Archives of Computational Methods in Engineering (2021) 28:423–447
https://doi.org/10.1007/s11831-019-09382-4

ORIGINAL PAPER

The Application of Soft Computing Models and Empirical Formulations for Hydraulic Structure Scouring Depth Simulation: A Comprehensive Review, Assessment and Possible Future Research Direction

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Received: 25 April 2019 / Accepted: 18 November 2019 / Published online: 30 November 2019

Abstract
Prediction of scouring characteristics is one of the major issues in hydraulic and hydrology engineering. Over the past five decades, numerous empirical formulations (EFs), based on the regression of scouring data observed from laboratory experiments in the field, have been developed to predict scouring characteristics (typically, the equilibrium scour depth); yet, these EFs are sensitive to uncertainty of effective parameters and in some cases could not comprehend the actual internal mechanism between variables. In the last 20 years, Soft Computing (SC) approaches have been increasingly adopted as an alternative for modeling scouring depth surrounding hydraulic structures. In this respect, several SC algorithms are examined as new era of modeling methodologies for extracting scouring depth equations. Lately, these algorithms have been vastly adopted for scouring simulation with various advanced version of SC such as hybrid intelligence models. The motivation of the current research is to exhibit all the established researches on the implementation of EF and SC models for multiple scouring depth modeling such as around pipeline, bridges abutment, piles and grade-control structures. A comprehensive review of the up-to-date researches on the scouring depth phenomena is presented, placing special emphasis on the recent applications of SC models and also recalling all the performed experimental laboratory studies. The review is included an informative evaluation and assessment of the surveyed researches. The improvement in prediction performance provided by the SC models when compared to empirical formulations is discussed and based on the current state-of-the-art, several research gaps are recognized, and possible future research directions are proposed.

1 Introduction

The scouring process is initiated by soil erosion at hydraulic structures including bridge piers and abutments, grade-control structures, piles, and pipelines [42, 44, 65, 149]. The quantification of scouring is a complex engineering problem, as this process is affected by both the water flow properties and the soil physical characteristics. Most of man-made hydraulic structures in rivers (e.g., bridges, spillways, breakwater etc.) cause scouring, which in turn can cause significant damage to the structure; therefore, quantifying this phenomenon is of much importance for river engineering and hydraulic structure sustainability [214].

Estimating accurately the depth of scouring is challenging, because of the complexity of the flow patterns which develop around hydraulic structures. In most studies, the scouring characteristics are assessed using experimental data and laboratory tests [226]. In this regard, several empirical formulations for computing the scouring depth were developed through regression of the experimental data by

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employing an effective related parameters (e.g., Froude number, velocity, sediment size, and specific weight of sediment) [226]. Empirical formulations are easy to use, but they often provide underestimated or overestimated estimates of the scouring depth. In addition, they do not provide any physical understanding of the scouring process.

Hence, new methods based on soft computing [i.e., artificial intelligence (AI) models] are emphasized to be implemented due to the less sensitivity into the experimental condition. Generally, AI models are applied for solving optimization problems and prediction [199, 234] and to perform sensitivity analysis of effective parameters in a special phenomenon [29].

This paper aims to provide a review of the state of the art regarding the application of these methods in estimating the scouring depth. The focus is on scouring around bridge piers, grade-control structures, piles, and pipelines. This review encompasses four decades of development in the field and offers a comprehensive summary to scholars and practitioners in hydraulic engineering.

2 Empirical Formulations

This section provides a brief overview of a few empirical formulations for the evaluation of equilibrium scour depth and, in some cases, temporal evolution of scouring, for scouring at bridge piers and abutments (Sect. 2.1) grade-control structures (Sect. 2.2), piles (Sect. 2.3) and pipelines (Sect. 2.4). This review is not meant to be comprehensive, which is beyond the scope of this paper. On the other hand, it provides an overview of the typical hydraulic, sediment and structure parameters that were found by several authors to be correlated with scouring. Many of the applications of soft computing models reviewed in Sect. 3 presented a comparison of scour prediction performance with empirical formulations.

2.1 Scouring at Bridge Piers and Abutments

A large number of experimental and field studies of pier and abutment scour depth have started since 1956 [48]. The brief details of the most used studies in this filed are reported as follows:

Jain and Fischer [120] investigated the scour depth around a circular bridge pier for high Froude numbers (over 1.5). They used data from both the field and laboratory experiments carried out using a rectangular flume ($27 \times 0.91 \times 0.46$(m)) with the different bed conditions (flat, dunes, antidunes, chutes and pools). They developed the following empirical formulation to predict the scour depth

$$\frac{d_s}{b} = 1.86\left(Fr - Fr_{cr}\right)^{0.25}\left(\frac{y}{b}\right)^{0.5} for Fr - Fr_{cr} > 0.15 \tag{1}$$

where d_s, b, Fr, Fr_{cr} and y are the equilibrium scour depth, the diameter of the bridge pier, the Froude number, the critical Froude number, and the water depth, respectively.

Based on the different performed tests, the observed scour depth varies between 8.4 and 15.9 cm. It was evidenced also that with high Froude number the scour depth is more than clear water condition. Kothyari et al. [136] investigated the temporal evolution of scour around bridge piers. They used a $30 \times 1 \times 0.6$(m) flume and circular piers with diameters of 65, 115 and 170 mm, with a range of median sediment diameter D50 between 0.24 and 0.78 mm. The flow velocity upstream of each pier varied between 0.1 and 1.35 m/s. They obtained a formulation for the scouring depth as follows

$$\frac{d_{se}}{b} = 0.66\left(\frac{d}{b}\right)^{0.25}\left(\frac{D}{d}\right)^{0.86}\left(\frac{U^2 - U_c^2}{\frac{\Delta\gamma_s}{\rho_f}d}\right)^{0.4}\alpha^{-0.3} \tag{2}$$

where d_{se}, b, d, D, U, U_c, γ_s, ρ_f and α are equilibrium scour depth, diameter of the circular bridge pier, size of the uniform sediment, depth of flow, flow velocity, critical flow velocity, specific weight of sediment, mass density of water, and opening ratio, respectively. In their study, the effects of sediment non-uniformity and unsteadiness on scour depth calculated and new model was developed for scour estimation.

Melville and Chiew [154] conducted laboratory experiments to estimate the scour depth over time, with pier diameters varying between 16 and 200 mm, and mean diameter of sediment ranging between 0.78 and 7.35 mm. They conducted tests with duration between 200 and 15,000 min and the mean approach flow velocity fluctuated between 0.171 and 1.208 m/s. They developed formulations to estimate the time for reaching equilibrium scour depth around a bridge pier

$$t_e(days) = 48.26\frac{D}{V}\left(\frac{D}{V_c} - 0.4\right)\frac{y}{D} > 6 \tag{3}$$

$$t_e(days) = 30.89\frac{D}{V}\left(\frac{V}{V_c} - 0.4\right)\frac{y}{D} \le 6 \tag{4}$$

where t_e, D, V, V_c and y are time for the equilibrium depth of scour to develop, cylindrical pier diameter, mean approach flow velocity, critical mean approach flow velocity for entrainment of bed sediment, and flow depth, respectively. Melville and Chiew [154] investigate the temporal evolution of scour hole shape and tried to find correlations between field and laboratory data in long term situations (more than 14,000 min). Finally, their research evidenced that flow intensity and shallowness are the most important controlling factors on scour depth.

Oliveto and Hager [187] developed a scouring depth formulation as function of time. They used experimental data obtained with two different rectangular flumes ($1 \times 10 \times 5$(m) and $0.5 \times 10 \times 5$(m)) and circular piers with eight different diameters (0.011, 0.022, 0.05, 0.064, 0.11, 0.257, 0.4, 0.5 m). The sediment size varied between 0.55 and 5.3 mm and the Froude number downstream of the bridge piers ranged between 1.43 and 3.67. Experiments were run for durations between 0.04 and 14 days. Oliveto and Hager [187] proposed for following expression for the dimensionless scouring depth

$$d_s/b = 0.067N\sigma^{-1.2}F_d^{1.5}\log(T) \tag{5}$$

where d_s, b, N, σ, F_d, and T are scour depth, bridge pier diameter, shape number, sediment non-uniformity, densiometric particle Froude number and time, respectively. This formulation has the advantage of accounting for the effect of the fluid viscosity and that most hydraulic parameters such as approach flow depth, cross-sectional velocity and median sediment size are taken into account.

Dey and Barbhuiya [68] studied scouring around three different types of abutments (semicircular, vertical walls, 45 wing-wall), using a flume with dimensions $20 \times 0.9 \times 0.7$(m) and median size of sediments ranging between 0.26 and 3.1 mm. The critical velocity varied between 0.031 and 0.0481 m/s. They investigated the effects of abutment length ratio, sediment gradation, sediment diameter ratio, uniform and non-uniform conditions. They developed three different expressions depending on the shape of the abutment as follows

$$d_{sm} = 5.85Fr_{cr}^{.314}h^{0.128}l^{-0.167} \quad \text{for vertical wall abutment} \tag{6}$$

$$d_{sm} = 6.484Fr_{cr}^{0.312}h^{0.101}l^{-0.231} \quad \text{for } 45^{\circ} \text{ wing} - \text{wall abutment} \tag{7}$$

$$d_{sm} = 7.287Fr_{cr}^{0.192}h^{0.103}l^{-0.296} \quad \text{for semicircular abutment} \tag{8}$$

where d_{sm}, Fr_{cr}, h, and l are maximum equilibrium scour depth, critical Froude number, approaching flow depth and transverse length of abutment, respectively. The above equations indicate that the equilibrium scour depth has an inverse relation with the abutment transverse length and were shown to provide estimates in agreement with previously measured scouring depths.

Mueller and Wagner [167] investigated bridge scouring based on field data for 79 sites located in 17 states in the United States. They collected 493 measurements of pier width, pier length, pier shape, skew, flow velocity, and sediment size (D_{16}, D_{50}, D_{84}, D_{95}). The authors have compared their observed scouring depths with different empirical formulations, among them Froehlich [95], HEC-18, HEC-18-K4, HEC-18-K4Mu and Hec-18-KMo. Mueller and Wagner [167] reported that HEC-18 formulation produced the estimates with better agreement with the observed values. HEC-18 relation was developed by US Federal Highway Administration (F.H.W.A) using collected database from laboratory test as follows:

$$\frac{d_s}{a} = 2K_1K_2K_3\left(\frac{a}{y_1}\right)^{0.35}Fr^{0.43} \tag{9}$$

where $d_s, y_1, a, Fr, k_1, k_2 and k_3$ are scour depth, upstream flow depth of the pier, pier width, Froude number of upstream of the pier, correction factors of pier nose shape, angle of flow and bed condition, respectively. The k_1, k_2 and k_3 are in range of [0.9 1.1], [1 5] and [1.1 1.3], respectively.

