carried out to identify the effect of parameters and development of empirical equations for scour depth estimation at abutments. The empirical formulae are suitable to a particular abutment conditions and the results varies significantly on different datasets. Related work on determination of scouring parameter, development of empirical equations, SC and hybrid techniques in predicting scour depth around different types of obstructions is presented in the following section.

2.2.1 Parameters Related to Scour at Bridge Abutments

There are various parameters involved in the scour phenomenon at abutments that can be classified as follows (Barbhuiya and Dey, 2004):

1. Parameters relating to the geometry of channel: width, cross-sectional shape and slope.
2. Parameters relating to the abutment: size, shape, orientation with respect to main flow and surface condition.
3. Parameters relating to the bed sediment: median size, grain size distribution, mass density, angle of repose and cohesiveness.
4. Parameters relating to the fluid: density, viscosity, gravitational acceleration and temperature.
5. Parameters relating to the approaching flow condition: mean flow velocity, flow depth, shear velocity and roughness.
6. Time of scouring can be taken as an additional parameter for an evolving scour hole.

2.2.2 Influence of Parameters on Scour Depth

(i) Approaching Flow Velocity

The effect of approaching flow velocity \((U)\) is included in the scour depth estimation formulae in the form of flow Froude number \((F_r)\) or shear velocity \((u_*)\). Zaghloul and McCorquodale (1975), Zaghloul (1983), Rajaratnam and Nwachkwu (1983) and Froehlich (1989) included the flow Froude number in their analyses. Kandasamy (1989) showed that the scour depth increases with increase in flow depth due to incorporation of the flow Froude number.

The shear velocity is recognized as an important parameter in representing the erosive action of the flowing stream for a given sediment size. It is also used to

When the approaching flow velocity is less than or equal to the critical velocity $U_c$ for bed sediments (i.e., $U/U_c \leq 1$), clear-water scour occurs; while live-bed scour occurs when $U/U_c > 1$. It is recognized that under clear-water conditions, the maximum scour depth occurs when $U = U_c$. For $U/U_c > 1$, that is under live-bed conditions, scour depth initially decreases with increase in approaching flow velocity reaching a minimum value and then increases again toward a second maximum.

(ii) **Approaching Flow Depth**

Approaching flow depth ($h$) is an important parameter to determine the depth of scour. Experimentations carried out by Gill (1972), Wong (1982), Tey (1984) and Kandasamy (1989) show that the maximum scour depth increases with increase in approaching flow depth for a constant value of the shear velocity ratio $u*/u_{*c}$; where $u_{*c}$ = critical shear velocity for sediment particles. It was also observed that the maximum scour depth increases at a decreasing rate with increase in approaching flow depth. According to Dey and Barbhuiya (2004a), for lesser flow depths, the equilibrium scour depth increases significantly with increase in $h$; whereas for higher flow depths, equilibrium scour depth is independent of flow depth.

(iii) **Abutment Length**

The abutment length ($l$) has been considered as an important factor and extensively used in scour depth formulations at abutments by researchers including Laursen (1963), Neill (1973), Cunha (1975), Wong (1982), Tey (1984), Kandasamy (1989), Melville (1992), Cardoso and Bettess (1999), Melville and Coleman (2000), Dey and Barbhuiya (2005).

(iv) **Abutment Shape**

The shape of the abutment significantly influences equilibrium scour depth. From the experimental report of Laursen and Toch (1956), Liu et al. (1961), Garde et al. (1961), Wong (1982) and Dey and Barbhuiya (2004a), it is found that vertical-wall abutments produce greater scour depth in comparison with spill-through, semicircular and wing-wall abutments. Dey and Barbhuiya (2004a) also found that semicircular abutments produce less scour than other two shapes.
Melville (1992, 1995, 1997) included a shape factor \( K_s \) in his formulation to represent the effect of the abutment shapes on the equilibrium scour depth. The commonly used abutment shapes with their corresponding shape factor values are given in Table 2.1. For spill-through abutments, the abutment length is considered as the length at mid-depth in the flow. The shape factors were derived from the laboratory experimental data of Gill (1972), Wong (1982), Tey (1984), Kwan (1984, 1988), Kandasamy (1989) and Dongol (1994).

