Neural Networks for Estimation of Scour Downstream of a Ski-Jump Bucket

H. Md. Azmathullah[1]; M. C. Deo[2]; and P. B. Deolalikar[3]

Abstract: The estimation of scour downstream of a ski-jump bucket has remained inconclusive, despite analysis of numerous prototypes as well as hydraulic model studies in the past. It is partly due to the complexity of the phenomenon involved and partly because of limitations of the traditional analytical tool of statistical regression. This paper addresses the latter part and presents an alternative to the regression in the form of neural networks. The depth of the scour hole developed along with its width and length is predicted using neural network models. A network architecture complete with trained values of connection weight and bias and requiring input of grouped parameters pertaining to discharge head, tail water channel depth, bucket radius, lip angle, and median sediment size is recommended in order to predict the depth, the location of maximum scour, as well as the width of scour hole. The neural network predictions have been compared with traditional statistical schemes. Although the common and simple feed forward back propagation network took a very long time to train as compared to some advanced schemes, it was found to impart equally reliable training as the latter. Use of causative variables in grouped forms was found to be more rewarding than that of their raw forms probably due to lesser scaling effect.

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Introduction

Provision of spillways in the structure of a dam enables disposal of flood water in excess of reservoir capacity and also control of water flow downstream. Out of several types of spillways the overfall, ogee, and breast wall spillways are more commonly used. Energy dissipation in such spillways may be in the form of ski-jump jet, which throws the water jet away from the bucket lip into the air, and then in the plunge pool formed at the point of impact on the tail water (Fig. 1). Because of impact of the high velocity jet, scour takes place both upstream and downstream of the point of impingement. The impact of the jet is transmitted through cracks and fissures of the rock by way of hydrodynamic pressure fluctuations causing hydraulic jacking action and also by the transient pressure fluctuation caused by air locking. Due to this the rock mass breaks into small pieces and consequently gets swept away downstream of the spillway. The erosion continues up to the point where the impinging jet energy is insufficient to exert breaking pressure on the rock or where the secondary currents produced are not strong enough to remove the rock blocks (Mason and Arumugam 1985). Scouring also continues until an equilibrium scour depth is reached, which corresponds to a situation where increased water depth in the scour hole precludes exertion of bed shear stress that is sufficient to cause further bed erosion or to a condition where the rate of bed erosion is balanced by the rate of deposition of material brought back into the scour hole by the return flow.

There are various hydraulic, morphologic, and geotechnical factors governing the depth of scour. These include (referring to Fig. 1) discharge intensity q, height of fall H_1, bucket radius R, bucket lip angle ϕ, type of rock, degree of rock homogeneity, time, and mode of operation of spillway. Various investigators over a period of several decades in the past have given empirical formulas based on laboratory as well as prototype observations in order to predict the scour depth downstream of the ski-jump bucket spillway. For example Veronese (1937), Damle et al. (1966), Chee and Padiyar (1969), Wu (1973), Martins (1975), Taraimovich (1978), Mason (1984), Wang (1987), Yildiz and Ergün (1994), Yildiz and Üzücek (1994), and Lopardo et al. (2002). The Bureau of Indian Standards (1985) suggests use of the Veronese formula given below for the estimation of ultimate depth of scour below tail water level

$$d_s = 1.90 q^{0.54} H_1^{0.225} \qquad (1)$$

An empirical formula, as above, involves idealization, approximation, and averaging of widely varying prototype conditions and could predict scour depths which may be considerably different from their actual values, e.g., in the case of Rana Pratap Sagar Dam across the Chambal River in India. The actual deepest scour was up to 24.7 m, which as per the Veronese formula should have been 32.0 m (q=47.6 m^3/s/m, H_1=26.6 m, and d_s=32 m). A similar study by Sen (1984) showed that the scour below Kariba spillway, which is a part of the dam built across the river Zambesi in Zimbabwe, was nearly double that of the one predicted by the Veronese formula.