2.2 Scouring at Grade-Control Structures

Many laboratory experiments were conducted to estimate the scour depth of downstream of grade-control structures. There are some well-known experiments which also used as alternatives to soft computing models are as follows. Bormann and Julien [41] conducted large scale flume experiments to investigate the scouring depth downstream of grade-control structures. They used a $27.4 \times 3.5 \times 0.91$(m) flume with flow rates ranging between 0.29 and 2.47 m/s. They proposed a relation for scouring depth estimation downstream of grade-control structures as follows

$$D_s = \left\{\left(\frac{\gamma \sin\varphi}{\sin(\varphi + \alpha) + B(\gamma_{s-}\gamma)}\right)^{0.8}\frac{C_d^2}{d_s^{0.4}}sin\beta\right\} - D_p \tag{10}$$

where D_s, γ, γ_s, φ, α, C_d, d_s, β and D_p are equilibrium scour depth, water specific weight, sediment specific weight, submerged angle of repose of bed sediment, maximum side angle of scour hole, jet diffusion coefficient, sediment size, jet angle near surface, and drop height of the structure, respectively. Different jet conditions were tested, and the proposed regression relation showed good agreement between measured and estimated scour depths.

D'Agostino and Ferro [62] investigated the relation between upstream head, weir height, and scouring depth based on different sources [61, 84, 164, 227]. Here, the scholars used self-similarity theory to improve maximum scouring depth prediction. Dey and Sarkar [71] investigated submerged jests on aprons by conducting experiments with a ($10 \times 0.71 \times 0.6$(m)) flume, sand-gravel beds with mean diameters varying between 0.26 and 5.53 mm, and flow velocity ranging between 1.21 and 1.52 m/s. They measured maximum scouring depths between 0.03 and 0.11 m and proposed a regression formulation for maximum scouring depth as follows

$$d_s = 2.59Fr^{0.94}L^{-0.37}h^{0.6}d^{0.25} \tag{11}$$

where d_s, Fr, L, h and d are the maximum scour depth, Froude number, apron length, tail water depth, and ratio of mean sediment diameter to sluice gate opening, respectively. The study also focused on the determination of the relation between scouring profile and scouring processes. The reported relations between the sluice opening and sediment size on scouring were adversely but densiometric Froude number has direct effect on measured scour depth.

2.3 Scouring at Piles

In coastal and ocean engineering fields, several experiments were conducted to investigate the interaction of piles and flow alluvial. The short review of notable laboratory investigations which referred in soft computing studies are presented as follows. Sumer and Fredsøe [216] carried out experiments with a flume with dimensions $(4 \times 1 \times 28(\mathrm{m}))$ with different pile group layouts: (1) tandem, (2) side by side, (3) staggered (4) triangular group and (5) square group. Two different types of pile were used (32 and 90 mm). The maximum flow velocity varied between 0.8 and 2.5 m/s with Keulegan–Carpenter (KC) number moderated between 3 and 37. Sumer and Fredsøe [216] measured the maximum scour depth for all pile layouts, with a maximum non-dimensional scour depth $\left(\frac{Scourdepth}{pilediameter}\right)$ between 0.03 and 4.45 m. In this study the influence of KC numbers was considered, and they showed that this coefficient has straight influence on scouring depth.

Bayram and Larson [37] investigated the scouring depth at piles in the field, using data from the Pacific coast of Japan for the period 1975–1996. The pile diameter was 0.6 m and the KC number varied between 8.2 and 22.5. They found an empirical relationship between relative scour depth and KC number; on the other hand, they did not find a significant correlation between KC number and width of the scour holes. Bayram and Larson [37] underlined the validity of their result for the only pile layout they considered.

Ataie-Ashtiani and Beheshti [11] studied the effect of scouring around piles in clear water by conducting flume dimensions $(4 \times 0.25 \times 0.41(\mathrm{m}))$ with different arrangements of pile groups. An aligned pile groups used to the flow and the influences of skewness were not considered. They concluded that normalized pile spacing (G/D) greatly affects the resulting scouring depth and the best arrangement of pile groups were suggested.

2.4 Scouring at Pipelines

One of the most major hazards in hydraulic engineering is scour around pipelines. The scour around pipelines is depend on flow pattern and bed movement. The interactions of bed-pipelines-fluid are very complex and laboratory studies are very limited. For better understanding on growth of scour dimensions around pipelines, the researchers used soft computing tools and laboratory datasets to increase accuracy of laboratory results. The most used laboratory tests which have been used in soft computing tools for prediction of scour around pipelines are presented here:

Moncada-M et al. [163] investigated scouring below pipelines in a rectangular channel with dimensions $(8.3 \times 0.5 \times 0.5(\mathrm{m}))$ with four different pipe diameters (2.34, 3.3, 4 and 4.8 cm). The mean sediment diameter D_{50} varied between 0.6 and 7.6 mm. The influence of Reynolds number, Froude number and position of pipe with respect to the bed were investigated, which led to the development of the following relationship

$$\frac{S}{D} = 2Fr\mathrm{sech}(1.7\frac{e}{D}) \tag{12}$$

where S, D, Fr and e are equilibrium scour depth just below the pipeline, pipe diameter, Froude number, and initial gap between pipe and undisturbed erodible bed, respectively. The results showed that Reynolds number between 8000 and 30,000 did not affect the scour depth, whereas scour depth increased linearly with the Froude number.

Dey and Singh [72] studied the scouring depth around underwater pipelines, with experiments performed in a flume $(12 \times 0.61 \times 0.7(\mathrm{m}))$ and three different Perspex pipelines, with critical shear velocity (U^*_{cr}) ranging between 1.3 and 7.2 cm/s. The effects of Froude number, flow depth relative to pipe diameter, pipe diameter to sediment size, non-uniform sediment gradation, pipe cross section, on the scouring development in time were investigated, which resulted in the following formulation for equilibrium scour depth longitudinal profile

$$\frac{z}{d_s} = a_0 + a_1\left(\frac{x}{d_s}\right) + a_2\left(\frac{x}{d_s}\right)^2 + a_3\left(\frac{x}{d_s}\right)^3 \tag{13}$$

where z, d_s, $a_{0,\ldots}$, a_3 and x are vertical distance, equilibrium scour depth in un-layered sediment, coefficients and horizontal distance, respectively. The authors concluded their study with the observation of the major influence of the different types of armor layers in sandy bed. Further, they indicated that secondary armored layer could affect scour depth if it was shielded.

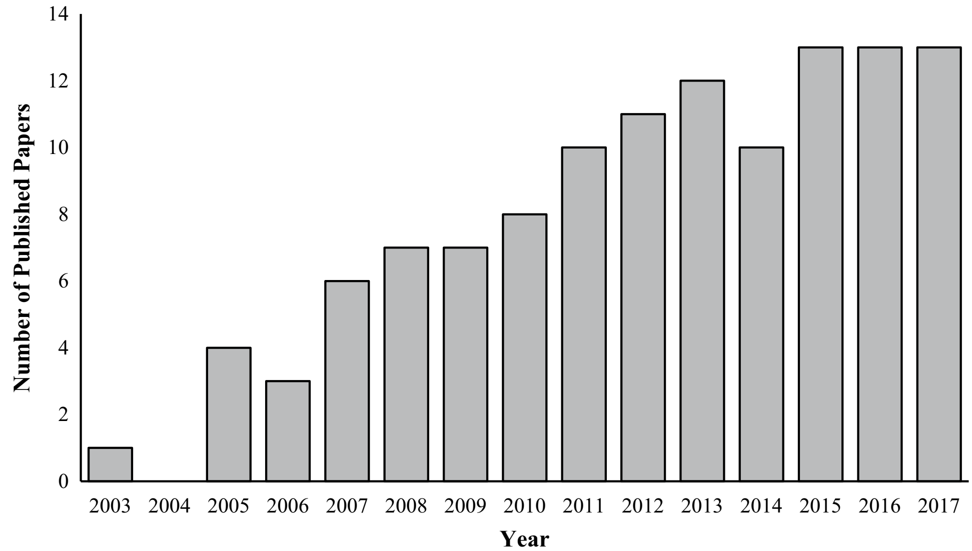

Fig. 1 The rate of the published papers on scouring simulation using the soft computing models over the past two decades

3 Soft Computing Models

The implementation of soft computing in the field of hydraulic engineering has massively increased over the past two decades. Figure 1 shows the increasing trend of published research on the use of soft computing models to simulate scouring since 2003. In general, soft computing algorithms have shown good potential for prediction or optimization; however, drawbacks have been reported regarding the sensitivity of these algorithms to noisy inputs, with significant impact on the results. Hence, researchers have sought to combine different algorithms to both increase the computational speed and facilitate the solution convergence. The improvement in computational and optimization or prediction performance can be obtained by combining nature-inspired algorithms [e.g., Genetic Algorithm (GA)] with classical Artificial Intelligence models.

As the rate of utilization of these algorithms is increasing, it is necessary to investigate the efficiency and similarity of the different available soft computing approaches. In this study the efficiency of these algorithms in comparison of standalone models and other hybrid models are investigated. In some cases, scholars applying soft computing methods utilized datasets obtained from studies based on physical models to derive empirical formulations for scouring.

Soft computing models have been applied for depth scouring simulation, categorized into several groups:

1. Fuzzy logic, of which the Adaptive Neuro Fuzzy Inference System (ANFIS) models are a well-known version [123].
2. Evolutionary Computing (EC) models that are based on Genetic Programming (GP) simulation [7].
3. Classical Artificial Neural Network (ANN) models with their various training algorithms [245].
4. Other Soft Computing (OSC) Models which can be divided as (a) Kernel methods based on statistical learning process, such as Support Vector Machine (SVM) models [87], (b) Decision tree models, also known as data mining models, such as the M5 tree models [202], and (c) Hybrid AI models that presented by integrating natural inspired optimization algorithms with the standalone AI model [170].

