output parameters, and ANN is used to define and measure the error regarding the sum squared

**Table 1** Statistical parameters

Data set	Statistical parameters	Variables								
		Sediment size, $d_{50}$ (mm)	Velocity (m/s)	Time (h)	Scour depth (mm)					
				Circular	Rectangular	Round nosed	Sharp nosed			
Training	Max	4.2	0.351	6	118	122	113	120		
	Min	0.42	0.184	0	55	55	53	53		
	Mean	2.31	0.261	3	84.26	87.89	82.512	84.77		
	SD	1.89	0.0515	2	14.17	14.99	13.06	13.8		
	Kurtosis	- 2.049	- 0.547	- 1.253	- 0.139	- 0.222	0.064	0.472		
Testing	Max	4.2	0.351	6	115	121	111	120		
	Min	0.42	0.184	0	54	55	54	55		
	Mean	2.31	0.261	3	84.512	88.345	83.32	84.14		
	SD	1.89	0.0515	2	14.206	14.58	13.23	13.33		
	Kurtosis	- 2.049	- 0.547	- 1.253	- 0.155	- 0.225	- 0.143	0.633		

differences between actual and desired outputs. The ANN can learn the problem and complexity involved in the relationship between the inputs and output and performs the nonlinear and uncertainty modeling without any prior knowledge. Hence, FFBP with TS-based FIS system used to estimate the depth of the scour. To skip the deficiency of a training algorithm all along the process, ANN used in combination with FIS with the introduction of FFBP. The disadvantages of ANN are overcome by training the FIS structure and associated parameters. ANFIS is considered to be the transparent technique [21]. If the size/amount of the available data is confined, then FIS is regarded as an efficient tool compared to ANN alone [22]. Therefore, it is believed that ANFIS is a very reliable and robust tool to estimate scour depth from around bridge piers [23].

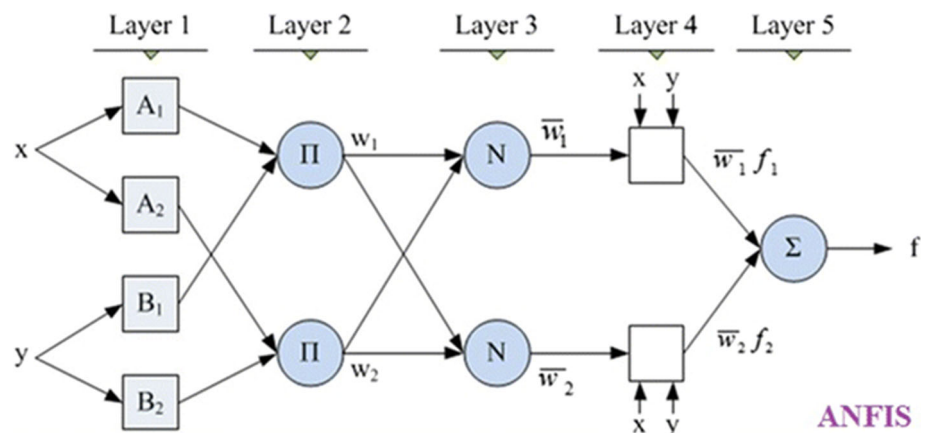
The first-order Takagi–Sugeno method of a fuzzy model with multi-input and single output (MISO) system is presented in Fig. 2. ANFIS uses linguistic rules for estimation and formulates if–then rules from its knowledge to ensure the proper prediction of scour depth.

The procedure followed by the model for predicting the scour depth is expressed by the six layers displayed below: (1) composed of inputs, (2) in layer 2, models are built based on multiple input variables (3 inputs), (3) suitable degree of membership function is selected and, (4)  $(3)^3 = 27$  fuzzy rules are generated for the inference operation, (5) training and validation, and (6) prediction of scour depth. In this method, three independent variables are chosen as inputs and one dependent variable (scour depth) as output.

The rules are generated during inference system operation and are represented in the form of equation as,  $R_u$ : if  $(x_1 \text{ is } A_u^1)$  ( $x_2 \text{ is } A_u^2$ ) and  $(x_3 \text{ is } A_u^3)$  then,  $f = C_1^u x_1 + C_2^u x_2 + C_3^u x_3 + C_4^u$  where  $u = 1, 2, 3, \dots, 27$  the number of rules.

### 3.2 Support vector machines (SVM)

In the high-dimensional feature space, simpler and linear hyperplane classifiers that have a maximal margin between

**Fig. 2** ANFIS architecture used in the study

the classes are obtained. SVM is a machine learning approach which provides maximized predictive accuracy automatically either by avoiding/minimizing or overwriting of data. SVM depends on a SRM (structural risk minimization) principle and convex optimization algorithm wherein which the empirical risk and the confidence interval of the learning machine are simultaneously minimized by maximizing the geometric margin. SVM can efficiently perform nonlinear regression by utilizing kernel trick. The computation is critically dependent upon the number of training patterns and selection of hyper-parameters and finding out their optimal values while modeling any time series.

A learning tool is derived from the past statistical learning algorithms, which is named as support vector machine (SVM) by Vapnik [24]. SVM acts as training algorithm and regression tool for linear and nonlinear classification. In case of nonlinear data, the SVM has the ability to map the data points of input space to the feature space of D-dimension by using different kernels, which is known as “Kernel trick,” i.e., the dot product of the data points,

$$\text{Given as: } K(x_i, x_j) = (x_i, x_j)(x_i, x_j),$$

$$\text{It can also be written as: } f(x) = \sum_{i=1}^n \alpha y_i K(x_i, x) + b$$

Each data points of input space are mapped into a D-dimensional space via kernel function, i.e., “Kernel trick,”  $K(x_i, x_j) = \phi(x_i, \bar{x})(x_j, \bar{x})$  dot product in the feature space. As the kernel functions can convert nonlinear data points them into linear ones. In this context, RBF (radial basis function) kernel gives the significant results compared to other kernels, which uses the Gaussian distribution. The SVM develops a different hyperplane margin between the points in the feature space and amplifies edge between two informational indexes of two input points. It makes an effort of constructing a fit curve with a kernel function and used on entire data points such that data points should lie between two largest marginal hyperplanes to minimize the error of regression [25]. The predictive capacity and classification error is dealt with learning some basic concept. Firstly, the hyperplane is separated, and then the process involves the selection of proper kernel function and SVM between hard and soft margin. The SVM model architecture is shown in Fig. 3.