Table 2.1 Abutment Shape Factors (Barbhuiya and Dey, 2004; Muzzammil, 2010)

<table>
<thead>
<tr>
<th>Abutment type</th>
<th>Abutment shape</th>
<th>Shape factor, ( K_s )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vertical wall</td>
<td>Vertical-wall</td>
<td>1.00</td>
</tr>
<tr>
<td>Semicircular</td>
<td>Semicircular ended</td>
<td>0.75</td>
</tr>
<tr>
<td>45° Wing-wall</td>
<td>45° wing-wall</td>
<td>0.75</td>
</tr>
<tr>
<td>Spill-through with slope horizontal : vertical</td>
<td>Spill-through with slope</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>0.5 : 1</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>1 : 1</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>1.5 : 1</td>
<td></td>
</tr>
</tbody>
</table>
(v) **Size of Sediments**

According to Garde *et al.* (1961) and Gill (1972), the sediment size has an influence on the maximum scour depth. Laursen (1960) found that the maximum scour depth was affected by the sediment size under clear-water scour but not under live-bed scour. Wong (1982) found that the scour depth increases with increase in bed sediment size for a constant value of $\tau_0/\tau_c$. For live-bed scour in uniform sediments, the amount of sediment being transported by the approaching flow into the scour hole at an abutment is equal to the sediment being picked-up from the scour hole at equilibrium conditions. Since sediment size does not have any effect on the existing balance of sediment continuity, the equilibrium scour depth is independent of the change in sediment size.

(vi) **Abutment Alignment**

The angle of approaching flow with respect to the abutment alignment plays an important role on scour depth. Garde *et al.* (1961), reported that for the same flow, sediment and abutment conditions, the maximum scour depth was greatest for the spur-diike having inclination of 90°, while the scour depth was smaller for all other inclinations towards upstream or downstream. Similar observations were also made by Kwan (1984). Zaghloul (1983) reported that the greatest and smallest equilibrium scour depth was observed when the spur-diike was inclined upstream and downstream, respectively. Melville (1992) incorporated the effect of abutment alignment in the form of alignment factor $K_\theta$ in the design equations.

(vii) **Channel Geometry**

Froehlich (1989) included the channel geometry effect in his equation in the form of flow Froude number. Melville and Ettema (1993) and Melville (1995) investigated the effect of the geometry of channel on the scour depth around an abutment spanning the floodplain and extending into the main channel. They represented the effect of the channel geometry on scour depth by a multiplying factor $K_G$, which is defined as the ratio of the scour depth at an abutment situated in a compound channel to the scour depth at an abutment situated in the corresponding rectangular channel of the same overall width as that of the compound channel and the same depth as that of the main channel of the compound section.
Time-variation of Scour

Anderson (1963) stated that an equilibrium scour depth is reached within a relatively short time, after which the increase in the depth of scour becomes virtually imperceptible. Carstens (1966), Gill (1972) and Zaghloul (1983) also believed that there exists an equilibrium scour depth. However, according to Rouse (1965), Bresuers (1967) and Kohli and Hager (2001), scour is an ever-increasing phenomenon and there is no real equilibrium scour depth. Gill (1972), Ettema (1980), Dargahi (1990), Kohli and Hager (2001) and Oliveto and Hager (2002) believed logarithmic time-variation of scour depth; while Kandasamy (1989), Whitehouse (1997), Cardoso and Bettess (1999) and Ballio and Orsi (2000) proposed an exponential time-variation of scour.

A detailed review of research related to scour at abutments can be found in (Barbhuiya and Dey, 2004).

2.2.3 Empirical Formulae

Various researches have been conducted to develop empirical formulae to predict the depth of scour around different type of obstructions with clear-water scour and live-bed condition. The equations that are developed in the recent past to estimate scour at abutment under clear-water condition are reviewed in this study.

Froehlich (1989) proposed equation (2.1) for clear-water scour depths by analysing the scour data of different researchers using statistical method:

\[ \frac{d_{sc}}{h} = 0.78K_s K_\theta \left( \frac{l}{h} \right)^{0.63} F_r^{1.16} \left( \frac{h}{d} \right)^{0.43} \sigma_g^{-1.87} + 1 \]  

(2.1)

where, \(K_s\) = abutment shape factor, \(K_\theta\) = abutment alignment factor, \(F_r\) = approaching flow Froude number, \(\sigma_g\) = geometric standard deviation.