3.1 Adaptive Neuro Fuzzy Inference System (ANFIS) Models

Jang [122] introduced for the first time the Adaptive Neuro Fuzzy Inference System (ANFIS). Within the field of computer science, ANFIS is a modeling technique which combines fuzzy calculations (Fuzzy Inferences System (FIS)) and neural networks (ANN) for solving non-linear problems, to find relations between inputs and outputs. The FIS component includes three elements: (1) a section of Fuzzy-If–Then rules; (2) a data base section which determines the Membership Function (MF); and (3) a section of joining fuzzy rules and generating system's results.

The If–Then rules are a useful tool for prediction and uncertainty analysis [121]. ANN training algorithms can reduce the prediction error and improve the designing of FIS rules. In the following sub-sections, the performance

Table 1 Application of fuzzy logic-based algorithms for prediction of scouring

Scholar(s)	Type of FL-based algorithm	Compared algorithm(s)	References of dataset(s)	Performance criteria
Scouring at bridge piers and abutments				
Firat [91]	ANFIS	RBNN, MLR	[83, 140, 154, 157, 210]	NRMSE, R, E
Cheng and Cao [53]	IFRIM	RBFNN/SVM/GP/M5	[167]	RMSE, MAE, R^2
Hosseini et al. [114]	ANFIS	FFBP/MNLR/RBF	[30, 47, 59, 126, 187, 236]	RMSE, MAE, R^2
Choi et al. [56]	ANFIS	ANN(BP)	[48, 69, 120, 209]	MAPE, R^2
Scouring at grade-control structures				
Azamathulla et al. [19]	ANFIS	–	[4]	R, R^2, AE, MSE
Azamathulla et al. [17, 20]	ANFIS	GEP, FFBP, FFCC, RBF	[16]	R, RMSE, AE, δ
Farhoudi et al. [86]	ANFIS	–	[85]	E_{NS}, SE
Keshavarzi et al. [129]	ANFIS	ANN	[130]	MAE, RMSE, R^2
Muzzammil and Alam [168]	ANFIS	ANN(FFBP)	[62]	MPE, R, RMSE
Najafzadeh et al. [177, 178]	ANFIS	SVM	[100, 229]; LIM and [70, 135, 148]	R, RMSE, SI, MAPE, BIAS
Eghbalzadeh et al. [78]	ANFIS	MLP	[71]	MAE, RMSE, CF
Scouring at piles				
Bateni and Jeng [35]	ANFIS	–	[37]	MAE, RMSE, R^2
Zounemat-Kermani et al. [247]	ANFIS	FFBP/RBF	[11, 58, 112, 246]	MAE, RMSE, R
Scouring at pipelines				
Mohamed et al. [159]	ANFIS	SVM		Error Tolerance

of ANFIS models in predicting scouring depth for various hydraulic engineering problems is reviewed.

3.1.1 ANFIS-Based Models for Scouring at Bridge Piers and Abutments

Firat [91] employed an ANFIS model for the prediction of scouring depth around bridges and compared the reliability of ANFIS against Radial Basis Neural Network (RBNN) and a few empirical formulations [111, 142, 154, 209] based on 156 datasets obtained from different references as reported in Table 1. The comparison revealed that the ANFIS model with R^2 values 0.918 and 0.905 respectively in training and testing phases can predict scouring depths more accurately.

Cheng and Cao [53] combined different fuzzy logic algorithms for bridge scouring depth simulation. The applied model consisted fuzzy logic and bee colony algorithm. The authors used 237 datasets from Mueller and Wagner [167], obtained from field observations in the USA, to compare the performance of their model with that of Radial Basis Function Neural Network (RBFNN), Support Vector Machines (SVM), Genetic Programming (GP) and Model Tree (MT) as well as several mathematical relations such as HEC-18, Froehlich [95] and Laursen and Toch [142]. The outcome of this comparison showed that the Intelligent fuzzy radial basis function neural networks inference model (IFRIM) model ($R^2_{Train} = 0.980, R^2_{test} = 0.871$) provided a better performance in predicting scouring depth compared to other AI or mathematical relations.

Hosseini et al. [114] simulated with ANFIS the maximum scour depth around short bridge abutments ($\frac{L}{y} < 1$). Their dataset consisted of both data from previous studies from literature and their own data, obtained conducting experiments in a flume ($14 \times 1 \times 1$ m). They considered three different shapes of abutment (semi-circular, vertical wall and wing-wall). A comparison was carried out between ANFIS, Feed Forward Back Propagation (FFBP), Multiple Non-Linear Regression (MNLR) and Radial Basis Function (RBF) for prediction of scouring depth, demonstrating the better prediction performance of ANFIS ($R^2_{Train} = 0.990, R^2_{test} = 0.980$) compared to the other models.

Choi et al. [56] showed that ANFIS $\left(MAPE_{Train} = 50.58\%, MAPE_{Test} = 1.23\%\right)$ provides more accurate prediction of scouring depth around bridges piers than Back Propagation Neural Network)BPNN(, based on data from previous experimental studies (Table 1).

3.1.2 ANFIS-Based Models for Scouring at Grade-Control Structures

Azamathulla et al. [19] used an ANFIS model to estimate the scouring location downstream of bucket spillways. Their results evidenced the capability of the ANFIS model

($R^2 = 0.922$) in determining location of scour compared to the observed data. Azamathulla et al. [17, 20] compared the performance of an ANFIS model in predicting depth and location of scour downstream of flip bucket spillways with Genetic Expression Programming (GEP), Feed Forward Computational Complexity (FFCC), FFBP, and RBF models. The performance of the GEP ($r = 0.992$) exhibited better accuracy in comparison with the other predictive models. Farhoudi et al. [86] found that ANFIS is a powerful tool ($R^2_{Train} = 0.990, R^2_{test} = 0.920$) to estimate scouring characteristics downstream of stilling basins USBR Type I, such as shape, maximum scouring depth, and time evolution. Keshavarzi et al. [129] simulated scouring in arch-shaped bed sills by using ANFIS and ANN and noted a better prediction performance by ANFIS ($R^2_{Train} = 0.998, R^2_{test} = 0.987$). Muzzammil and Alam [168] employed ANFIS and FFBP to predict scouring depth downstream of grade-control structures, using the data set by D'Agostino and Ferro [62] for non-uniform sediment beds, with ANFIS ($R_{Train} = .99, R_{Test} = .98$) showing a better prediction performance than FFBP.

Mohammad Najafzadeh et al. [177, 178] compared ANFIS and SVM for scour prediction in contracted channels, and also compared their models to empirical formulations derived from the datasets they considered. Their results showed that ANFIS ($R_{Train} = 0.9, R_{Test} = 0.89$) has better scour depth prediction performance when compared to AI and regression models. Eghbalzadeh et al. [78] employed ANFIS and Multi-Layer Perceptron (MLP) to predict equilibrium scouring depth downstream of sluice gates, based on experiments with uniform non-cohesive sediment. Their results showed a better scouring depth prediction performance by the MLP model ($RMSE_{Train} = 0.106, RMSE_{Test} = 0.140$).

3.1.3 ANFIS-Based Models for Scouring at Piles

Bateni and Jeng [35] simulated scouring depth around group of piles with ANFIS, using the laboratory dataset from Bayram and Larson [37], and compared the predicted results to regression models from previous studies. The ANFIS outputs ($R^2_{Train} = 1, R^2_{test} = 0.912$) turned out to be more accurate in comparison with other regression models. Zounemat-Kermani et al. [247] used ANFIS, FFBP and RBF to predict scouring depth around pile groups, using previous datasets [11, 210]. In their study, FFBP showed the better prediction performance ($R_{Train} = 0.9951, R_{Test} = 0.772$).

3.1.4 ANFIS-Based Models for Scouring at Pipelines

Mohamed et al. [159] modeled scouring depth around gas pipelines in underwater condition, using ANFIS and SVM. The ability of different types of membership function was studied and the best one was selected.

3.2 Evolutionary Computing (EC) Models

Evolutionary Computing (EC) models are AI models based on evolutionary theory. Among the various EC models, Genetic Algorithms (GA) are among the most popular algorithms and are used widely in different fields of engineering. The concept of GA is inspired by Darwin's theory in biology. Holland [113] introduced GA to engineers for solving operation research problems (e.g., optimization of fitness function) [113]. These algorithms have excellent performance in solving nonlinear functions with many constraints, and their performing times are lower than classical methods such as Simplex method.

GA include four stages: (1) initialization of existing population, (2) cross over, (3) mutation, and (4) iteration until convergence [64]. All four components make use of different probabilistic calculations.

For prediction of scouring, GA have been used in two ways:

1. Combined with other calculation methods such as finite elements to increase their prediction performance.
2. Used as component of AI models to improve the prediction performance.

Another version of EC models is Genetic Programming (GP), which is a type of GA. The main application of GP is the fitting of relation between inputs and outputs by using mathematical operators (power, minus, plus, division and product). The fitting procedure is iterative, and the selection of each operator follows GA rules such as cross over and mutation. One of the advantages of GP is that it derives relationships between inputs and outputs which can be used as estimator models. The GP also does not need primary objective function in first step therefore GP could present better performance in estimation problems.

Genetic Expression Programming (GEP) was devised by Ferreira and Gepsoft [89] for solving complex problems. GEP is a very useful tool for expressing relationships between variables in datasets. Like GA models, GEP models use crossover and mutation operators but adopt additional mathematical operators to improve the prediction performance when compared to GP models. The architecture of GEP model includes GA and expression tree rules to find relationships between parameters.