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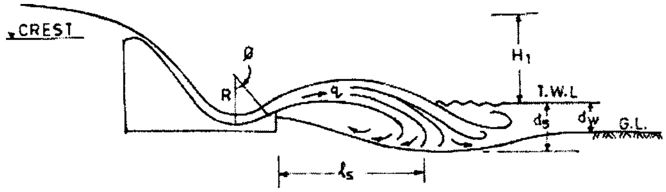

Fig. 1. Spillway and scour hole notations

Despite analyzing a wide range of reliable prototype as well as model data the problem of scour prediction has remained inconclusive. It is felt that this is partly due to the complexity of the phenomenon involved and partly because of the limitation of the analytical tool commonly used by most of the earlier investigators, namely, statistical regression. Conventional statistical analysis is now being replaced in many cases by the alternative approach of neural networks. Neural networks have advantages over statistical models like their data-driven nature, model–free form of predictions, and tolerance to data errors.

The objective of this study was to compile past observations on depth and pattern of scour, supplement them with fresh observations if necessary, and reanalyze resulting data bases using the technique of neural networks with a view towards seeing if better predictions are possible. Not only depth but width and length of the scour hole were also considered for prediction in this study in view of their importance in the plunge pool design. Separate network models were developed for prototype as well as for hydraulic model data. Use of basic network architectures like feed forward back propagation (FFBP) along with relatively advanced configurations like radial basis functions (RBF) was made. The neural network predictions have been compared with the traditional statistical schemes. The studies incorporated use of the neural network tool box in *MATLAB* (2003) as well as the software in the package *SNNS* (1995).

Data Collection

Past measurements of scour parameters made during numerous laboratory investigations carried out at the Central Water and Power Research Station (CWPRS), Pune, India were first compiled for potential use in the current study. These studies were conducted on various sectional as well as comprehensive models. The sectional models were scaled to the range of 1:40–1:60, whereas comprehensive models had their scales varying from 1:50 to 1:100. A look at these observations revealed that additional measurements were necessary to make them more comprehensive; especially with respect to pattern of scour including width and distance of maximum scour depth from the spillway bucket lip (length). New hydraulic model studies were therefore conducted on three different bucket designs. The three hydraulic models simulated the dams across rivers Subarnarekha, Ranganadi, and Parbati Rivers in India.

The first dam was 52 m high and 720 m long. Its spillway consisted of 13 spans of 15 m wide each with crest at elevation 177 m. Radial gates of size 15 m × 16 m regulated the flow over this spillway. The design outflow flood was 26,150 m^3/s. This corresponded to a maximum water level at an elevation of 192.37 m. The ski-jump bucket with bucket radius of 25 m and lip angle of 32.5° was provided at the toe for energy dissipation. The scour pattern downstream of the spillway, simulated by a 1:100 geometrically similar Froudian model, was obtained by reproducing the river in erodible sand.

The second (Ranganadi River) dam was 60 m high, made up of concrete with a rockfill portion on its right side. It had an overflow spillway with seven spans of 10 m width and 12 m height. The spillway catered to a maximum outflow flood of 12,500 m^3/s. This corresponded to the maximum water level of 568.3 m and the full reservoir level of 567 m with the crest level of the spillway at 544 m. The ski-jump bucket modeled by a 1:60 scale model served as an energy dissipator at the toe of the spillway. It had a bucket radius of 18 m with 35° as the lip angle.

The dam corresponding to the third spillway was 85 m high. It was designed to pass a maximum discharge of 1,850 m^3/s at the full reservoir level of 2,198 m elevation. It had three spans, 6 m wide and 9 m high, separated by 6 m thick piers, and fitted with radial gates. An apron and a plunge pool along the downstream side fronted the bucket, which had a bucket radius of 28 m with the lip angle of 30°. This model based on Froude's law had a scale of 1:50. The downstream bed was made up of 2 mm diameter cohesionless sand particles. The riverbanks in this portion were assumed to be nonerodible and rigid.