Strum and Janjua (1994) carried out experiments in a flume with a fixed-bed main channel and a movable-bed floodplain, where the abutment terminated. The authors derived the equation (2.2) for clear-water scour depth at abutments in floodplains by dimensional and least-square regression analysis:

\[ \frac{d_{sc}}{h} = 7.7 \left( \frac{F_r}{M} F_{rc} - 0.35 \right) \]  

(2.2)
Melville (1992, 1995, 1997) proposed an equation to estimate the depth of scour at abutments based on empirical relationships containing different factors or coefficients representing the effect of flow depth, abutment size, flow intensity, sediment characteristics, abutment shape, abutment alignment and channel geometry on scour depth. The proposed relationship is given in equation (2.3).

\[ d_{se} = K_{hl}K_dK_oK_G \]  
(2.3)

According to author’s findings, the scour depth scales with the abutment length for short abutments \((l/h \leq 1)\); whereas for long abutments \((l/h \geq 25)\), the scour depth scales with the flow depth. For all other abutments \((1 < l/h < 25)\), the scour depth is proportional to \((hl)^{0.5}\). The coefficient based on flow depth and abutment size (Melville, 1997) is given by

\[
K_{hl} = \begin{cases} 
2l, & \text{for } l/h \leq 1 \\
2(hl)^{0.5}, & \text{for } 1 < l/h < 25 \\
10h, & \text{for } l/h \geq 25 
\end{cases} \]  
(2.3a) 
(2.3b) 
(2.3c)

Kandasamy and Melville (1998) developed another formula for maximum scour depth at piers and abutments aligned perpendicular to the flow as follows:

\[ d_{se} = K_sK_2hl^n(1-n) \]  
(2.4)

where, \(K_s\) is the shape factor, \(K_2 = 5\) and \(n = 1\) for \(h/l \leq 0.04\); \(K_2 = 1\) and \(n = 0.5\) for \(0.04 < h/l < 1\) and \(K_2 = 1\) and \(n = 0\) for \(h/l > 1\).

Melville and Coleman (2000) presented an integrated approach adding a time factor for the estimation of the equilibrium scour depth at an abutment:

\[ d_{se} = K_{hl}K_iK_{d50}K_sK_oK_GK_t \]  
(2.5)

where \(K_{hl}\) represents the effects of flow depth and abutment length, \(K_i\) is the flow intensity factor, \(K_{d50}\) is a factor reflecting the effects of abutment length and sediment size, \(K_G\) approach channel geometry factor, \(K_t\) is the time factor and \(K_s, K_o\) are as defined in the previous equations.

Dey and Barbhuiya (2004b) proposed an equation of clear-water scour depth at short abutments as follows:

\[ \frac{d_{se}}{l} = 5.16K_s\left(\frac{h}{l}\right)^{0.18}\left(\frac{U_c}{\Delta g l}\right)^{0.26} \]  
(2.6)
Dey and Barbhuiya (2005) derived another set of formulae for three different types of abutments which are given below:

\[
\frac{d_{sc}}{l} = 7.281 F_e^{0.314} \left(\frac{h}{l}\right)^{0.128} \left(\frac{l}{d_{50}}\right)^{-0.167}
\]  
(for vertical-wall abutment) \quad (2.7a)

\[
\frac{d_{sc}}{l} = 8.319 F_e^{0.312} \left(\frac{h}{l}\right)^{0.101} \left(\frac{l}{d_{50}}\right)^{-0.231}
\]  
(for 45°-wing wall abutment) \quad (2.7b)

\[
\frac{d_{sc}}{l} = 8.689 F_e^{0.192} \left(\frac{h}{l}\right)^{0.103} \left(\frac{l}{d_{50}}\right)^{-0.296}
\]  
(for semi-circular wall abutment) \quad (2.7c)


where, \( F_e = \frac{U_e}{(\Delta g t)^{0.5}} \) is the excess abutment Froude number and \( U_e = U - 0.5 U_c \) is the excess approaching flow velocity.