### 3.3 Development of ANFIS model

In this study, the ANFIS model is developed and tested to predict scour depth with respect to different pier shapes using various input parameters. Sediment size, the velocity of flow and time are the input parameters. The ANFIS model is carried out in MATLAB software with Gbell membership functions. Three membership functions with

27 fuzzy rules are adopted for the GbellMF. The details of the ANFIS model developed are listed in Table 2.

Every node in layer 1 is identified as fuzzification layer, and each node represents a fuzzifiers/membership value to a linguistic variable. Along these lines, two GaussMF can be allotted to every given input. Premise/Introducing parameters are parameters present within the layer 1. About layer 2, every point of node executes a fuzzy T-norm operation [19]. The rule firing strength is the outcome of the second layer. In layer 3, findings of layer 2 are normalized. After the fusion of the input variables in layer 4 linearly, estimated depth of live-bed scour obtained in layer 5 through weighted average. NFS premise parameters expressed above have to be optimized, this is the main point of the learning stage. Hybrid (ANN + FIS) learning algorithms are provided primarily the fusion of the gradient descent (GD) and least squares method (LSM). Indeed, the performance of the tool is demonstrated that such an approach lowers the complexity and uncertainty of the algorithm with the increase in capacity and efficiency of learning [26].

The ANFIS model is trained and tested to predict scour depth concerning different pier shapes using Sediment quantity in the flow, the velocity of flow and time as the input parameters. MATLAB is the platform used to develop the ANFIS model with all triangular, trapezoidal, Gbell and Gauss membership functions. Among all MF's, Gaussian MF with gradient discrete and least square error principle showed good correlation between measured and predicted scour depths. Because of those principles, ANFIS with Gauss MF model shows better results as illustrated in the present work. While developing ANFIS model 27 fuzzy rules for 3 input parameters and 1 output parameter are generated. The details of the test condition of the ANFIS model for predictions are presented in Table 2. The estimated simulations obtained from the ANFIS models are compared with experimental values for validation of soft computing models.

In a word, input selection, number, and type of membership functions, learning algorithm are responsible for the effectiveness of the tool in estimating the scour depth. The ANFIS model proposed here uses three membership functions for every given input. This consumes more time and ruins transparency of the fundamentals of the tool. However, better results can be obtained without increasing the complexity of the tool, and this will be expressed and the purpose will be achieved.



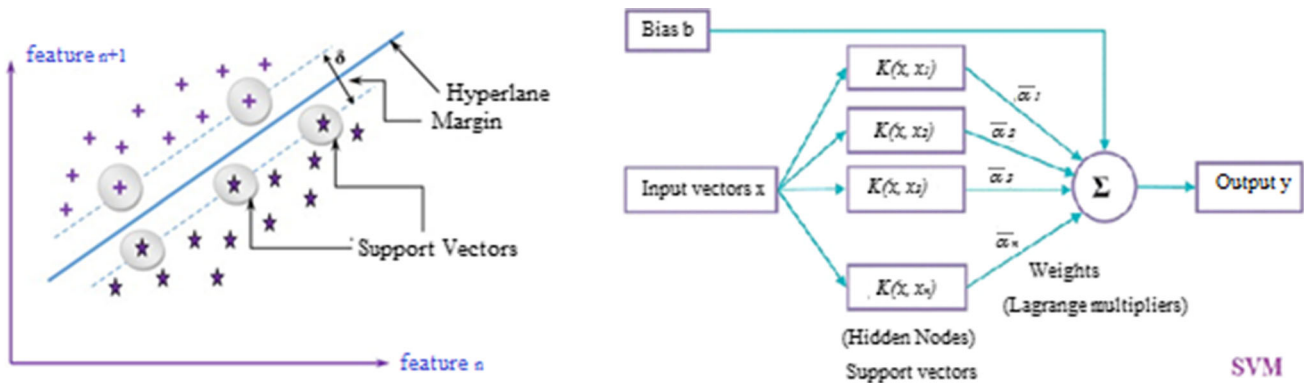


Fig. 3 SVM architecture

**Table 2** Details of ANFIS model

ANFIS architecture	
Number of membership functions	2–3
Algorithm selected	Hybrid
Number of epoch runs given	400–500
Generated fuzzy inference system	Partition of grids
Membership function (MF) type	Constant
Number of fuzzy rules generated	27
Type of membership function (MF) used	Gbell

### 3.4 Development of radial basis function-support vector machine (RBF-SVM) algorithm

In this paper, the SVM model is also adopted to predict the scour depth with respect to different pier shape using sediment size, velocity and time as input variables. The SVM models are developed using MATLAB software for linear, polynomial, sigmoid, quadratic and radial basis (RBF) kernel functions. The RBF kernel showed good correlation between observed and predicted scour depths among other kernel functions. The RBF is the favorite choice of the kernel type used in SVM. The “ $\gamma$ ” is an adjustable parameter of the RBF kernel function. This is for, mainly because of RBF’s localized and finite responses/confined and limited responses across the range of the original  $X$ -axis. The simulations of the SVM model with RBF kernel function are discussed in the present paper. The performance and estimation accuracy of the SVM with different kernels depending on the model parameters, namely SVM parameter ( $C$ ), kernel width parameter-Gamma ( $\gamma$ ), and epsilon parameter ( $\varepsilon$ ). The four K-fold cross-validation search is used to identify and finalize optimal parameters. Optimal parameters ( $c$ ,  $\gamma$ , and  $\varepsilon$ ) are chosen for a number of trials with various

combinations of  $C$  (ranges from 1 to 1000),  $\gamma$  (ranges 1 to 10) and  $\varepsilon$  (ranges 0.001–10) for the radial basis kernel function. The obtained optimal SVM parameters for RBF kernel functions are shown in Table 3. The predicted values from the models are compared with the measured values.

### 3.5 Particle swarm optimization-tuned support vector machine (PSO-SVM) and its development

PSO was first proposed by Kennedy and Eberhart [27]. In PSO, every particle (swarm) makes utilization of its individual memory and learning picked up by the swarm overall to locate the best arrangement. Every one of the particles has a best alternation solution, which is assessed by good capacity to be enhanced and has speeds which coordinate the development of the particles. The best position of every particle is achieved on its own and neighboring particle involvement during the time spent in the movement of the particles. For each epoch, every particle is updated with the following two “best” values called pbest and gbest.