The experiments were conducted for various discharges as well as reservoir levels, with spillway gates fully and partially open. The discharge on the hydraulic model was measured on the standing wave flume or Rehbock weir. The accuracy of discharge measurement was ±2%. The various depths such as tail water depth, head over crest and other parameters were measured by using a point gauge having a graduation of 0.1 mm. The depth of scour was observed in a free formed plunge pool which was subsequently filled with sand having d_{50} size of 2 mm. Observations were made with four discharge passes, (25, 50, 75, 100% of the maximum discharge) each with fully open as well as partially open gates. Every run continued over a period of 3 h on the model, which was found to be sufficient to reach the equilibrium scour. Experience shows that the equilibrium scour depth would be reached within this period, although the evolution of progressive scour depth is a function of time. The scour pattern, as measured by the maximum scours depth as well as its location and width was recorded for each run. Eight experimental runs (indicating different discharges) were taken on each of the three models indicated above.

Dr. Masoud Ghodsian of Tarbiat Modarres University, Tehran, Iran (E-mail: ghods@modares.ac.ir) also kindly provided additional scour data resulting from his previous work. In the end, 95 input–output pairs were compiled as shown in Table 1. The ranges of various parameters so obtained are also given in Table 1.

Dimensional Analysis

Referring to Fig. 1 the equilibrium depth of scour (d_s), measured from tail water surface, can be written as a function of discharge per meter width or unit discharge of spillway (q), total head (H_1), radius of the bucket (R), lip angle of the bucket (ϕ), tail water depth (d_w), mean sediment size (d_{50}), acceleration due to gravity (g), and densities of water and sediment ρ_w and ρ_s

$$d_s = f(q, H_1, R, \phi, d_w, d_{50}, g, \rho_w, \rho_s) \tag{2}$$

In the present study the standard deviation of sediment bed material has not been considered. The maximum width of the scour hole (w_s) as well as the distance of maximum scour depth from the spillway bucket lip (length l_s), corresponding to the condition of the maximum scour depth, can be written in a similar form as