The empirical formulae for the estimation of scour depth at bridge abutment are based on datasets of laboratory measurements. They do not accurately predict environmental conditions and thus tend to give conservative estimates. An alternative method to overcome the variations involved with experimental and theoretical estimations is soft computing based techniques.

### 2.2.4 Soft Computing Approaches

SC techniques have been used as a powerful tool in hydraulic and water resource engineering problems. The main reason for the popularity of SC is the synergy derived from its components. SC’s main characteristic is its intrinsic capability to create hybrid systems that are based on an integration of constituent technologies. This integration provides complementary reasoning and searching methods that allow us to combine domain knowledge and empirical data to develop flexible computing tools and solve complex problems.

#### 2.2.4.1 ANN and Evolutionary Methods

This section presents some of the related work by researchers using ANN and evolutionary methods for prediction of scour depth at different types of hydraulic structures.
ANNs have been successfully applied to solve problems in various field of hydrology (ASCE, 2000a, 200b), rainfall-runoff modeling and reservoir operations (Baboic et al., 2001). ANNs have also been applied in many branches of science, including hydraulic engineering (Jeng et al., 2005).

Liriano et al. (2001) and Azamathulla et al. (2012a) applied neural network to predict scour depth at culvert outlets. Kambekar et al. (2003) estimated scour around a group of pile using ANN. The authors’ developed feedforward back-propagation (FFBP) and feedforward cascade correlation (FFCC) networks to predict the scour depth and width. Negam et al. (2003) investigated the capability of ANN model to predict the maximum scour depth downstream of sudden expanding stilling basins. Azamathulla et al. (2006) estimated scour below spillway using neural network. The authors’ reported that the ANN predicted scour depth is more accurate when compared to empirical formulae.

Sung-Uk Choi et al. (2006), Lee et al. (2007), Bateni et al. (2007a), Azamathulla et al. (2007a), Shin et al. (2010) and Gamal et al. (2013) employed ANN for predicting scour depth around bridge piers. The results indicate that ANN can be use efficiently to estimate maximum scour depth around bridge piers.

Guven et al. (2008) did a pioneer study to apply GP as a tool for prediction of local scour downstream of grade-control structures. The objective of this study was to verify the superiority of GP over regression models. The proposed GP-based formulation results were compared with other equations and found to be more accurate. The generated equations are so simple that anyone not familiar with GP can easily use.

Azamathulla et al. (2010) applied GP and ANN to predict scour depth around bridge pier. The performance of GP was compared with regression equations and ANNs in predicting the scour depth at bridge piers and found to be more effective.

Mohammadpour (2011), Mohammadpour et al. (2012) estimated the time to equilibrium scour depth at long abutments using GP. The comparative analysis between GP, ANNs and empirical methods indicate that the ANN model produced better results compared to GP and non-linear regression techniques, however, GP equation is more useful for practical purposes.

Khan et al. (2012) and Muzzammil et al. (2015) presented the use of GEP, which is an extension of GP, as an alternative approach to estimate bridge pier scour depth. The performance of GEP was found to be significantly better than regression-based
models in predicting bridge pier scour depth. Azamathulla et al. (2012b) employed GEP as an alternative soft computing tool to predict equilibrium scour below underwater pipeline across river. From the results obtained with GEP model, author’s concluded that GEP is a very promising approach to predict the river pipeline scour depth. Moussa (2013) employed GEP and ANN to simulate local scour depth downstream stilling basin. It is reported that GEP approach gives satisfactory results compared to ANN and multiple linear regression modeling.

2.2.4.2 Hybrid Techniques

Bateni et al. (2007b) and Zounemat-Kermani et al. (2009) presented ANFIS based approach for estimating maximum scour depth at pile groups. The author’s concluded that the performance of ANFIS was more effective than the existing empirical formulae.

Bateni et al. (2007c) carried out a study on application of ANNs and ANFIS for prediction of scour around bridge pier. The author’s reported that the FFBP performed better than RBF, ANFIS and the previous empirical approaches. The experimental results also showed the better performance of ANIFS over RBF model. Muzzammil et al. (2009) employed ANNs and ANFIS models for predicting scour depth at piers in non-uniform sediments. It was found that ANNs perform better compared to regression methods. Further, it is reported that ANFIS performed better over ANN models. It was also found that the ANFIS gives more accurate estimation of scour depth when it was trained with dimensionless data rather than original data.