Keeping in mind the merits of swarm intelligence, PSO is used to avoid over-fitting or underfitting of the SVM model due to the improper selection of SVM and kernel parameters, PSO is used to select suitable parameters of SVM. PSO is an optimization method, which not only has a strong global search capability but also is very easy to implement. So, it is very suitable for parameters selection of SVM. The number of support vectors used in PSO-SVM models is same for all kernel functions (87); this indicates that every training data set is utilized as support vector. This clearly proves that there is no noise in the training data set. It is noticed that the performance of these models depends on the best selection of SVM and kernel parameters. By interfacing PSO with SVM, generalization

**Table 3** Optimal SVM parameters for different pier shapes

Optimal SVR parameters	Circular	Rectangular	Round nosed	Sharp nosed
C	388	800	60	221
Gamma ( $\gamma$ )	2	1	3	2
Epsilon ( $\epsilon$ )	0.1	0.1	0.1	0.1
Train (CC)	0.9195	0.883	0.8745	0.8697
Test (CC)	0.913	0.813	0.8508	0.844

performance of the PSO–SVM models shows improvement that of SVM models Ghasemi et al. [28], Harish et al. [29].

A PSO–SVM algorithm is used in different problems Harish et al. [29]. Because of the various advantages of PSO mentioned such as, easy to implement compared other algorithm such as genetic algorithm where a cross mutation have to be made. The error globalization capacity of PSO–SVM is better compared to SVM and neural network and fuzzy inference system. Therefore, SVM is tuned using PSO and ANN and FIS is hybridized to improve the performance of SVM and ANN by enhancing the error generalization capacity of the individual models.

The steps followed in the evolutionary algorithm PSO–SVM is given below.

### 3.6 Performance analysis

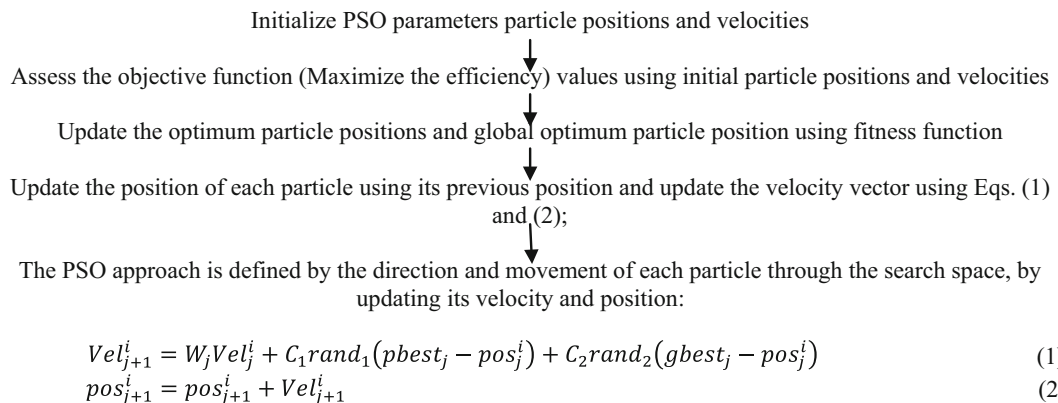
The performance of ANFIS and SVM models are evaluated by adopting statistical measures as followed.

1. Normalized root-mean-square error (NRMSE)

$$\text{NRMSE} = \left( \frac{\text{RMSE}}{X_{\max} - X_{\min}} \right) \times 100 \quad \text{where}$$

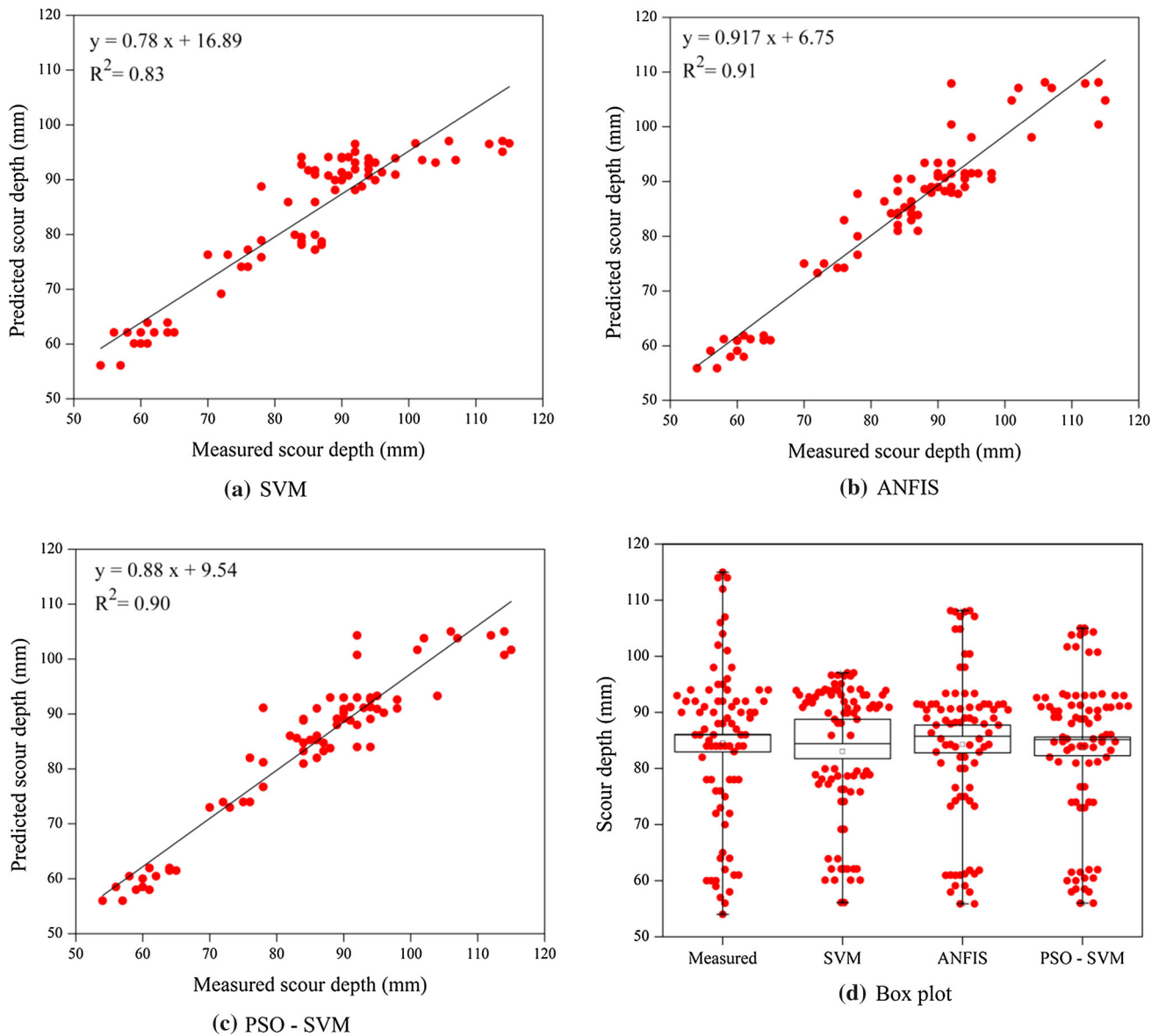
$$\text{RMSE} = \sqrt{\left( \frac{\sum_{i=1}^N (X_i - Y_i)^2}{N} \right)}$$