Table 2 Applications of genetic-based algorithms for prediction of scouring

Scholar(s)	Type of genetic-based algorithm	Compared algorithm(s)	References of dataset(s)	Performance criteria
Scouring at bridges				
Azamathulla et al. [17, 20]	GP	ANN(RBF)	[139, 160]	RMSE, R^2, AE
Feng et al. [88]	GA	–	–	RMSE
Azamathulla [14, 15]	GEP	ANN(RBF)	[31, 33]	RMSE, R^2, MAE, δ
Khan et al. [131]	GEP	ANN	–	AAE, RMSE, R^2
Huang et al. [116]	GA + FE	–		RMSE
Wang et al. [228]	GP	–	[48, 82, 136, 154]	R, RMSE, MAPE
Mohammadpour et al. [161]	GP	ANN	[30, 33]	RMSE, R^2, MAE
Mohammadpour et al. [162]	GEP	ANN(FFBP/RBF)	[30, 33]	AE, δ, R^2
Muzzammil et al. [169]	GEP	–	[66]	R, RMSE, MAD, MPE
Najafzadeh et al. [177, 178]	GEP	MT, EPR	[94, 137, 156, 190, 194]	R, RMSE, MAE, RSE, RAE
Scouring at grade-control structures				
Guven et al. [105]	GEP	–	[41, 61, 164]	R, MSE, MAPE
Azamathulla et al. [24]	GP	–	[5, 133, 205, 212, 238]	R, RMSE, δ
Guven and Azamathulla [106]	GEP	GP	[24]	R, RMSE, δ
Azamathulla [14, 15]	GEP	–	[55]	R^2, RMSE
Moussa [166]	GEP	ANN(FFNN)	MSc Thesis	R^2, SE, AMRE
Onen [188]	GEP	ANN(FFBP)	–	R^2, RMSE
Zahiri et al. [243]	GEP	GA, M5 Tree	(Mario A. [55, 146, 147, 152, 224]	R^2, RMSE, AE
Onen [189]	GEP	–		R^2, RMSE
Najafzadeh et al. [183]	GEP	MT/EPR	[71, 110]	R, RMSE, BIAS
Pourzangbar et al. [195]	GP	FFNN/LMBP	[143, 215, 233]	R, RMSE, BIAS, SI
Pourzangbar et al. [196]	GP	FFNN/LMBP	[93, 222, 225]	R, RMSE, BIAS, SI
Sattar et al. [204]	GEP	–	[41, 61, 62, 84, 227]	R^2, E_{SN}, RAE, D
Najafzadeh et al. [182]	GEP	MT/EPR	[70, 100, 135, 229]	RMSE, R, R^2 DR
Scouring at piles				
Guven et al. [107]	LGP	ANFIS	[220]	R^2, RMSE, MAE
Scouring at pipelines				
Azamathulla and Ghani [18]	GP	ANN (RBF)	[72, 163]	MAE, RMSE, R^2, δ
Azamathulla et al., [21]	LGP	ANFIS	[72, 163]	MAE, RMSE, R^2, δ
Najafzadeh and Barani, [172]	GP	–	[72, 163]	RMSE, R^2
Azamathulla and Mohd. Yusoff [23]	GEP	–	[72, 163]	RMSE, R^2
Najafzadeh and Sarkamaryan [181]	GEP	MT/EPR	[72, 163]	R, RAE, RSE, MAE, RMSE
Sharafati et al. [206]	GP	GLUE, SUFI	[150, 165, 197, 218]	MAPE, RMSE

3.2.1 EC Models for Scouring at Bridge Piers and Abutments

Azamathulla et al. [17, 20] used GP and RBF for prediction of scouring depth around bridges. They used 398 different types of data sets from Mueller and Wagner [167] and obtained the better prediction performance using GP (R^2_{Test} = 0.819). Feng et al. [88] combined GA and finite element to fit a formulation relating scouring depth and natural frequency of bridges. This developed model has a better performance in comparison of usual formula. Azamathulla [14, 15] compared GEP and RBF in estimating the scouring depth around bridge abutments, using 317 datasets from previous studies (Table 2), with GEP showing the better scouring prediction performance (R_{Train} = 0.960, R_{Test} = 0.890). Khan et al. [131] compared GEP and ANN for prediction of scouring depth around bridge piers by using 370 data sets from field observations by Landers et al. [139], again with GEP showing the better scouring prediction performance (R_{Train} = 0.790, R_{Test} = 0.730). Huang et al. [116] developed a model based on GA and finite element to estimate scouring depth around bridge piers. They used GA as tools for finding relationships between scouring depth and natural frequency. The developed model was better performance in comparison of regression models.

Wang et al. [228] estimated scouring depth around bridge piers by using previous laboratory studies and GP. The estimated results were compared to those provided by regression models and the advantages of GP were defined ($R_{Train} = 0.93, R_{Test} = 0.86$). Mohammadpour et al. [161] predicted equilibrium scour time by using GP and ANN models. They reported that GP ($R^2 = 0.86$) would be a superior predictor when used as regression techniques. Mohammadpour et al. [162] compared GEP and ANN (RBF and FFBP) to predict scour dimension and time variation for short bridge abutments ($\frac{L}{y} < 1$), based on their own laboratory dataset as well as datasets from previous studies. GEP models provided more accurate predictions than the other models $\left(R^2_{Train} = 0.998, R^2_{Test} = 0.997\right)$. Muzzammil et al. [169] used GEP to estimate scour depth at bridge piers in cohesive soil, using the dataset from Debnath and Chaudhuri [66], showing improvement in prediction performance ($R = 0.930$) when compared to Chaudhari's empirical formulations ($R = 0.84$). Najafzadeh et al. [177, 178] estimated the maximum scouring depth around bridge piers using GEP, model tree and Evolutionary Polynomial Regression (EPR), including the impact of debris flow (considered in their dataset). They reported that EPR models ($R_{Train} = 0.959, R_{Test} = 0.909$) produced more accurate results than the other models.

3.2.2 EC Models for Scouring at Grade-Control Structures

Guven et al. [105] employed GEP as predictor of scour location and maximum scour depth downstream of grade-control structures and obtained with GEP ($R_{Train} = 0.980, R_{Test} = 0.970$) a better prediction performance than regression-derived formulations. which were taken from field measurements. Azamathulla et al., [24] applied GP to estimate scour at ski-jump bucket spillways, using different datasets (Table 2). They suggested that GP ($R = 0.977$) would be a useful tool for this filed of engineering. Guven and Azamathulla [106] used GEP to predict scour depth downstream of flip bucket spillways and compared its performance with USBR and BIS. The GEP ($R_{Train} = 0.943, R_{Test} = 0.917$) has good agreements with measured data from fields. Azamathulla [14, 15] used GEP for estimation of scouring depth downstream of sills, using a dataset from Chinnarasri and Kositgittiwong [55] and comparing with the output from regression formulations. They found GEP $\left(R^2 = 0.967\right)$ had a better prediction performance. Moussa [166] investigated the local scouring downstream of stilling basins for trapezoidal channel, using GEP and FFNN as their predictor techniques and reporting a better prediction performance by GEP$\left(R^2_{Train} = 0.867, R^2_{test} = 0.960\right)$. Onen [188] analyzed the capability of GEP and FFBP of prediction scouring depth around side weirs. They conducted three different sets of experiments in a flume with a sharp-edged side weir and obtained close prediction results with GEP ($R^2 = 0.965$) and FFBP ($R^2 = 0.956$). Onen [189] simulated flow pattern in curved channel and the scour depth around side-weir were investigated. Next, they entered the laboratory parameters in GEP models. They compared the ability of GEP, MLR, MNRL in estimation of scouring depth. The GEP ($R^2_{Train} = 0.927, R^2_{test} = 0.928$) was superior in prediction of scouring depth in comparison of others. Najafzadeh et al. [183] used GEP, model tree and EPR for estimating scouring downstream of sluice gates, using datasets from previous studies (Table 2), finding MT ($R_{Train} = 0.950, R_{test} = 0.960$) as the method providing the most accurate predictions. Pourzangbar et al. [195] predicted scouring depth around sea walls with GEP and ANN, for induced broken waves. GEP $\left(R_{test} = 0.896\right)$ had in general a better prediction performance compared to the ANN model. Ali Pourzangbar et al. [196] investigated scouring phenomena around coastal structures by using ANN (RBF, LMBP) and GP, for nonbreaking induced waves. GP ($R_{Train} = 0.981, R_{test} = 0.922$) proved to be a better estimator of scouring depth around sea walls. Sattar et al. [204] used GEP for predicting the scouring depth downstream of grade-control structures, using 256 datasets from field measurements in Poland from previous studies (Table 2). They computed the uncertainty of GEP models by using Monte Carlo simulations. GEP ($R^2_{Train} = 0.970, R^2_{test} = 0.930$) produced more accurate scouring depth predictions than existing empirical formulations. Najafzadeh et al. [182] compared GEP, MT, EPR and empirical formulations in estimating the scouring depth in rectangular channels, with GEP $\left(R_{Train} = 0.79, R_{test} = 0.89\right)$ showing the better prediction performance.

3.2.3 EC Models for Scouring at Piles

Guven et al. [107] applied Linear Genetic Programming (LGP) and ANFIS for prediction of scouring depth around circular piles. They used data sets from Sumer et al. [220] and obtained better more accurate scour depth prediction with LGP ($R^2_{Train} = 0.993, R^2_{test} = 0.991$). Johari and Nakhaee [124] developed a model based on ABAQUS and GEP to predict maximum the displacement in bored pile walls. The ability of this new model was more than existing relations.

3.2.4 EC Models for Scouring at Pipelines

Azamathulla and Ghani [18] assessed the capability of GP, ANN (RBF), and other empirical formulations of estimating scouring depth around pipelines. Their datasets came from two previous studies [41, 61] and their analysis found that GP ($R^2_{Train} = 0.960, R^2_{test} = 0.891$) has the better scouring depth prediction performance. Azamathulla et al. [21] used LGP and ANFIS for prediction of scouring depth below submerged pipelines using datasets from literature (Table 2). LGP and ANFIS had similar prediction performances ($R^2_{Train} = 0.862, R^2_{test} = 0.830 forLGP, R^2_{Train} = 0.899, R^2_{test} =, 0.824 forANFIS$) in both cases better than the existing empirical formulations. Najafzadeh and Barani [172] discussed about the application of GP in predicting the scouring depth that studied by Azamathulla and Ghani [18]. They suggested new strategy for selecting effective parameters on scouring by using GP. Azamathulla and Mohd. Yusoff [23] estimated the scouring depth around river pipelines using GEP, using laboratory datasets from [73, 163]. They suggested GEP ($R^2_{Train} = 0.901, R^2_{test} = 0.709$) as useful tools for assessment of scouring depth in comparison of traditional formulations. Najafzadeh and Sarkamaryan [181] assessed the scouring depth below pipelines in sea beds with GEP, MT and EPR, and the laboratory datasets listed in Table 2. From their analysis, EPR provided the more accurate predictions ($R_{Train} = 0.918, R_{test} = 0.964$). Sharafati et al. [206] studied the wave-induced scouring around pipelines using GP, Generalized-Likelihood Uncertainty Estimation (GLUE) and Sequential Uncertainty Fitting (SUFI) models. They used laboratory datasets from Lucassen [150], Mousavi et al. [165], Pu et al. [197], Sumer and Fredsøe [218] and found that the GLUE model ($RMSE_{Train} = 0.03, RMSE_{test} = 0.03$) produced the more accurate predictions.