Keshavarzi et al. (2012) applied ANFIS model for prediction of local scour depth and pattern scouring around concave and convex arch shaped circular bed sills. The performance of ANFIS model was compared with the previously presented ANN models. It was observed that ANFIS models produced a good performance than ANN for convex and concave bed sills.

Azamathulla et al. (2007b) employed ANFIS to develop an adaptive model to predict scour below flip-bucket spillway. The comparative analysis with regression equations and ANN models indicate the highly satisfactory performance of ANFIS. Azamathulla et al. (2008) also worked on prediction of scour depth for ski-jump type of spillways. The performance of ANFIS has been compared with regression formulae, FFBP, FFCC and RBF neural network configurations. Azamathulla et al.
(2009a) evaluates the performance of ANFIS in predicting scour around trajectory spillways. The results were very promising compared to regression equations and ANN. Azamathulla et al. (2009b) estimated the location of maximum scour and the lip angle of the bucket using ANFIS. The comparison of ANFIS estimated results with the regression equations shows that the ANFIS predicted scour location has a much closer agreement with the actual measured values.

Azamathulla et al. (2011) used ANFIS to estimate the scour depth at culvert outlets and compared the results with RBF neural network and regression equations. The ANFIS model provides more accurate results than regression equations.

Muzzammil (2010), Muzzammil et al. (2011) studied the application of ANNs and ANFIS for estimation of scour at bridge abutment. It is concluded that ANN with FFBP model provide a better prediction of scour depth than FFCC and RBF. Moreover, the performances of all the ANN models were found to be better than regression methods. It was also concluded that ANFIS outperformed ANN models.

Guven et al. (2009) carried out a study to predict circular pile scour from ocean and lake waves using linear genetic programming (LGP) and ANIFS. LGP models were compared with ANFIS model results. The scour depth estimation of the LGP and ANFIS models are quite better than regression methods. Further, the author’s reported that the performance of LGP is superior to ANFIS models.

Laucelli and Giustolisi (2011) carried out a study for modeling scour depth downstream of Grade-Control Structures by a multi-objective evolutionary Polynomial Regression (MO-EPR) which combines numerical regression and evolutionary computing. Results of this model were compared with two regressive models available in literature that have been trained on the same data used for MO-EPR. The proposed modeling paradigm was found more reliable on unseen data prediction.

From the reviewed literature, it is revealed that SC techniques can provide more accurate results than empirical or regression models for predicting scour depth around different types of hydraulic structures. From the available literature, it is found that among the soft computing techniques, FFBP neural network, GEP and ANFIS are mostly used for predicting scour depth around different types of hydraulic structures.

It is also observed that most of the studies are related to pier scour. Although, most of the expenditure related to bridge scour goes towards repairing abutment scour. Therefore, in the present, the suitability and applicability of various SC techniques can provide more accurate results than empirical or regression models for predicting scour depth around different types of hydraulic structures.
methods and hybrid techniques to predict scour depth at bridge abutment is investigated.

For quick reference, a brief summary of the related literature reviewed in terms of title of literature, methods/techniques adopted, types of hydraulic structures considered, parameters/variables used, types of statistical measures selected along with the findings has been presented in table 2.2.
### Table 2.2 Summary of the Reviewed Literature