Table 1. Data Base Used

Sl. number	Discharge intensity q ($m^3/s/m$)	Total head H_1 (m)	Bucket radius R (m)	Bed material size d_{50} (m)	Lip angle ϕ (rad)	Tail water depth d_w (m)	Depth of scour d_s (m)	Location of max scour lip l_s (m)	Width of scour w_s (m)	Data source
1	0.1703	0.5083	0.400	0.004	0.472	0.1667	0.5500	1.1116	0.85	a
2	0.1792	1.4268	0.406	0.002	0.612	0.2300	0.2439	1.9512	0.85	a
3	0.0842	1.4268	0.609	0.002	0.698	0.1500	0.2246	2.0202	0.92	a
4	0.0634	1.1328	0.406	0.002	0.612	0.0300	0.1128	0.9807	1.63	a
5	0.0266	1.3659	0.610	0.002	0.698	0.1700	0.1259	0.9756	0.92	a
6	0.1616	1.7962	0.254	0.002	0.349	0.2337	0.3608	1.9055	1.50	a
7	0.0709	1.4146	0.610	0.002	0.698	0.1600	0.1922	1.7378	0.92	a
8	0.0204	0.3505	0.180	0.008	0.524	0.0286	0.1218	0.6970	0.60	a
9	0.0374	0.3328	0.140	0.008	0.524	0.0687	0.2360	0.7200	0.60	a
10	0.0093	1.0718	0.406	0.002	0.612	0.2340	0.0762	0.5742	1.63	a
11	0.1239	1.3659	0.406	0.002	0.612	0.1800	0.1677	1.4634	0.85	a
12	0.1446	1.3902	0.406	0.002	0.126	0.2650	0.2165	1.6463	0.85	a
13	0.0399	1.3902	0.610	0.002	0.698	0.1800	0.1485	1.4329	0.92	a
14	0.0471	0.3827	0.140	0.008	0.524	0.0286	0.3470	0.7500	0.60	a
15	0.0204	0.3104	0.180	0.008	0.524	0.0687	0.0889	0.5000	0.60	a
16	0.0204	0.2991	0.140	0.005	0.524	0.1000	0.1235	0.5300	0.65	a
17	0.0186	1.0822	0.406	0.002	0.612	0.2150	0.1037	0.7165	1.23	a
18	0.0285	0.3188	0.140	0.008	0.524	0.0687	0.1609	0.6300	0.60	a
19	0.1616	1.7962	0.254	0.002	0.780	0.2337	0.3608	2.0709	1.50	a
20	0.0471	0.3676	0.140	0.008	0.524	0.0437	0.3238	0.7000	0.60	a
21	0.0089	1.3415	0.610	0.002	0.698	0.1780	0.0512	0.5183	0.92	a
22	0.0725	1.3415	0.406	0.002	0.612	0.0900	0.0854	0.9146	0.85	a
23	0.0250	1.0922	0.406	0.002	0.612	0.2500	0.1098	0.8781	1.63	a
24	0.1616	1.7962	0.254	0.002	0.174	0.2337	0.2998	1.4482	1.50	a
25	0.1626	1.4146	0.406	0.002	0.612	0.2480	0.2317	1.8902	0.85	a
26	0.087	1.1532	0.406	0.002	0.612	0.0330	0.1169	1.0163	1.63	a
27	0.1616	1.7962	0.254	0.002	0.523	0.2337	0.2998	2.1439	1.50	a
28	0.0204	0.3354	0.100	0.008	0.524	0.0437	0.1360	0.4950	0.65	a
29	0.0398	1.3902	0.610	0.002	0.698	0.1800	0.1485	1.4329	0.92	a
30	0.0285	0.3589	0.250	0.008	0.567	0.0286	0.1642	0.6500	0.65	b
31	0.0435	1.1125	0.300	0.002	0.612	0.2480	0.1113	0.9502	1.63	b
32	0.0374	0.3328	0.250	0.003	0.567	0.0687	0.1772	0.7000	0.65	b
33	0.0374	0.3015	0.250	0.008	0.567	0.1000	0.1516	0.6700	0.65	b
34	0.0374	0.3015	0.250	0.002	0.567	0.1000	0.2135	0.6500	0.60	b
35	0.0471	0.3827	0.250	0.008	0.567	0.0286	0.3085	0.8200	0.65	b
36	0.0285	0.3188	0.250	0.008	0.567	0.0687	0.1432	0.6400	0.65	b
37	0.0204	0.2991	0.250	0.008	0.567	0.1000	0.0512	0.4550	0.65	b
38	0.0285	0.2875	0.300	0.002	0.612	0.1000	0.1570	0.5500	0.65	b
39	0.1532	1.0750	0.560	0.002	0.611	0.1460	0.3800	1.8400	2.06	b
40	0.0511	0.9650	0.560	0.002	0.611	0.1460	0.2900	1.3400	1.56	b
41	0.2042	1.1300	0.560	0.002	0.611	0.1460	0.4000	2.0400	1.65	b
42	0.1021	1.0300	0.560	0.002	0.611	0.1460	0.3400	1.8000	1.78	b
43	0.2042	1.4740	0.560	0.002	0.611	0.1460	0.4200	2.2400	2.14	b
44	0.1532	1.4850	0.560	0.002	0.611	0.1460	0.4000	2.1440	2.10	b
45	0.0511	1.5050	0.560	0.002	0.611	0.1460	0.2900	1.8400	1.80	b
46	0.1021	1.5000	0.560	0.002	0.611	0.1460	0.368	2.2400	2.00	b
47	0.0285	0.3589	0.180	0.008	0.524	0.0286	0.1725	0.6500	0.65	c
48	0.0374	0.3578	0.140	0.008	0.524	0.0437	0.2112	0.7100	0.65	c
49	0.0471	0.3113	0.140	0.008	0.524	0.1000	0.2459	0.6000	0.65	c
50	0.0285	0.2875	0.180	0.008	0.524	0.1000	0.1297	0.6300	0.65	c
51	0.0374	0.3578	0.200	0.008	0.524	0.0437	0.2032	0.7250	0.65	c
52	0.0471	0.3827	0.180	0.008	0.524	0.0286	0.3199	0.7800	0.65	c
53	0.0471	0.3676	0.180	0.008	0.524	0.0437	0.3036	0.7750	0.65	c
54	0.0204	0.3354	0.100	0.008	0.524	0.0437	0.136	0.4950	0.65	c