3.3 Artificial Neural Network (ANN) Models

Artificial Neural Network (ANN) models are inspired by the human brain's processes to make decisions. They simulate the pattern of connections between inputs and outputs by using neurons. Neural Networks consisted of three layers including input, hidden and output. The relationship between inputs and outputs is built through a training process, which is iterative and continues until certain performance criteria are met. The performance criteria are measures of estimation error, such as RMSE, R^2 and MAE. There are several types of ANN algorithms, and the most widely used are described below.

Feed Forward Neural Network (FFNN) models are simplest type of ANN models. The information is passed in one way only and there are no loops. FFNN models can be Single Layer Perceptron (SLP) or Multi-Layer Perceptron (MLP). SLP is not commonly used because it just produces linear relationship between inputs, whereas MLP can produce more complex and meaningful relationships between inputs. For FFNN MLP models, inputs are entered in networks by means of nodes, then an existed network is trained with preselected optimization algorithms (e.g., Levenberg–Marquardt) and the hidden layer tries to map meaningful relations between inputs. In order to find these relations, various mathematical functions, such as log-sigmoid, hyperbolic tangent sigmoid and linear are used. By trial and error, the best relationship is selected based on the performance criteria.

Another type of ANN models is the Radial Basis Function (RBF), introduced by Broomhead and Lowe [45] based on the radial basis function used for classification, forecasting and function approximation. The main difference between RBF and MLP lies in the mathematical functions that are used for finding patterns between data. RBF models use gaussian, multiquadric, inverse quadratic, inverse multiquadric, poly harmonic splines and thin plate splines.

Group Method of Data Handling (GMDH) was introduced by Ivakhnenko [118] for solving higher level complex problems. In computer calculus, GMDH is one the most powerful tools to find relations between parameters in complex datasets. It can be used in different fields of engineering, such as prediction, data analysis and feature reorganization. The main component of GMDH models, which are iterative, is the base function used to find relations between inputs and outputs. The most superior base function used in GMDH models is the Kolmogorov-Gabor polynomial function. Different GMDH models have been developed and this model has been combined with other approaches such as fuzzy and evolutionary algorithms.

3.3.1 ANN-Based Models for Scouring at Bridge Piers and Abutments

Sung-Uk and Sanghwa [221] used Back Propagation Neural Network (BPNN) for prediction of scouring depth around bridge abutments and compared their outputs to those obtained using empirical formulations derived from field data such as Jain and Fischer [120], Melville [155]. The obtained better prediction performance using the ANN (BPNN) model ($MAPE_{Train} = 68.18\%, MAPE_{test} = 14.63\%$). Lee et al. [144] estimated scouring depth around bridge piers using a BPNN model, based on 387 measured datasets from thirteen states of USA, with better accuracy ($R_{Train} = 0.9226, R_{test} = 0.9559$) than existing empirical formulations. Bateni et al. [34, 36] compared two ANN models called MLP-Back Propagation (MLP-BP) and Radial Basis Function-Orthogonal Least Squares (RBF-OLS) to an ANFIS model for estimation of scour depth around bridge

Table 3 Applications of neural network-based algorithms for prediction of scouring

Scholar(s)	Type of neural network-based algorithm	Compared algorithm(s)	References of dataset(s)	Performance criteria
Scouring at bridges				
Sung-Uk and Sanghwa [221]	ANN(BPNN)	–	[48, 69, 120, 209]	MAPE
Lee et al. [144]	BPNN			RMSE, R
Bateni et al. [34, 36]	(MLP/BP; RBF/OLS)	ANFIS	[136, 154, 187]	MAE, RMSE, R^2
Azamathulla et al. [13]	RBF	–	[138, 160]	R, AE, RMSE
Bateni et al. [34, 36]	BPNN/Bayesian NN	–	[48, 82, 103, 111, 136, 154, 187, 235]	MAE, RMSE, R^2
Firat and Gungor [92]	GRNN	FFNN	[83, 157, 210] [140, 154]	R, E, RMSE
Shin and Park [211]	ANN(LMBP)		[43, 167, 237]	R, SSE
Yousefpour et al. [240]	ANN(MLP), ANN(RBF), ANN(GRNN)	–	–	R, RMSE
Adhikari et al. [2]	BPNN		Filed data	MSE, MAE, R, R^2
Ismail et al. [117]	FFNN	–	[136, 187]	MSE
Najafzadeh et al. [175, 176]	GMDH-BP	ANFIS, RBF-NN	From PhD Thesis, Yokoub [239]	MAPE, RMSE, BIAS, SI
Yousefpour et al. [241]	MLP, GRNN, RBF	–	Filed data	RMSE, R^2
Cheng et al. [52]	ERBFNN	M5, SVM, BPNN, GP	[167]	MAE, RMSE, R^2
Sarshari and Mullhaupt [203]	MLP, BPNN	–	[50, 120, 136, 155]	RMSE, R
Toth [223]	ANN-ASSYM	–	[75, 95, 167]	MAE, RMSE, BIAS, POUE, PHOE, PHUE
Fujail et al. [96]	MLP-GA		[31, 59, 67]	R, RMSE
Najafzadeh et al. [174]	GMDH-BP	GMDH-PSO, GMDH-GSA	[68]	MAPE, RMSE, BIAS, SI
Khan et al. [132]	ANN-GENETIC FUNCTION	–	–	E_{NS}, AAE, RMSE, R^2
Najafzadeh et al. [180]	NF-GMDH	NF-GMDH-PSO, NF-GMDH-GA, NF-GMDH-GSA	[137, 156, 190, 194]	MAE, RMSE, BIAS, SI, R
Scouring at grade-control structures				
Azmathullah et al. [27, 28]	ANN(RBF), ANN(FFBP)	ANFIS	[5, 133, 205, 212, 238]	R, RMSE
Azmathullah et al. [27, 28]	ANN (RBF), ANN (FFBP)	–	[63]	R, RMSE, AE
Azmathullah et al. [26]	ANN (FFCC), ANN (FFBP)	–	[5, 133, 205, 212, 238]	R,AE, δ
Zadeh and Kashefipour [242]	ANN(FFNN)	–	[61, 62]	RMSE, R^2
Elshafie et al. [79]	ANN	–	[198]	RAE
Guven [104]	DNN	–	[41]	MSE, R^2
Karami et al. [126]	RBF/FFBP	–	[54]	MAE, RMSE, R^2
Azamathulla and Haque [22]	ANN(FFBP)	–		R
Noori and Hooshyaripor [185]	FFBP/MLP	–	[16, 98, 99]	RMSE, R^2
Balouchi et al. [32]	MLP/RBF	M5		RMSE, MAE, MARE
Najafzadeh [170]	NF-GMDH-PSO	GEP	[41, 62, 84, 164, 227]; Mario A [146, 147]	R, RMSE, SI, BIAS
Roushangar et al. [200]	FFNN	GEP	[41, 62, 164, 227]	R, RMSE, MAE, R^2
Karbasi and Azamathulla [127]	MLP	ANFIS, SVM, GMDH, GEP	[1, 49, 71]	MBE, RMSE, MAE, R^2
Haghiabi [108]	MLP-MARS	–	–	EMSE, R^2

Table 3 (continued)

Scholar(s)	Type of neural network-based algorithm	Compared algorithm(s)	References of dataset(s)	Performance criteria
Scouring at piles				
Kambekar and Deo [125]	FFNN/FFBP	–	[37]	R, MAE
Namekar et al. [184]	MLP/RBF	–	NOT AVAILABE	NOT AVAILABE
Moghadam et al. [158]	RBF	–	NOT AVAILABE	NOT AVAILABE
Sadeghiamirshahidi et al. [201]	BPNN	–	[8, 9]	R
Najafzadeh et al. [175, 176]	GMDH-LM	ANFIS, RBF-NN	[74, 219, 220]	R, RMSE, MAE
Baziar et al. [38]	FFBP/RECURRENT	–	[46, 90, 186]	R^2, RMSE
Najafzadeh [171]	NF-GMDH	GMDH-PSO, GMDH-GSA	[6, 10, 11]	R, RMSE, BIAS, SI
Beheshti and Ataie-Ashtiani [39]	NF-GMDH		[6, 10, 11]	RMSE
Hosseini et al. [115]	BAGGED NN	–	[6, 11]	MAE, RMSE, R
Scouring at pipelines				
Kazeminezhad et al. [128]	FFBP	–	[197, 218]	R, SI, BIAS
Najafzadeh et al. [173]	GMDH-BP	ANFIS, MT	[134, 150, 165, 218]	R, RMSE, MAPE
Haghiabi [109]	MLP	–	[21]	MSE, RMSE, R^2
Najafzadeh and Saberi-Movahed [179]	GMDH-GEP	GEP, GMDH, ANN	[51]	R, RMSE, MAPE, BIAS

piers, based on 1700 data points from previous studies (Table 3). The MLP $\left(R^2_{Train} = 0.977, R^2_{test} = 0.9644\right)$ showed the better agreement with field measurements. Azamathulla et al. [13] applied a RBF model for predicting scour depth around bridge piers, and the results obtained using the HEC-18 regression model were used for evaluating its accuracy of RBF model. In this regard, the results were shown that RBF ($R = 0.9615$) was more robustness.

Bateni et al. [34, 36] studied about the capability of Bayesian Neural Network (BPN) models of estimating equilibrium and time dependent scour depth around bridge piers. Based on 180 collected datasets, the BPM model ($R^2_{Train} = 0.979, R^2_{test} = 0.969$) showed better prediction performance than BPNN. Firat and Gungor [92] evaluated the performance of Generalized Regression Neural Networks (GRNN) and FFNN in predicting scouring depth around piers, based on datasets from previous laborotary experiments (Table 3). Their results showed that GRNN ($R_{Train} = 0.884, R_{test} = 0.935$) was a better predictor.