<table>
<thead>
<tr>
<th>Research Title/Reference</th>
<th>Methods</th>
<th>Types of obstruction</th>
<th>Factors/Variables</th>
<th>Measure of errors</th>
<th>Findings (Best method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prediction of maximum scour depth downstream of sudden expanding stilling basins using artificial neural networks. Negam et al. (2003)</td>
<td>MLP, Regression model (RM)</td>
<td>Stilling basin</td>
<td>Acceleration due to gravity, density of the movable soil, gate opening height, upstream water depth, mean particle diameter, mean velocity under the gate</td>
<td>$R^2$, MRAE</td>
<td>MLP</td>
</tr>
<tr>
<td>Prediction of Local Scour around Bridge Piers using ANN. Choi et al. (2006)</td>
<td>ANN-FFBP, EM</td>
<td>Piers</td>
<td>Water depth; pier width, velocity, Median grain diameter</td>
<td>MAPE</td>
<td>ANN-FFBP</td>
</tr>
<tr>
<td>Neural network modeling for estimation of scour depth around bridge piers. Lee et al. (2007)</td>
<td>ANN-FFBP, EM</td>
<td>Piers</td>
<td>Flow depth, mean velocity, grain diameter, geometric standard deviation of the grain size distribution and the critical velocity</td>
<td>RMSE, R</td>
<td>ANN-FFBP</td>
</tr>
<tr>
<td>Artificial Neural network prediction of maximum scour hole downstream hydraulic structures. Soliman (2007)</td>
<td>ANN-FFBP</td>
<td>Stilling basins</td>
<td>Discharge, velocity, gate opening, bed material and length of apron</td>
<td>$R^2$</td>
<td>ANN-FFBP</td>
</tr>
<tr>
<td>Bayesian neural networks for prediction of equilibrium and time-dependent scour depth around bridge piers. Bateni et al. (2007a)</td>
<td>Bayesian neural networks (BNN), EM</td>
<td>Piers</td>
<td>Flow depth and mean velocity, critical flow velocity, median grain diameter and pier diameter</td>
<td>MAE, RMSE, $R^2$</td>
<td>BNN</td>
</tr>
<tr>
<td>Radial Basis Function to predict bridge pier scour Azamathulla et al. (2007a)</td>
<td>ANN-RBF, EM</td>
<td>Pier</td>
<td>Pier width, flow depth, median grain size, flow velocity</td>
<td>R, AE, D, RMSE</td>
<td>RBF</td>
</tr>
<tr>
<td>Research Title/Reference</td>
<td>Methods</td>
<td>Types of obstruction</td>
<td>Factors/Variables</td>
<td>Measure of errors</td>
<td>Findings (Best method)</td>
</tr>
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<tr>
<td>Genetic Programming Approach for Prediction of Local Scour Downstream of hydraulic structures. Guven et al. (2008)</td>
<td>GP, RM</td>
<td>Grade-control structures</td>
<td>Flow velocity of the upstream from the pier, flow depth of the upstream from the pier, Median grain size, pier width, pier length, pier skew angle, pier shape</td>
<td>R, MAPE</td>
<td>GP</td>
</tr>
<tr>
<td>Neural network formula for local scour at piers using field data. Shin et al. (2010)</td>
<td>ANN-FFBP, EM</td>
<td>Piers</td>
<td>Flow velocity of the upstream from the pier, flow depth of the upstream from the pier, Median grain size, pier width, pier length, pier skew angle, pier shape</td>
<td>SSE, R, Avg. Standard Error</td>
<td>ANN-FFBP</td>
</tr>
<tr>
<td>Genetic programming to predict bridge pier scour. Azamathulla et al. (2010)</td>
<td>ANN-RBF, GP, RM</td>
<td>Pier</td>
<td>Approach velocity, particle mean diameter, pier width, length of the pier, standard deviation of grain size distribution</td>
<td>R², RMSE, AE</td>
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<tr>
<td>Gene-expression programming to predict pier scour depth using laboratory data. Khan et al. (2012)</td>
<td>GEP, ANN, EM</td>
<td>Pier</td>
<td>Approach velocity, particle mean diameter, pier width, length of the pier, standard deviation of grain size distribution</td>
<td>R², RMSE, AAE,</td>
<td>ANN</td>
</tr>
<tr>
<td>Prediction of equilibrium scour time around long abutments. Mohammadpour et al. (2012)</td>
<td>GP, ANN, EM</td>
<td>Abutment</td>
<td>Approach velocity, particle mean diameter, pier width, length of the pier, standard deviation of grain size distribution</td>
<td>R², AE and D</td>
<td>GP</td>
</tr>
<tr>
<td>Soft computing for prediction of river pipeline scour depth. Azamathulla et al. (2012b)</td>
<td>GEP, RM</td>
<td>Pipeline across river</td>
<td>Approach velocity, particle mean diameter, pier width, length of the pier, standard deviation of grain size distribution</td>
<td>R², RMSE</td>
<td>GEP</td>
</tr>
<tr>
<td>Modeling of local scour depth downstream hydraulic structures in trapezoidal channel using GEP and ANNs, Moussa (2013)</td>
<td>ANN, GEP</td>
<td>Stilling basin</td>
<td>Approach velocity, particle mean diameter, pier width, length of the pier, standard deviation of grain size distribution</td>
<td>R², AMRE, SE</td>
<td>GEP</td>
</tr>
<tr>
<td>Artificial neural network prediction of maximum scour around bridge piers due to aquatic weeds’ racks. Gamal et al. (2013)</td>
<td>ANN-FFBP, EM</td>
<td>Piers</td>
<td>Approach velocity, particle mean diameter, pier width, length of the pier, standard deviation of grain size distribution</td>
<td>R², AMRE, SE</td>
<td>GEP</td>
</tr>
</tbody>
</table>
Table 2.2 Summary of the Reviewed Literature (contd…)