2. Normalized mean bias (NMB)



where  $pos_j^i$  is the current position of the particle  $i$  with subscript  $j$  representing iteration count,  $Vel_j^i$  is the search velocity of the  $i^{th}$  particle,  $C_1$  and  $C_2$  are the cognitive and social scaling parameters,  $rand_1$  and  $rand_2$  are the random numbers with interval  $[0,1]$  applied to the  $i^{th}$  particle,  $W_j$  is the particle inertia,  $pbest_j$  is the best position found by the  $i^{th}$  particle (personal best) and  $gbest_j$  is the global best position found among all the particles in swarm. The particle inertia controls the balance of global and local search abilities, where a larger  $W_j$  facilitates a global search. Particle  $i$  flutter toward a new position using Eqs. (1) And (2), which allow all particles in the swarm to update their  $pbest_j$  and  $gbest_j$ .

Repeat steps 2–4 until the target is achieved (target= NRMSE).



**Fig. 4** Scatter and box plot of measured versus predicted scour depth of SVM, ANFIS and PSO-SVM models in testing phase for circular pier

$$\text{NMB} = \sum_{i=1}^N \left( \frac{Y_i - X_i}{X_i} \right) = \left( \frac{\bar{Y}}{\bar{X}} - 1 \right)$$

3. Nash–Sutcliffe coefficient (NSE)

$$\text{NSE} = 1 - \left( \frac{\sum_{i=1}^N (X_i - Y_i)^2}{\sum_{i=1}^N (X_i - \bar{X})^2} \right)$$

4. Correlation coefficient (CC)

$$\text{CC} = \frac{\sum_{i=1}^N (X_i - \bar{X}) \cdot (Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^N (X_i - \bar{X})^2 \cdot \sum_{i=1}^N (Y_i - \bar{Y})^2}}$$

where  $X$  is the observed/measured values;  $Y$  is the predicted values;  $\bar{X}$  is the mean of actual data;  $n_x$  is no. of data set points whose ARE value is less than  $x\%$   $N$  is no. of total data set points.

## 4 Results and discussion

### 4.1 Prediction of scour depth for circular pier

In the first test case, a circular-shaped pier of 51 mm diameter is considered in the prediction of scour depth. The ANFIS and SVM models are applied to the data and the results obtained from the models are shown in Fig. 4. To evaluate the performance of the ANFIS and SVM models,



**Table 4** Statistical outcomes of SVM, ANFIS and PSO–SVM models

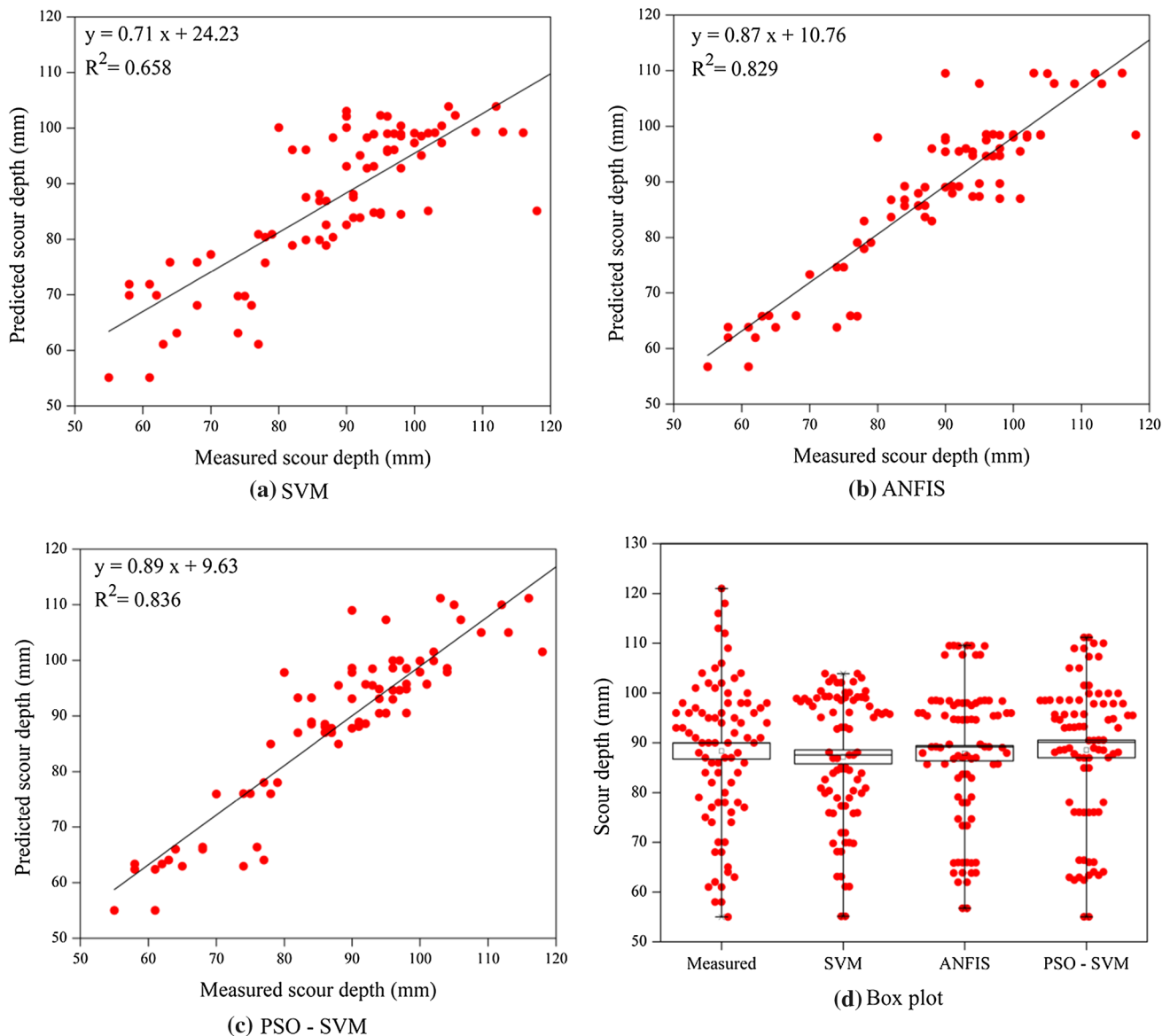
Pier shapes	Statistical indices	Soft computing models					
		SVM		ANFIS		PSO–SVM	
		Train	Test	Train	Test	Train	Test
Circular	CC	0.919	0.913	0.96	0.95	0.953	0.949
	NRMSE	9.13	9.82	6.05	6.92	6.85	7.47
	NMB	– 0.014	– 0.017	0.0	– 0.003	– 0.002	– 0.009
	NSE	0.83	0.82	0.927	0.91	0.91	0.90
Rectangular	CC	0.88	0.81	0.93	0.91	0.92	0.915
	NRMSE	10.60	13.04	8.15	6.04	8.95	9.01
	NMB	– 0.008	– 0.01	0.0	– 0.005	0.007	0.002
	NSE	0.78	0.65	0.86	0.83	0.84	0.83
Round nosed	CC	0.87	0.85	0.95	0.95	0.945	0.95
	NRMSE	12.17	13.62	6.52	7.32	7.14	7.31
	NMB	0.005	– 0.004	0.0	– 0.01	0.004	– 0.01
	NSE	0.69	0.66	0.91	0.90	0.89	0.9
Sharp nosed	CC	0.87	0.84	0.93	0.91	0.9	0.92
	NRMSE	10.48	11.07	7.53	8.59	9.03	8.08
	NMB	– 0.017	– 0.01	0.0	0.008	– 0.014	0.007
	NSE	0.74	0.71	0.87	0.82	0.81	0.84