Shin and Park [211] used the Levenberg–Marquart–Back Propagation (LMBP) model as predictor of the local scour depth around bridge piers, for 410 data points. The outputs indicated that LMBP ($R_{Train} = 0.971, R_{test} = 0.869$) can be applied as successful predictor.

Yousefpour et al. [240] compared three different ANN models (MLP, RBF and GRNN) for bridge foundation scour estimation, finding MLP ($R_{Train} = 0.950, R_{test} = 0.810$) as the better performing model. Adhikari et al. [2] employed BPNN to assess the risk of scouring around bridges. The BPNN ($R^2 = 0.9819$) generated good outputs for this assessment. Ismail et al. [117] combined adaptive activation function and FFNN to estimate scouring depth around bridge piers. They considered 1595 data points from previous studies [136, 187]. The application of this new model ($R^2_{Train} = 0.9207, R^2_{test} = 0.8785$) yielded better prediction results in comparison of traditional relations. Najafzadeh et al. [175, 176] compared GMDH-BP, ANFIS and RBFNN to predict scour depth around abutment in cohesive soils, considering 121 datasets from Yokoub [239]. They found GMDH-BP ($RMSE_{Train} = 0.20, RMSE_{test} = 0.25$) to generate the better predictions. Yousefpour et al. [241] assessed the condition of scour-prone bridges using MLP, RBF and GRNN and field datasets from the Texas Department of Transportation. The outputs from MLP ($R^2 = 0.89$) showed the better agreement with the field measurements. Cheng et al. [52] developed a model based on artificial bee colony and RBF. This hybrid model was compared with M5, SVM, GP and BPNN for prediction of equilibrium scouring depth around bridge piers. They use a dataset from Mueller and Wagner [167] as inputs for their models. The performance of ERBFNN ($R^2_{Train} = 0.968, R^2_{test} = 0.877$) was excellent in comparison to other models.

Sarshari and Mullhaupt [203] discussed the performance of MLP and BPNN in estimating the equilibrium scour depth near bridge piers. They compared their outputs to empirical formulations such as those developed by Breusers and Raudkivi [42, 44], Hancu [111], Laursen [141]. Their results highlighted a better prediction performance by MLP ($R = 0.8214$). Toth [223] increased the efficiency of ANN by hybridization to asymmetric error function $\left(RMSE_{test} = 0.51\right)$. They reported that this combination can help reduce the underestimation of scouring depth. They used a wide variety of laboratory datasets from previous studies. Fujail et al. [96] applied GA to a MLP model to estimate maximum equilibrium scouring depth. This combination increased the efficiency of the MLP model ($R_{Train} = 0.9834, R_{test} = 0.9829$) in predicting scouring depth. Najafzadeh et al. [174] developed a GMDH model by using GSA and PSO, to predict the scouring around bridge abutments in coarse sediments with thinly armored beds. They used laboratory outputs from Dey and Barbhuiya [68] as their inputs. GMDH-BP ($R_{Train} = 0.96, R_{test} = 0.93$) produced better results and good convergence was shown between predicted and observed outputs. Khan et al. [132] studied the scour patterns around bridge piers, developing a model given by the combination of ANN and a GA, where the GA was added to improve the scouring depth estimation. They used previous datasets from other researchers as reported in Table 3. Their model $\left(R^2_{Train} = 0.89, R^2_{test} = 0.970\right)$ provided better scouring estimates than empirical formulations.

Najafzadeh et al. [180] combined a neuro-fuzzy approach with a GMDH network model. They also used PSO, GA and GSA to improve the efficiency of their combined model for estimation of scouring under debris flow effects. Based on different datasets (Table 3), their model ($RMSE_{Train} = 0.367, RMSE_{test} = 0.388$) showed the better prediction performance among different models.

3.3.2 ANN-Based Models for Scouring at Grade-Control Structures

Azmathullah et al. [27, 28] compared ANN (RBF, FFBP and FFCC) and ANFIS in predicting scouring depth below spillways, using the datasets from previous studies listed in Table 3. While FFBP and FFCC outputs were underestimated, the prediction performance of RBF and ANFIS was found to be similar, although the overall performance of ANFIS ($R = 0.95$) was better. Azmathullah et al. [27, 28] compared RBF and FFBP for the estimation of scouring downstream of ski-jump spillways. They conducted experiments in Central Water and Power Research Station (CWPRS), Pune, India, and also considered datasets from previous studies (Table 3). The FFBP model ($R = 0.98$) generated more accurate predictions. Azmathullah et al. [26] evaluated the performances of FFBP and FFCC for prediction of the scouring depth downstream of ski-jump spillways, and compared the obtained results with empirical formulations such as Martins [153], Veronese [227], Wu [232]. FFBP ($R = 0.92$) turned out to be the most performing estimation model. Zadeh and Kashefipour [242] applied ANN (FFNN) for predicting scour (equilibrium scouring depth and location of maximum scouring depth) in loose beds located downstream of grade-control structures, using datasets from D'Agostino and Ferro [62], D'Agostino and Ferro [62] and finding that FFNN $\left(R^2 = 0.982\right)$ can be applied successfully to this type of studies. Elshafie et al. [79] studied the effect of air entrainment on scour depth by using ANN. Their results indicated that ANN has a better prediction performance than traditional formulations. Guven [104] used multi-output Descriptive Neural Network (DNN) for estimating the scouring depth downstream of grade-control structures and compared his model's performance with regression models. The comparison was shown that DNN ($R^2_{Train} = 0.988, R^2_{Test} = 0.974$) has satisfactory results. Karami et al. [126] estimated the time variation of scour around spur dikes by using RBF and FFBP. They reported that existing empirical formulations showed good performances although ANN $\left(R^2 = 0.97\right)$ performed slightly better. Azamathulla and Haque [22] assessed the performance of a FFBP model in predicting the scouring depth downstream of culvert outlets and showed good agreement ($R = 0.973$) between predicted values and laboratory measurement results. Noori and Hooshyaripor [185] predicted the scouring depth downstream of ski-jump spillways using FFBP and MLP, quantifying the uncertainty of their results though Monte Carlo simulations. They used 95 measured datasets from three dams located in India. The FFBP model ($R^2_{Train} = 0.979, R^2_{Test} = 0.992$) provided better predictions than existing empirical formulations. Balouchi et al. [32] investigated the application of ANN (MLP and RBF) and M5 model tree for estimating the scouring depth in live–bed condition. The MLP model ($R^2_{Train} = 0.9054, R^2_{Test} = 0.9003$) proved to be more accurate in the prediction of the scour hole geometry. Roushangar et al. [200] used FFNN and GEP for prediction of scouring depth for three different hydraulic structures, ski-jump spillways, sharp-crested weirs and grade-control structures. The performance of FFNN ($R^2 = 0.885$) and GEP ($R^2 = 0.874$) were quite similar to each and superior to empirical formulations. Najafzadeh [170] investigated the efficiency of NF-GMDH-PSO and GEP models in the estimation of the maximum scouring depth downstream of culvert outlets. They considered several datasets from Bormann and Julien [41], D'Agostino and Ferro [62], Lenzi and Comiti [146, 147], Falciai and Giacomin [84], Mossa [164]. The NF-GMDH-PSO ($R^2_{Train} = 0.934, R^2_{Test} = 0.910$) had a better prediction performance than GEP in this study, and both models produced better results than available empirical equations. Karbasi and Azamathulla [127] evaluated the performance of FFBP, ANFIS, SVR and GMDH and GEP in predicting the scouring depth downstream of sluice gates as a result of two-dimensional horizontal jets. Their results indicated that ANN ($R^2_{Train} = 0.972, R^2_{Test} = 0.968$) performed better than other algorithms. Haghiabi [108] applied MLP and Multivariate Adaptive Regression Splines to estimate the scour depth downstream of ski-jump spillways. They concluded that MARS model has better efficiency for modeling spillway.

3.3.3 ANN-Based Models for Scouring at Piles

Kambekar and Deo [125] compared FFCC and FFBP when predicting the scouring depth around pile groups, using field datasets from the Pacific coast of Japan and data from Bormann and Julien [41]. They found the outputs from ANN models to satisfactorily predict observations and suggested ANN ($R = 0.91$) as an excellent estimator for scouring depth. Namekar et al. [184] compared MLP and RBF for prediction of scouring in underwater sea piles, finding MLP-LM to have the better performance in comparison with other models. Moghadam et al. [158] used RBF model to predict distribution of fragmentation on piles, obtaining excellent agreement with field observations. Najafzadeh et al. [175, 176] compared the performance of GMDH-LM, ANFIS and RBFNN models for predicting scouring depth around vertical piles under regular waves. 93 datasets from Dey et al. [74], Sumer and Fredsøe [217] were used as input for their analysis, which revealed that the outputs from the GMDH-LM model ($R = 0.983$) had the better agreement with the scouring observations. Najafzadeh [171] predicted scour depth around pile groups in clear water by using NF-GMDH, NF-GMDH-PSO and NF-GMDH-GSA models, using datasets from Amini et al., [6], Ataie-Ashtiani and Beheshti [11], with the NF-GMDH-GSA model ($R = 0.950$) showing the better prediction performance. Beheshti and Ataie-Ashtiani [39] discussed the application of NF-GMDH in forecasting scour depth and proposed it as reliable tool in forecasting studies ($RMSE = 0.0912$). Hosseini et al. [115] applied Bagged Neural Network (BNN) for estimation of scour depth around pile groups. They used datasets from Amini et al. [6], Ataie-Ashtiani and Beheshti [11] as their inputs and showed that BNN ($RMSE = 0.114$) could provide accurate prediction for the scouring depth.