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<tr>
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<tbody>
<tr>
<td>Scour prediction at bridge piers in cohesive bed using gene expression programming. Muzzammil et al. (2015)</td>
<td>GEP, RM</td>
<td>Piers</td>
<td></td>
<td>R, MPE, MAD, RMSE</td>
<td>GEP</td>
</tr>
<tr>
<td>Neural network and neuro-fuzzy assessments for scour depth around bridge piers. Bateni et al. (2007c)</td>
<td>MLP, RBF, ANFIS, EM</td>
<td>Piers</td>
<td>Flow depth, mean velocity, critical flow velocity, mean grain diameter and pier diameter</td>
<td>R², RMSE, MAE</td>
<td>MLP</td>
</tr>
<tr>
<td>Estimation of pile group scour using adaptive neuro-fuzzy approach. Bateni et al. (2007b)</td>
<td>ANFIS, EM</td>
<td>Pile group</td>
<td>Wave height, wave period, and water depth</td>
<td>R², RMSE, MAE</td>
<td>ANFIS</td>
</tr>
<tr>
<td>An ANFIS based approach for predicting the scour below Flip-Bucket Spillway. Azamathulla et al. (2007b)</td>
<td>ANFIS, FFBP, FFCC, RBF, RM</td>
<td>Flip-bucket Spillway</td>
<td>Head between the upper water level and the tail water level, water discharge per unit width, radius of the bucket, lip angle of the bucket, tail water depth, mean sediment size.</td>
<td>AE, RMSE, D</td>
<td>ANFIS</td>
</tr>
<tr>
<td>ANFIS-based approach to predicting scour location of spillway. Azamathulla et al. (2009)</td>
<td>ANFIS, EM</td>
<td>Trajectory bucket spillway</td>
<td>Total head, radius of the bucket, mean sediment size, lip angle of the bucket, tail water depth, discharge of spillway</td>
<td>R², AE, MSE, D</td>
<td>ANFIS</td>
</tr>
<tr>
<td>ANFIS-based approach for scour depth prediction at piers in non-uniform sediments. Muzzammil et al. (2009)</td>
<td>FFBP, FFCC, RBF, ANFIS, RM</td>
<td>Piers</td>
<td>Flow depth, pier width, the approach flow velocity and sediment gradation parameter</td>
<td>MAPE, RMSE, R</td>
<td>ANFIS</td>
</tr>
<tr>
<td>Estimation of current-induced scour depth around pile groups using neural network and adaptive neuro-fuzzy inference system. Zounemat-Kermani et al. (2009)</td>
<td>FFBP, RBF, ANFIS, RM</td>
<td>Pile groups</td>
<td>Flow depth, mean velocity, critical flow velocity, grain mean diameter, pile diameter, distance between the piles</td>
<td>R, RMSE, MAE</td>
<td>FFBP</td>
</tr>
</tbody>
</table>
Table 2.2 Summary of the Reviewed Literature (contd…)