the measured scour depth values are plotted against the predicted values. Figure 4 illustrates the results and the performance between predicted and measured values of testing data set. The performance analysis of the models is also compared in Table 4, i.e., NRMSE value of Gbell = 6.921, trapezoidal = 9.48, RBF = 9.82 and NSE of Gbell = 0.83, trapezoidal = 0.752, RBF = 0.65 and it can be observed that NRMSE is less and NSE is more in Gbell. Hence, Gbell MF is giving good performance compared to other models. It is noticed from the analysis that ANFIS—GbellMF showed a good performance in comparison with ANFIS-trapezoidal MF and SVM—RBF kernel function. Therefore, to avoid underfitting of SVM and optimization technique, PSO is used to tune the SVM and kernel parameters. From Fig. 4c and Table 4, it is noticed that PSO–SVM (polynomial) showed improved efficiency and accuracy than RBF-SVM in terms of all the model performance indices. PSO–SVM (polynomial) indicates almost similar accuracy and efficiency as ANFIS in terms of CC but showed less efficient and reduced error generalization capacity with NSE of 0.90, NMB of – 0.009 and NRMSE of 7.47. During regression analysis, results of all models in the classical model values or experimental values are represented by coefficient determination ( $R^2$ ). Among all three models the PSO–SVM model with polynomial kernel function gives high accuracy compared to an SVM model with an  $R^2$  of 0.91 and almost the same accuracy as of ANFIS (GbellMF) model with an  $R^2$  of 0.90 to predict scour depth in case of pier with a circular shape.

Therefore, ANFIS with GbellMF and PSO–SVM could be taken as best hybrid models to predict scour depth in case for circular pier. The above results are illustrated in the form of innovative Box–Whisker plot. The plot represents the spread of the predicted values, and a skeletal type of box-and-whisker plot is used in the study. The standard error is considered to evaluate the performance of the models, and it is shown in Fig. 4d that the standard error is less in Gbell membership function as compared to other models.

### 4.2 Prediction of scour depth for rectangular pier

In the second case, the prediction of scour depth is made for the rectangular-shaped pier. The pier of 36 mm wide and 44 mm length is used in the study. The ANFIS model with Gbell and trapezoidal MF and SVM model with RBF kernel functions is applied to predict scour depth. Plots of the measured values versus predicted values are shown in Fig. 5. From Table 4, NRMSE of Gbell = 9.156, trapezoidal = 11.004, RBF = 13.04 and NSE of Gbell = 0.828, trapezoidal = 0.752, RBF = 0.65. It is shown that Gbell MF is giving good performances in the prediction of scour depth because of less NRMSE and more NSE. Similarly, in case of rectangular pier to avoid the underfitting of SVM and optimization technique PSO is used to tune the SVM and kernel parameters. From Fig. 5c and Table 4, it is noticed that PSO–SVM (polynomial) showed improved



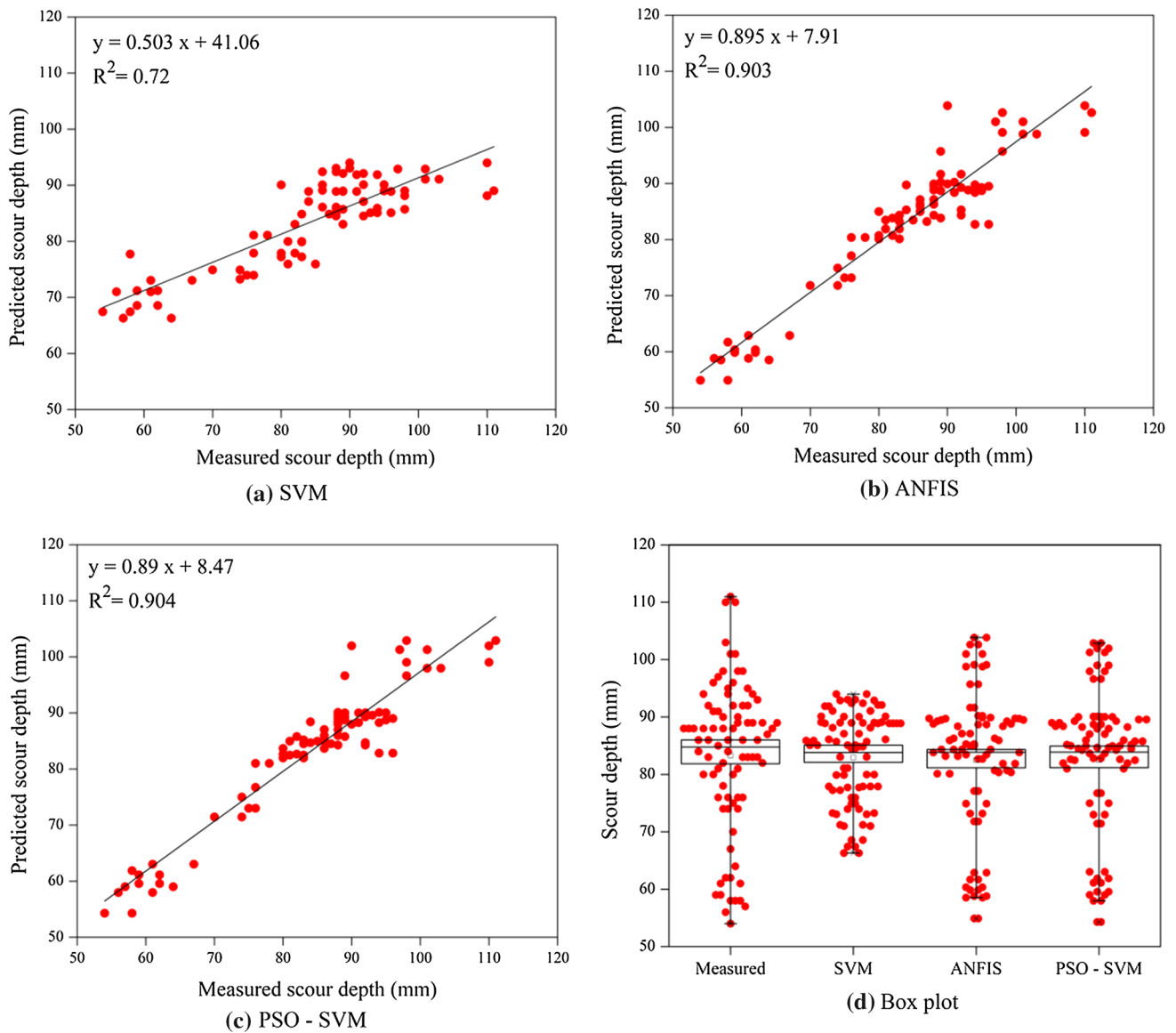
**Fig. 5** Scatter and box plot of measured versus predicted scour depth of SVM, ANFIS and PSO-SVM models in testing phase for rectangular pier