Table 1. (*Continued.*)

Sl. number	Discharge intensity q ($m^3/s/m$)	Total head H_1 (m)	Bucket radius R (m)	Bed material size d_{50} (m)	Lip angle ϕ (rad)	Tail water depth d_w (m)	Depth of scour d_s (m)	Location of max scour lip l_s (m)	Width of scour w_s (m)	Data source
55	0.0285	0.2875	0.200	0.008	0.524	0.1000	0.1207	0.6200	0.65	c
56	0.0285	0.3438	0.180	0.003	0.524	0.0437	0.1607	0.6500	0.65	c
57	0.0471	0.3426	0.180	0.008	0.524	0.0687	0.2808	0.7800	0.65	c
58	0.0374	0.3328	0.180	0.008	0.524	0.0687	0.181	0.7000	0.65	c
59	0.0374	0.3578	0.180	0.008	0.524	0.0437	0.2172	0.7100	0.65	c
60	0.0471	0.3113	0.100	0.008	0.524	0.1000	0.2394	0.7000	0.65	c
61	0.0204	0.3505	0.200	0.008	0.524	0.0286	0.0816	0.5250	0.65	c
62	0.0471	0.3426	0.100	0.008	0.524	0.0687	0.3153	0.7200	0.65	c
63	0.0374	0.3015	0.140	0.008	0.524	0.1000	0.1848	0.7000	0.65	c
64	0.0285	0.3438	0.200	0.008	0.524	0.0437	0.1542	0.6500	0.65	c
65	0.0285	0.3589	0.140	0.008	0.524	0.0286	0.1986	0.5800	0.65	c
66	0.0204	0.3354	0.200	0.008	0.524	0.0437	0.0752	0.4700	0.65	c
67	0.0204	0.3104	0.100	0.008	0.524	0.0687	0.135	0.4500	0.65	c
68	0.0204	0.3505	0.140	0.008	0.524	0.0286	0.139	0.5000	0.65	c
69	0.0285	0.2875	0.140	0.008	0.524	0.1000	0.1405	0.6000	0.65	c
70	0.0471	0.3827	0.100	0.008	0.524	0.0286	0.3587	0.8150	0.65	c
71	0.0374	0.3729	0.200	0.008	0.524	0.0286	0.2263	0.7500	0.65	c
72	0.0285	0.3589	0.100	0.008	0.524	0.0286	0.2065	0.6100	0.65	c
73	0.0471	0.3426	0.200	0.008	0.524	0.0687	0.2693	0.7200	0.65	c
74	0.0471	0.3676	0.200	0.008	0.524	0.0437	0.292	0.7600	0.65	c
75	0.0204	0.3304	0.140	0.008	0.524	0.0687	0.1309	0.5000	0.65	c
76	0.0204	0.3354	0.180	0.008	0.524	0.0437	0.1068	0.6600	0.65	c
77	0.0285	0.3438	0.100	0.008	0.524	0.0437	0.1839	0.6050	0.65	c
78	0.0471	0.3426	0.140	0.008	0.524	0.0687	0.3091	0.6700	0.65	c
79	0.0471	0.3113	0.250	0.008	0.524	0.1000	0.243	0.6900	0.65	c
80	0.0204	0.3505	0.100	0.008	0.524	0.0286	0.1424	0.4900	0.65	c
81	0.0374	0.3328	0.100	0.008	0.524	0.0687	0.2426	0.6600	0.65	c
82	0.0471	0.3676	0.100	0.008	0.524	0.0437	0.3343	0.7300	0.65	c
83	0.0204	0.3104	0.200	0.008	0.524	0.0687	0.0643	0.5000	0.65	c
84	0.0285	0.3438	0.140	0.008	0.524	0.0437	0.1765	0.6500	0.65	c
85	0.0285	0.3188	0.180	0.008	0.524	0.0687	0.1526	0.6500	0.65	c
86	0.0204	0.2791	0.100	0.008	0.524	0.1000	0.1255	0.5000	0.65	c
87	0.0374	0.3729	0.140	0.008	0.524	0.0286	0.2685	0.7400	0.65	c
88	0.0471	0.3113	0.180	0.008	0.524	0.1000	0.2497	0.7650	0.65	c
89	0.0285	0.3188	0.100	0.003	0.524	0.0678	0.1706	0.5550	0.65	c
90	0.0204	0.3354	0.140	0.008	0.524	0.0437	0.1325	0.4200	0.65	c
91	0.0374	0.3015	0.180	0.008	0.524	0.1000	0.156	0.6850	0.65	c
92	0.0374	0.3578	0.100	0.008	0.524	0.0437	0.2755	0.7150	0.65	c
93	0.0374	0.3729	0.180	0.008	0.524	0.0286	0.2382	0.7200	0.65	c
94	0.0374	0.3729	0.100	0.008	0.524	0.0286	0.2915	0.7200	0.65	c
95	0.0204	0.2791	0.180	0.008	0.524	0.1000	0.0785	0.5500	0.65	c
Min.	**0.0089**	**0.2791**	**0.100**	**0.002**	**0.174**	**0.0286**	**0.0512**	**0.4200**	**0.60**	
Max.	**0.2042**	**1.7962**	**0.610**	**0.008**	**0.780**	**0.2650**	**0.55**	**2.2400**	**2.14**	