3.3.4 ANN-Based Models for Scouring at Pipelines

Kazeminezhad et al. [128] used a FFBP model to predict wave-induced scour depth around pipelines, considering datasets from previous studies [197, 218]. The FFBP model ($R = 0.98$) showed better prediction performance than empirical formulations. Najafzadeh et al. [173] applied GMDH-BP, ANFIS and MT to predict the scour depth below pipelines caused by waves, using data from laboratory experiments [134, 150, 218]. They reported a higher prediction performance by the GMDH model ($R^2_{Train} = 0.930, R^2_{Test} = 0.930$) when compared with other AI models. Haghiabi [109] assessed the use of multivariate adaptive regression spline (MARS) and MLP models for prediction of scouring depth around pipelines, using 90 datasets from Azamathulla et al. [21], with the MARS model ($R^2_{Train} = 0.986, R^2_{test} = 0.987$) having the better prediction performan. Najafzadeh et al. [180] employed GMDH-GEP, GEP, GMDH and ANN for three-dimensional prediction of scouring around pipelines. Data from Cheng et al. [51] were used to compared them. Their analysis revealed that the GMDH-GEP model ($R_{Train} = 0.960, R_{test} = 0.960$) had the better prediction performance when compared to other empirical formulations or AI models.

3.4 Other Soft Computing (OSC) Models

In addition to models based on Fuzzy Logic, Evolutionary Computing and Artificial Neural Network, other AI models have been developed. A Support Vector Machine (SVM) model was first introduced by Cortes and Vapnic [60]. This model uses empirical risk as objective function instead of minimizing the prediction error. It can be used as regression and classification tool. For training SVM, different kernel functions are used (exponential, Gaussian, sigmoid, laplacian polynomial and rational quadratic). A Model Tree is based on breaking choices into small subchoices for making decisions. It is a very useful tool to find regression relationships between inputs, through an iterative process. M5 is a class of Model Tree which used regression functions instead of class label. The standard deviation is criteria for stopping procedures.

3.4.1 OSC-Based Models for Scouring at Bridge Piers and Abutments

Pal et al. [192] estimated the scour depth around bridges using RBF and polynomial kernel-based SVR and ANN (BPNN and GRNN) models, considering a dataset including 493 field measurements. They reported that RBF based SVR models ($R^2 = 0.897$) provide the better prediction performance of the measured data. Pal et al. [191] used M5 and BPNN models for predicting the scouring depth around bridges, using a dataset from Mueller and Wagner [167]. The obtained results from the M5 model ($R = 0.930$) had the similar performance with BPNN ($R = 0.937$). Etemad-Shahidi et al. [80] investigate the capability of a M5 model to estimate the scouring depth around circular piers, considering various datasets (Table 4). They concluded that the M5 model has a better prediction performance in comparison with empirical formulations. Sharafi et al. [207] applied a SVM model with six different kernel

Table 4 Applications of other soft computing algorithms for prediction of scouring

Scholar(s)	Type of OSC-based algorithm	Compared algorithm(s)	References of dataset(s)	Performance criteria
Scouring at bridges				
Pal et al. [192]	SVR-RBF, SVR-KERNEL	BPNN, GRNN	[167]	RMSE, R^2
Pal et al. [191]	M5	BPNN	[167]	R, RMSE
Etemad-Shahidi et al. [80]	M5	–	[48, 50, 82, 103, 111, 120, 136, 154, 187, 210, 235]	SI, BIAS, I_a
Sharafi et al. [207]	6 types of SVM	MLP, ANFIS	[138, 160]	RMSE, MARE, MSRE
Afzali [3]	MHBMO	–	[95, 231]	MAE, RMSE, R^2
Chou and Pham [57]	SAFCAS	–	[119, 140, 154, 157, 167]	R, RMSE, MAPE
Ebtehaj et al. [77]	SALEM	SVM, ANN	[138, 160]	RMSE, MARE
Sreedhara et al. [213]	PSO-SVM	ANFIS	[193]	MRMSE, RMSE, NMB, R, E_{NS}
Scouring at grade-control structures				
Goel and Pal [101]	SVM	FFBP	[41, 62]	R, RMSE
Ayoubloo et al. [12]	SVM	M5, CART	[26]	R, MAE, RMSE, BIAS
Samadi et al. [202]	M5	CART	[151] [25]	R, RMSE, MAE
Goyal et al. [102]	SVM	M5, ANN	(H. Md. [27, 28]	RMSE, R
Scouring at piles				
Etemad-Shahidi and Ghaemi [81]	SVM	MT, ANN	[37, 217]	R, DR, RMSE, SI, I_a
Ghazanfari-Hashemi et al. [97]	SVM	MLP, BPNN	[37, 217]	R, RMSE, SI
Ebtehaj et al., [76]	SVM	ELM, ANN	[6, 10, 11]	R^2, RMSE, BIAS, SI
Scouring at pipelines				
Zhang et al. [244]	MAXIMUM ENTROPY	–	–	

functions (polynomial, sigmoid, exponential, Gaussian, Laplacian and rational quadratic) for prediction of the scouring depth around bridge piers, and compared its performance with AI models (MLP and ANFIS). The SVM-polynomial model ($RMSE = 0.078$) provided the better predictions. Afzali [3] used a Modified Honey Bee Mating Optimization (MHBMO) algorithm as estimator of scour depth around bridge piers. They used 463 data points from Froehlich [95], Wilson Jr. [231] and compared the prediction of their model with those obtained with the HEC-18 (2001, 2012), FDOT, [95, 120] empirical formulations. Their analysis revealed a better prediction performance by the MHBMO model ($R^2 = 0.678$). Chou and Pham [57] developed a SVR model with a firefly algorithm "as a robust nature optimization algorithm" to estimate scour characteristics around bridge piers. Based on data from field measurements (Table 4), they suggested that their model is a good estimator of scouring characteristics. Ebtehaj et al. [77] assessed the performance of a Self-Adaptive Extreme Learning Machine (SALEM) model with regression models and AI models (SVM and ANN), obtaining with SALEM more accurate prediction results ($RMSE = 0.091$). Sreedhara et al. [213] used a hybrid model (PSO-SVM) and an ANFIS model with Gbell membership functions to predict scour depth around bridge piers, using the data from laboratory experiments by Pankaj [193]. They reported better prediction results with the ANFIS model with Gbell function ($R_{Train=}0.96, R_{test} = 0.95$) in comparison with the SALEM model and other empirical formulations.

3.4.2 OSC-Based Models for Scouring at Grade-Control Structures

Goel and Pal [101] compared RBF and polynomial kernel-based SVM and BPNN models in predicting maximum scouring downstream of grade-control structures, considering data from Bormann and Julien [41], D'Agostino and Ferro [62]. The SVM model results failed to predict observations from the laboratory tests but showed good agreement with the field observations. Overall, the SVM model ($CC = 0.67$) showed better prediction performance than ANN model.

Ayoubloo et al. [12] studied the capability of three AI models (SVM, M5 and CART) of estimating scouring depth downstream of ski-jump spillways, using 95 data points from Azmathullah et al. [26]. The CART model (R = .987) showed the better prediction performance.

Samadi et al. [202] employed a Model Tree and a CART model to predict scour depth downstream of free over-fall spillways. They used datasets from Azar [25], Mahboobi [151] for their investigation, which revealed that the CART model ($R_{Train} = 0.9857, R_{test} = 0.9837$) generally had the lower error in predicting scour depths. Goyal et al. [102] investigated the prediction performance of SVM, M5 and ANN models in estimating scouring downstream of a ski-jump spillways, using observations from the laboratory experiment by Azmathullah et al. [27, 28]. The performances of genetic programming (GP) and SVM models were similar to each other and higher than ANN models.

3.4.3 OSC-Based Models for Scouring at Piles

Etemad-Shahidi and Ghaemi [81] compared SVM, MT and ANN models in predicting pile groups scour due to waves, based on datasets from Bayram and Larson [37], Sumer and Fredsøe [216]. They obtained similar prediction results although they indicated the MT models (R = 0.92) as the easy to implement for non-experts user for prediction of scour depth. Ghazanfari-Hashemi et al. [97] used SVM, ANNs (MLP and BPNN) for predicting scour around pile groups and, using the experimental datasets from Bayram and Larson [37], Sumer and Fredsøe [216], found that the SVM model provided the better prediction performance. Ebtehaj et al. [76] assessed the performances of SVM, extreme learning machine (ELM) and ANN models in predicting scour at pile groups in hydraulic conditions. Using the datasets indicated in Table 4, the ELM model (R = 0.95) produced better predictions compared to other AI and regression models.

3.4.4 OSC-Based Models for Scouring at Pipelines

Zhang et al. [244] conducted laboratory experiments of scouring at submarine pipelines and investigated the efficiency of Maximum Entropy versus regression models for estimating the scour depth. They showed good prediction of their experimental results by their Maximum Entropy model.

4 Research Assessment and Evaluation

- In the light of the reviewed EF studies, it seems that there was a massive implementation in the field of scouring depth computation using several empirical formulations that are varied from one case to another based on the physical criteria, experimental set-up, soil particles mechanism. Generated formulations were diverse and apparently differ from one application to another.
- Obviously, the presented problem of the scouring depth computation is associated with multiple source of uncertainty and non-stationarity. Hence, developing new methodologies for comprehending such stochastic problem is highly essential for attaining an informative and insightful vision.
- Most of the conducted soft computing models were developed based on the collected experimental laboratory presented in the open-source researches. However, one observation can be noticed that the selected data set for specific investigation of scouring prediction problem should be carefully defined. This is owing to the fact, modeling experimental dataset should be harmonized to avoid any irrelevant uncertainties.
- The applications of soft computing models were noticed at the early of 2000s. Various version of classical AI models including ANN, ANFIS, genetic based algorithms, GMDH, SVM. In general, the classical SC models were demonstrated an acceptable degree of modeling for scouring depth for multiple hydraulic engineering applications. However; up to recently, there was a noticeable progression of the implementation of SC models through the development of complementary models or hybridized models.
- Among several performance indicators used for modeling evaluation, correlation coefficient (*R*), root mean square error (*RMSE*), mean absolute error (*MAE*), mean absolute percentage error (*MAPE*) and Nash–Sutcliffe coefficient (E_{NS}). Those performance metrics are widely used for evaluation of the predictive models. However, there are some related limitations in their assessment such as there is no insightful visualization for the predictability performance for the minimum or maximum values of the simulated dataset. Hence, other metrics are highly emphasized to be explored for modeling assessment such as relative absolute error (*RAE*) as well as normalized performance indicators like Integral normalized root squared error (*INRSE*) [208], Willmott's index (*WI*) [230], normalized root mean square error (*NRMSE*) [40] and Legate and McCabe's index (*LM*) [145].