<table>
<thead>
<tr>
<th>Research Title/Reference</th>
<th>Methods</th>
<th>Types of obstruction</th>
<th>Factors/Variables</th>
<th>Measure of errors</th>
<th>Findings (Best method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear genetic programming for prediction of circular pile scour. Guven et al. (2009)</td>
<td>LGP, ANFIS, RM</td>
<td>Circular pile</td>
<td>Bed grain size, pile diameter, wave period, wave height, maximum flow velocity, maximum shear velocity</td>
<td>R², RMSE, MAE</td>
<td>LGP</td>
</tr>
<tr>
<td>Prediction of scour around hydraulic structure using soft computing technique. Azamathulla et al. (2009b)</td>
<td>FFBP, FFCC, RBF, ANFIS, RM</td>
<td>Trajectory spillways</td>
<td>Discharge intensity, total head, radius of the bucket, lip angle of the bucket, tail water depth, mean sediment size</td>
<td>R, AE, RMSE, D</td>
<td>ANFIS</td>
</tr>
<tr>
<td>Scour depth modelling by a multi-objective evolutionary paradigm. Laucelli and Giustolisi (2011)</td>
<td>MO-EPR, EM</td>
<td>Grade-control structures</td>
<td>Channel width, median grain size, tailwater depth, water discharge per unit weir width, quasi-uniform grain-size distribution</td>
<td>R², MRD, RMSE, MRE, MO-EPR</td>
<td></td>
</tr>
<tr>
<td>ANFIS approach to the scour depth prediction at a bridge abutment. Muzzammil (2010)</td>
<td>FFBP, FFBC, RBF, ANFIS, RM</td>
<td>Abutment</td>
<td>Abutment length, flow depth, mean velocity, sediment size</td>
<td>R, MAPE, RMSE</td>
<td>ANFIS</td>
</tr>
<tr>
<td>ANFIS-based approach to scour depth prediction at abutments in armored beds. Muzzammil et al. (2011)</td>
<td>FFBP, FFBC, RBF, ANFIS, RM</td>
<td>Abutment</td>
<td>Abutment length, flow depth, mean velocity, sediment size, armor-layer thickness, size of armor-layer, critical velocity ratio, shape factor</td>
<td>R, MAPE, RMSE</td>
<td>ANFIS</td>
</tr>
<tr>
<td>ANFIS-based approach for predicting the scour depth at culvert outlets. Azamathulla et al. (2011)</td>
<td>RBF, ANFIS, RM</td>
<td>Culvert outlets</td>
<td>Outlet shape, culvert shape, outlet diameter, sediment size, tail water depth, exit velocity, densimetric Froude number, width of the receiving channel</td>
<td>R², RMSE, MAE, D</td>
<td>ANFIS</td>
</tr>
<tr>
<td>Prediction of scouring around an arch-shaped bed sill using neuro-fuzzy model. Keshavarzi et al. (2012)</td>
<td>ANN, ANFIS</td>
<td>Arch-shaped bed sill</td>
<td>Discharge, Head water, sill radius, velocity, Froude Number, channel width</td>
<td>R², RMSE, MAE</td>
<td>ANFIS</td>
</tr>
</tbody>
</table>

MRAE: Mean relative absolute error, MRE: Maximum relative error MAE: Mean absolute error, RMSE: Root means square error, AAE: Average Absolute Error, CE: coefficient of efficiency, SE: Standard error, MAPE: Mean average percentage error, MPE: Mean percentage error, MAD: Mean absolute deviation, AMRE: Absolute mean relative error, AE: Average error, MRD: Mean relative deviation, D: Average absolute deviation, CE: Coefficient of efficiency, R: Correlation coefficient, R²: Coefficient of determination.
2.3 Chapter Summary

This chapter has provided a comprehensive review of the current status of research in the field of hydraulic engineering for predicting scour depth based on empirical equations and SC-based methods. The primary focus of literature review was to identify SC methodologies to be employed for the present study.

Previous studies have shown that ANN and evolutionary methods are acceptable techniques for predictive modeling in the hydraulic engineering domain and are superior in performance when compared to the tradition methods. Previous studies on ANN-based methods have shown that multilayered feed forward network with back propagation algorithm is most commonly employed for scour depth estimation around different types of obstructions. It is also observed that hybrid models produced better results than the standalone SC models. The review shows that the available literature on application of SC models and hybrid techniques to predict scour depth at abutment is limited. Further, SC methodologies are associated with difficulties such as success in a given problem and unpredictable level of accuracy. The suitability and applicability of SC methods and hybrid techniques must therefore be assessed for every problem. In the following chapter, a detailed study on SC methodologies and the various issues in relation to SC model development are presented.