efficiency and accuracy than RBF-SVM regarding all the model performance indices. PSO-SVM (polynomial) shows less accuracy and efficiency compared to ANFIS in terms of all the model performance indices given in the present study as CC of 0.91, NSE of 0.83, NMB of 0.002 and NRMSE of 9.01. During regression analysis, results of all models in the classical model values or experimental values are represented by coefficient determination ( $R^2$ ). Among all three models the PSO-SVM model with polynomial kernel function gives high accuracy compared to the SVM model with an  $R^2$  of 0.836 and almost the same accuracy as of ANFIS (GbellMF) model with an  $R^2$  of 0.829 in case of pier with a rectangular shape. Therefore, PSO-SVM with polynomial kernel function is taken as best

hybrid model to predict scour depth in case of rectangular pier shape. The plot represents the spread of the predicted values, and a skeletal type of box-and-whisker plot is used in the study. Also, from box plot in Fig. 5d, it is clear that the standard error is less in Gbell MF in comparison with trapezoidal MF and RBF-SVM and PSO-SVM (polynomial).

### 4.3 Prediction of scour depth for round-nosed pier

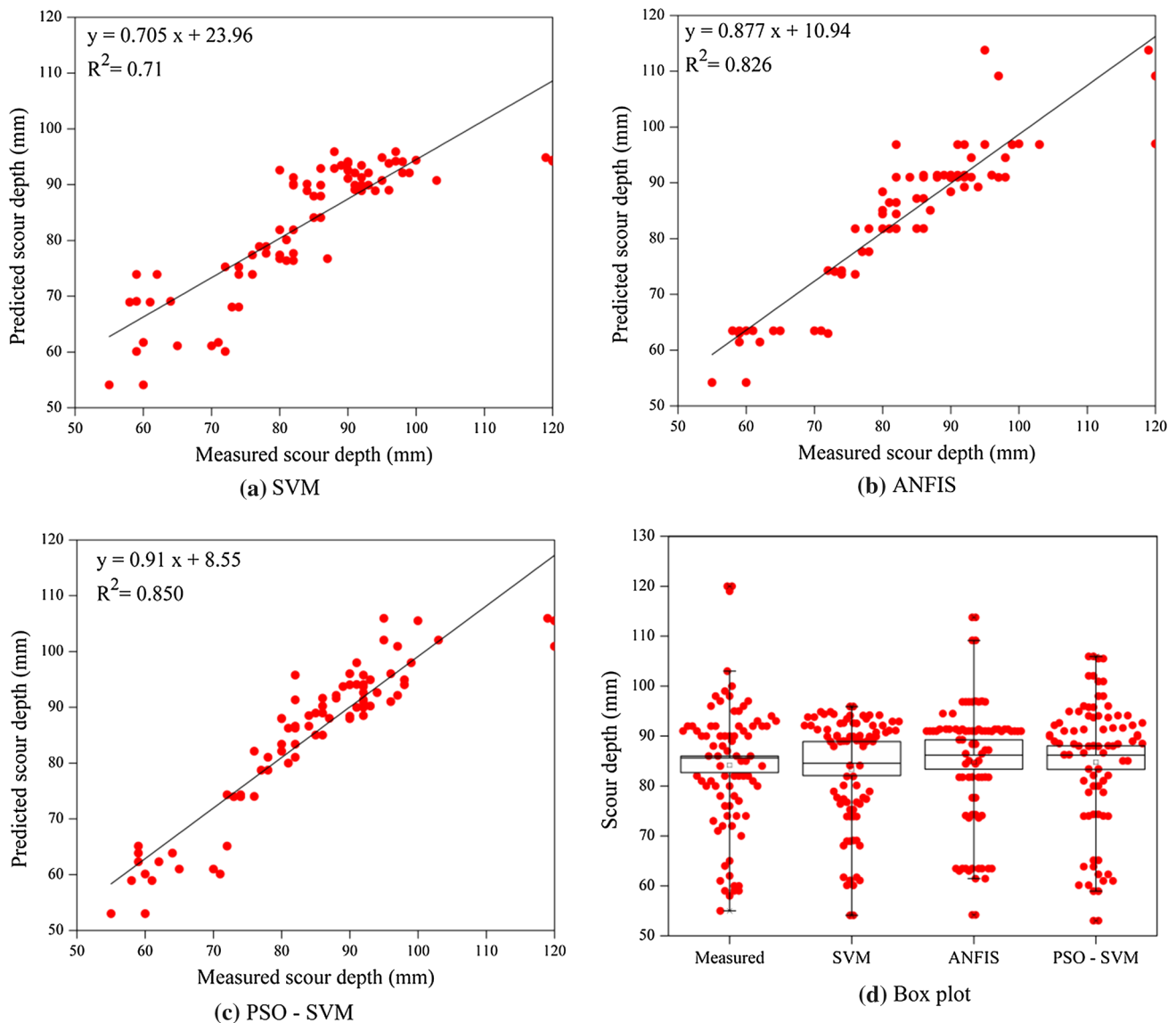
In the next stage, the round-nosed pier of 36 mm wide and 60 mm length is considered. The ANFIS and SVM models are run to predict scour depth around round-nosed pier. The