Table 5 Number of published papers on the use of soft computing approaches in predicting scouring

Application area	Number of published papers
Bridge	48
Grade-control structures	41
Piles	13
Pipelines	19

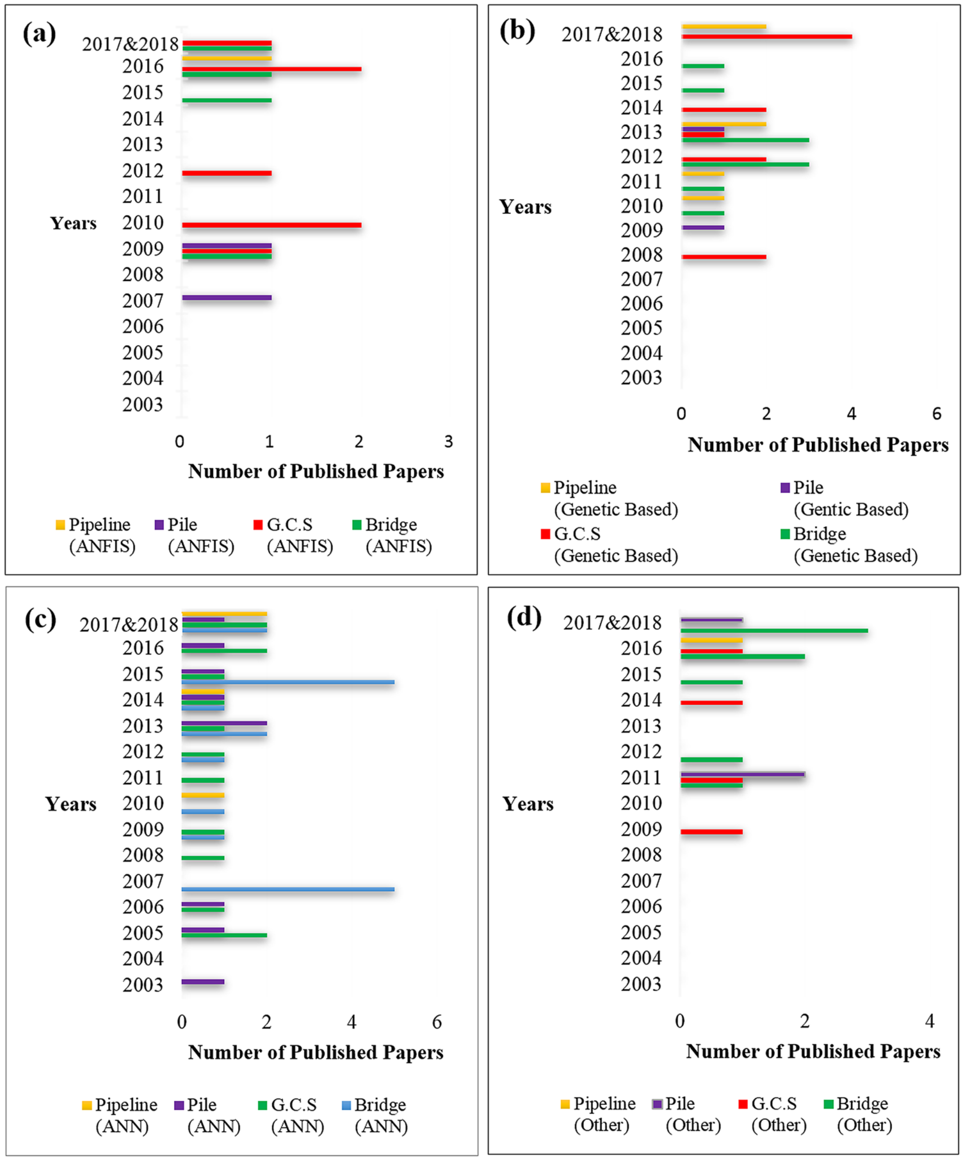

Fig. 2 **a** Published papers using ANFIS models, **b** published papers using EC models, **c** published papers using ANN, **d** published papers using OSC models

- This manuscript was reviewed the SC applications in predicting scouring at bridges, grade-control structures, piles and pipelines, as summarized in Table 5 and Fig. 2. Among, several hydraulic engineering applications, bridge depth scouring was received the highest attention of investigation. This is owing to the significant of this problem for the bridge sustainability.
- As shown in Figs. 1a, b, ANN model was used predominantly as the first approach for the prediction of scouring depth in this type of studies but the rate of utilizing other approaches especially genetic based algorithms was increased over the recent years. Also, utilizing some approaches such as SVM, M5 model tree were rapidly increased. In most of studies ANN model used for comparing the ability of new suggested model.

5 Future Research Trends

Although soft computing models, like the more traditional empirical formulations, are predictive tools that do not provide a physically-based understanding of the processes involved in the scouring process, our review shows a generally superior prediction performance of the former. This fact, together with the increasingly easier access to progressively larger computational resources, not only for academics but also for industry practitioners, suggest that a wider use of soft computing approaches for scour prediction would be desirable in the future.

The application of empirical formulations to predict scour for a specific project is essentially an exercise of selection, among the available formulations from literature, of the most suitable formulation(s) based on the type of structure considered and the available hydraulic, sediment and structure data. The application of a soft computing model, instead, requires (1) the construction, using literature or own observation, of a suitable dataset of scouring data from laboratory or field measurements consistent with the data available for the specific project and (2) the development of the scour prediction formulation based on soft computing algorithms. Although step (1) may be time consuming, it allows for "tailoring" the derivation of the prediction formulation to the conditions and data available for the specific project considered. Step (2) involves a learning curve especially for non-experts in this type of techniques, but is expected to provide a reward in terms or improved prediction accuracy. In addition, developing a soft computing model still take significantly less time than developing a numerical or physical model for scouring. However, based on the surveyed studies on the scouring depth prediction, several gaps were recognized where emphasis some future possible researches:

1. There are some obscures in all utilized datasets that influence accuracy of prediction. In most of studies the minor scaling effect, prototype scale, maintaining factors, water resource problems other related fields have not considered in available datasets. Most of previous studies applied similar datasets and many of these datasets did not considered these effective parameters. It is essential to observe and quantify all of these parameters in new physical models and then the efficiency of SC models can be investigated.
2. The data management scenario should be considered for achieving more accurate results. By using various shapes and more geotechnical details such as rock specification, rock bed classifications, the efficiency of predictor models increased.
3. In most of previous studies on site field factor did not considered; thus, changes in the utilized dataset as input attributes to the models is highly influential for more precise prediction.
4. It is important to consider the uncertainty of input parameters for the prediction of scouring depth. It is necessary to understanding the initial assumption for the prediction of scouring depth.
5. The criterions for comparison of different kind of algorithms should be developed. Considering a benchmark modeling strategy is important to validate the new explored models.
6. The hybridization of methodologies and its effect on results in each step should be defined to give researchers a guideline that which part of algorithm has weakness for the prediction of scouring depth. By considering the previous results, it is obvious that there are lacks utilization of hybrid soft computing models as an advanced machine learning models by integrating nature optimization algorithms or coupling with pre-processing data approaches for the prediction of scouring depth.

Compliance with Ethical Standards

Conflict of interest We have no conflict of interest to declare.

Appendix: Notations

RBNN	Radial Basis Neural Network
MLR	Multiple Linear Regression
ERBFNN	Hybrid of (RBFNN + Fuzzy Logic (FL) + Artificial Bee Colony)
FFBP	Feed Forward Back Propagation
RBF	Radial Basis Function
MNLR	Multiple Non Linear Regression
GEP	Genetic Expression Programming
GP	Genetic Programing
SVM	Support Vector Machine
SVR	Support Vector Regression
GRNN	General Regression Neural Network
MT	Model Tree
ANFIS	Adaptive Neuro Fuzzy Inference System
GA	Genetic Algorithm
FE	Finite Elements
GMDH	Group Method of Data Handling
FFCC	Feed Forward Computational Complexity Normalized
NRMSE	Root Mean Square Error
E	Efficiency
R^2	Coefficient of Determination
MAPE	Mean Absolute Percent Error
RMSE	Root-Mean-Square Error
AE	Average Error
δ	Average Absolute Deviation)
AAE	Average Absolute Error
MAD	Mean Absolute Deviation
R	Correlation Coefficient
MPE	Mean Percentage Error
RAE	Relative Absolute Error
RSE	Relative Squared Error
MAE	Mean Absolute Error
SSE	Sum of Squared Error
MSE	Mean Squared Error
BIAS	Mean Signed Error
POUE	Percentages of Overall Under Estimation Error
E_{NS}	Nash–Sutcliffe Efficiency
SI	Scatter Index

D & I_a	Index of Agreement
MSRE	Mean Squared Relative Error
MARE	Mean Absolute Relative Error
NMB	Normalized Mean Bias
SE	Standard Error
CF	Correlation Factor
AMRE	Absolute Mean Relative Error
DR	Discrepancy Ratio

Notation for empirical formulations:

- Bridge

Ds: equilibrium scouring depth, b: diameter of bridge pier, Fr_{cr}: critical Froude number, y and y: flow depth, U: velocity, α: opening ration, ρ_g: gravitational density, Fd: densiometric particle Froude number, T: dimensionless time, σ: sediment non-uniformity, N: shape number, l: transverse length of abutment, q: discharge, KS: shape factor, Fr: Froude number, Re: Reynolds number.

- G.C.S:

φ = Submerged angle of repose of bed sediment , γ_s = Specific Weight of Sediment γ = Specific Weight of water Cd = Jet diffusion coefficient y_0 = Jet thickness entering in tail water β = jet angle D_p = drop height of structures h = tail water depth , KC = The Keulegan–Carpenter q = discharge, Ucr = Critical velocity Re = Reynolds Number, Fr = Froude number, GS = Sediment specific gravity, Ucr = Critical velocity. d_{50} = median particle size

- Pipelines:

e: gap between the pipes; D: pipe diameter, h = water depth, Fr = Froude number, GS = Sediment specific gravity, U_{cr} = Critical velocity. θ_{cr} = critical shields number, KC = The Keulegan–Carpenter number τ_0 = shields number, d_{50} = median particle size q = discharge; Re: Reynolds Number

- Piles:

H: water depth; Fr: Froude number, GS: Sediment specific gravity; U_{cr}: Critical velocity;θ_{cr} = critical shields number; KC: The Keulegan–Carpenter number;τ_0: shields number; d_{50}: median particle size, q: discharge.

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