[a]Numerous research reports of hydraulic model studies conducted at Central Water and Power Research Station, India.

[b]New model studies with respect to dams along river, Subernarekha, Ranganadi and Parbati.

[c]Personal communication from Dr. Masoud Ghodsian of Tarbiat Modarres University, Tehran, Iran.

$$w_s = f(q, H_1, R, \phi, d_w, d_{50}, g, \rho_w, \rho_s) \tag{3}$$

$$I_s = f(q, H_1, R, \phi, d_w, d_{50}, g, \rho_w, \rho_s) \tag{4}$$

Using the Buckingham π theorem, nondimensional equations in functional forms can be obtained as below

$$\frac{d_s}{d_w} = f\left(\frac{q}{\sqrt{qd_w^3}}, \frac{H_1}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \phi\right) \tag{5}$$

$$\frac{w_s}{d_w} = f\left(\frac{q}{\sqrt{gd_w^3}}, \frac{H_1}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \phi\right) \tag{6}$$

$$\frac{I_s}{d_w} = f\left(\frac{q}{\sqrt{gd_w^3}}, \frac{H_1}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \phi\right) \tag{7}$$

The above functional relationships have been worked out in the present study, in which the ratio of sediment density to water density, ρ_s/ρ_w would be constant and can be eliminated from the analysis.

Statistical Regression Models

The above dimensionless groups of parameters were related to each other in the present study on the basis of nonlinear regression using 80% of the measurements selected randomly. This yielded the following equations in order to estimate the maximum scour depth, maximum scour width, and distance of maximum scour location from the bucket lip, respectively:

$$\frac{d_s}{d_w} = 6.914\left(\frac{q}{\sqrt{gd_w^3}}\right)^{0.694}\left(\frac{H_1}{d_w}\right)^{0.0815}\left(\frac{R}{d_w}\right)^{-0.233}\left(\frac{d_{50}}{d_w}\right)^{0.196}(\phi)^{0.196} \tag{8}$$

$$\frac{l_s}{d_w} = 9.85\left(\frac{q}{\sqrt{gd_w^3}}\right)^{0.42}\left(\frac{H_1}{d_w}\right)^{0.28}\left(\frac{R}{d_w}\right)^{0.043}\left(\frac{d_{50}}{d_w}\right)^{0.037}(\phi)^{0.34661} \tag{9}$$

$$\frac{w_s}{d_w} = 5.42\left(\frac{q}{\sqrt{gd_w^3}}\right)^{-0.015}\left(\frac{H_1}{d_w}\right)^{0.55107}\left(\frac{R}{d_w}\right)^{0.1396}\left(\frac{d_{50}}{d_w}\right)^{0.242}(\phi)^{-0.16} \tag{10}$$

Validation of the above Eqs. (8)–(10) was made with the help of the remaining 20% of observations, which were not involved in their derivation. Comparison between predicted and observed values of scour depth, length and width for the validation set is qualitatively shown in Figs. 2–4, respectively. (Square symbols are indicated at the end of legends.)