**Fig. 6** Scatter and box plot of measured versus predicted scour depth of SVM, ANFIS and PSO-SVM models in testing phase for round-nosed pier

predicted values are plotted against the measured values as shown in Fig. 6. The statistical parameters for the models (Table 4) are obtained as NRMSE for Gbell = 7.33, trapezoidal = 9.28, RBF = 13.63 and NSE for Gbell = 0.9, trapezoidal = 0.84, RBF = 0.67. Therefore, to avoid the underfitting of SVM and optimization technique, PSO is used to tune the SVM and kernel parameters. From Fig. 9c and Table 4, it is noticed that PSO-SVM (polynomial) showed improved efficiency and accuracy than RBF-SVM regarding all the model performance indices. PSO-SVM (polynomial) shows almost similar accuracy and efficiency as that of ANFIS in terms of CC of 0.95 with NSE of 0.90, NMB of  $-0.01$  and NRMSE at 7.31. Therefore, ANFIS with GbellMF and PSO-SVM (polynomial) is taken as the

best hybrid models to predict scour depth for round-nosed pier. During regression analysis, results of all models in the classical model values or experimental values are represented by coefficient determination ( $R^2$ ). Among all three models the PSO-SVM model with polynomial kernel function gives high accuracy compared to the SVM model with an  $R^2$  of 0.904 and almost the same accuracy as that of the ANFIS (GbellMF) model with an  $R^2$  of 0.903 in case of pier with round nose shape. The above results are illustrated in the form of innovative Box-Whisker. Plot represents the spread of the predicted values, and a skeletal type of box-and-whisker plot is used in the study. From the performance analysis, it can be observed that Gbell MF performs well in the prediction of scour depth in



**Fig. 7** Scatter and box plot of measured versus predicted scour depth of SVM, ANFIS and PSO-SVM models in testing phase for sharp-nosed pier

comparison with that trapezoidal MF and RBF-SVM kernel function and almost equal to PSO-SVM (polynomial) in predicting scour depth in case of pier with round nose shape. It is also observed from the box plot (Fig. 6d), the standard error in Gbell MF is less as compared to other two models.

#### 4.4 Prediction of scour depth for sharp nose pier

In this case, a sharp nose-shaped pier of 36 mm wide and 65 mm length is considered. Gbell and trapezoidal MF are used in ANFIS and RBF kernel functions are used in SVM models to predict scour depth. For the performance

analysis of the model, the predicted values are plotted against measured values as shown in Fig. 7. The statistical parameters are calculated from the models are tabulated in Table 4. NRMSE for Gbell = 0.858, trapezoidal = 9.85, RBF = 11.07 and NSE of Gbell = 0.83, trapezoidal = 0.77, RBF = 0.71 is obtained from the model. Gbell MF is having less NRMSE and more NSE. Hence, it is showing better performance in the prediction of scour depth for a sharp-nosed pier in comparison with the other two models. And also to avoid the underfitting of SVM and optimization technique PSO is used to tune the SVM and kernel parameters. From Fig. 7c and Table 4, it is noticed that PSO-SVM (polynomial) showed improved efficiency and

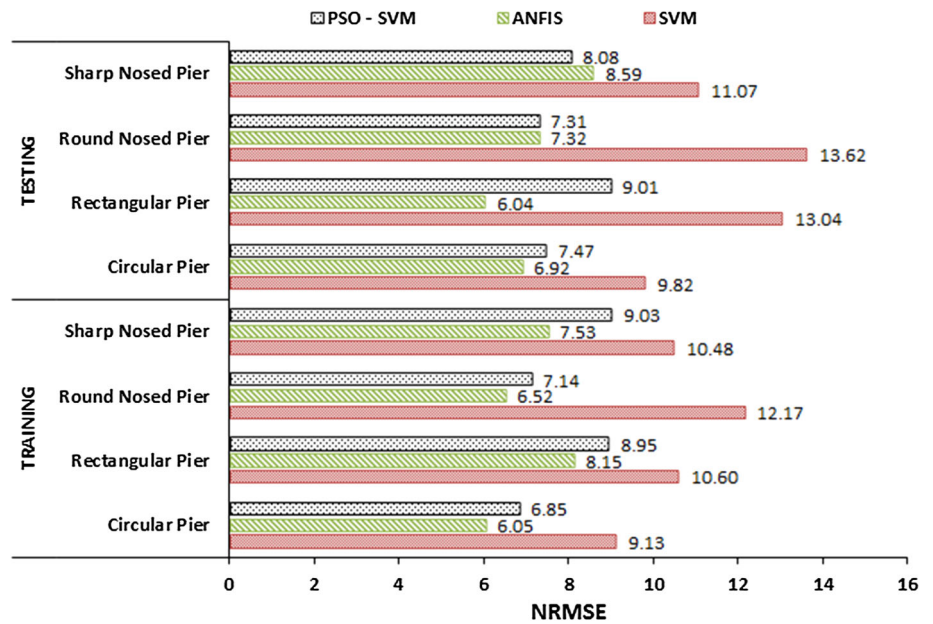
accuracy than RBF-SVM regarding all the model performance indices. PSO–SVM (polynomial) showed almost similar accuracy and efficiency as that of ANFIS in terms of CC of 0.92 but showed a marginal increase in efficiency and reduced error generalization capacity with NSE of 0.84, NMB of 0.007 and NRMSE of 8.08. Therefore, PSO–SVM (polynomial) and ANFIS with GbellMF are taken as best hybrid models and best soft computing technique to predict scour depth. During regression analysis, results of all models in the classical model values or experimental values are represented by coefficient determination ( $R^2$ ). Among all three models the PSO–SVM model with polynomial kernel function gives high accuracy compared to

ANFIS and SVM models with an  $R^2$  of 0.850 to predict scour depth in case of pier with the sharp nose shape. The above results are illustrated in the form of innovative Box–Whisker. The plot represents the spread of the predicted values, and a skeletal type of box-and-whisker plot is used in the study. From box plot in Fig. 7d, it can also be observed that the standard error is less even though the variance is more in Gbell MF.

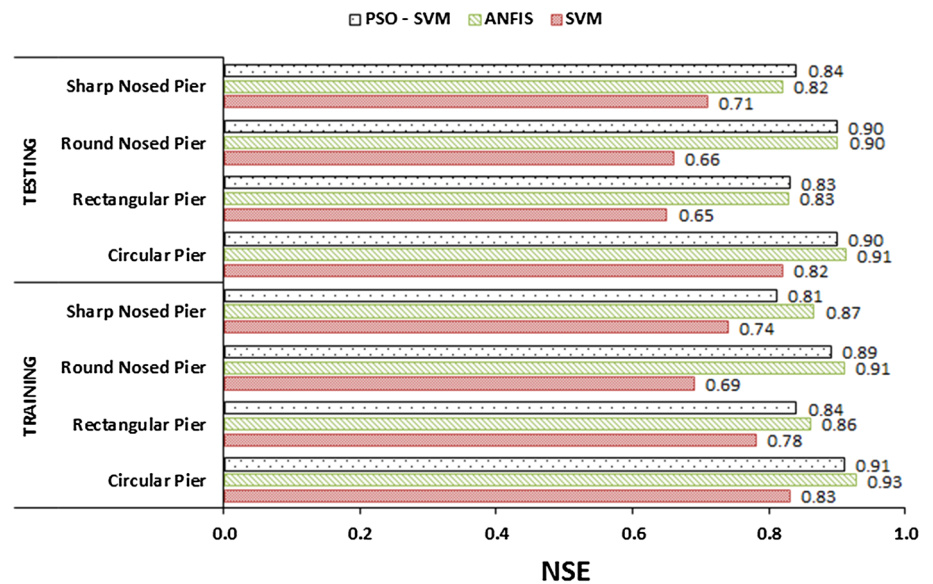
### 4.5 Comparative analysis

To select the most accurate model, ANFIS-Gbell, ANFIS-trapezoidal and SVM-RBF kernel function and PSO–SVM

**Fig. 8** NRMSE of SVM, ANFIS and PSO–SVM models for different pier shapes

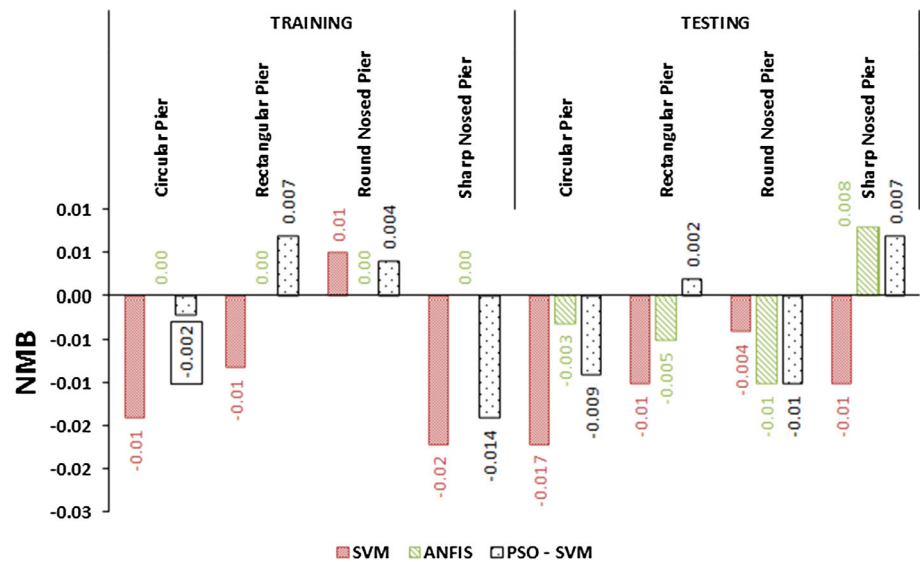


**Fig. 9** NSE of SVM, ANFIS and PSO–SVM models for different pier shapes





**Fig. 10** NMB of SVM, ANFIS and PSO–SVM models for different pier shapes



(polynomial) approaches are applied for given experimental data set for different pier shapes. The results obtained from both train and test conditions for all the performance indices by all three models are shown in Table 4. The performance of the models is evaluated using the different model performance indices such as, correlation coefficient (CC), normalized root-mean-square error (NRMSE), normalized mean bias (NMB) and Nash–Sutcliffe coefficient error (NSE).

It is common to see that all models performed better in training stage rather than testing stage. In Figs. 8 and 9, Gbell MF shows reliable results compared to other models based on CC, NRMSE, NMB and NSE. Similarly, Fig. 10 indicates that SVM results for both training and testing are under-predicted compared to ANFIS and PSO–SVM models. Hence, it is clear from the above results that ANFIS-GbellMF outperformed the SVM, and PSO–SVM with polynomial kernel function in the prediction of scour depth for pier with different shapes considered in the present discussion is the best model in terms of model performance indices and Box–Whisker plot representation. Later, the PSO–SVM model with polynomial kernel function is considered as best hybrid model to predict scour depth around pier with all shapes in terms of coefficient of determination ( $R^2$ ).

From overall results and discussions in the present study implies that the PSO–SVM model with polynomial kernel function is considered as best, efficient and accurate alternate algorithm to predict scour depth around the pier with circular, rectangular, round nose and sharp nose shapes. With respect to the results obtained, the pier with circular shape is considered as the best shape both by classical/experimental model, and with reference to those

experimental values the PSO–SVM model values considered in the present study.

## 5 Conclusions

The ANFIS, SVM and PSO–SVM models are developed to predict scour depth around the pier with different shapes are analyzed and compared with experimental values and with each other. From the study, the following conclusions are drawn.

1. The application of ANFIS-Gbell MF, ANFIS-trapezoidal MF and SVM-RBF and PSO–SVM with polynomial kernel functions in the prediction of scour depth for different pier shapes are discussed in this study. From the above results and discussions, the PSO–SVM model with polynomial kernel function is considered as efficient and accurate evolutionary approach to predict scour depth around the pier with different shapes.
2. PSO–SVM with polynomial kernel function takes the advantages of overcoming the local minima problem of ANFIS and minimum structural risk minimization of SVM and the best of quick and fast global optimizing capacity and the ability of PSO.
3. The PSO–SVM model approach fulfills the purpose of the present study to predict scour depth around the pier with different shapes by reducing the error of generalization to the least or minimized by optimizing the performance of the SVM model.
4. The results obtained in terms of all model performance indices and coefficient of determination show that

PSO–SVM with polynomial kernel function gives a better prediction in terms of accuracy even though the results of the ANFIS model with GbellMF are marginally close to the PSO–SVM model.

- The performance of PSO–SVM with polynomial kernel function with high accuracy and efficiency for predicting scour depth around the circular pier compare to rectangular, round-nosed and sharp-nosed piers and it could serve a better alternate for scour depth prediction.

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### Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

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