A quantitative comparison is shown in Table 2 referred to later (last three rows) in terms of four error measures namely, (1) correlation coefficient, r, which presents the degree of association between predicted and true values; (2) the average error (+ or −) (AE), which is a parameter commonly understood in engineering applications, and which considers algebraic difference between predicted and true values; (3) the average absolute deviation, d, which does not even out positive or negative errors as in AE; and (4) root mean square error (RMSE), which is preferred in many iterative prediction and optimization schemes. Expressions for these measures are given in Appendix I.

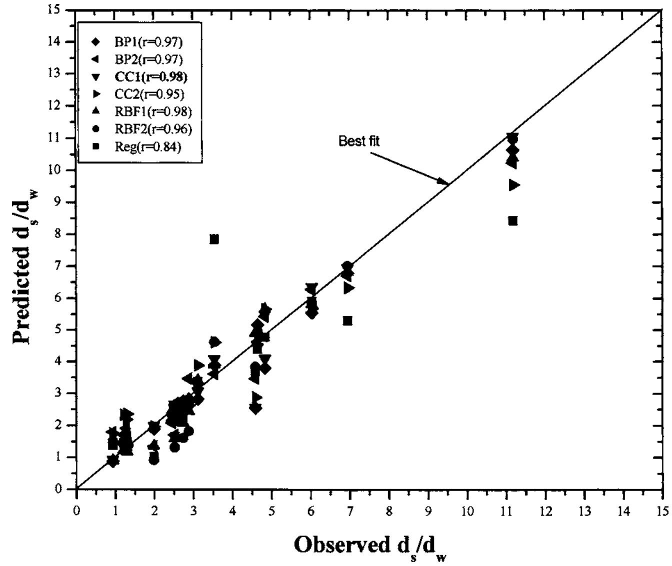

Fig. 2. Observed versus predicted relative scour depth

Referring to the last three rows of Table 2, although the percentage error and "RMSE" involved in the scour depth prediction are small the correlation coefficient is low, and absolute deviation is high, indicating that the prediction made using the statistical technique may be viewed with skepticism. In addition the width prediction was highly unsatisfactory. An alternative method of data mining was therefore employed as described below.

Neural Network Models

As known widely by now neural networks provide a random mapping in between an input and an output vector by mimicking the biological cognition process of our brain. A typical network would consist of three layers of neurons namely, input, hidden, and output, with each neuron acting as an independent computational element. Neural networks derive their strengths from a

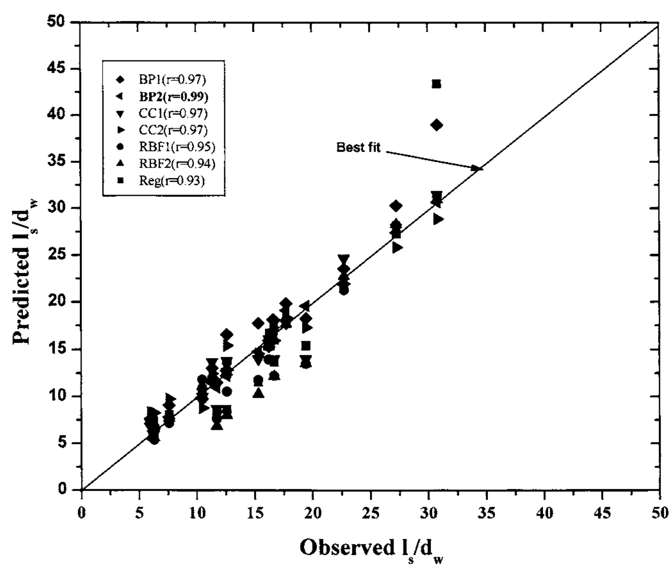

Fig. 3. Observed versus predicted relative scour length (from bucket lip)

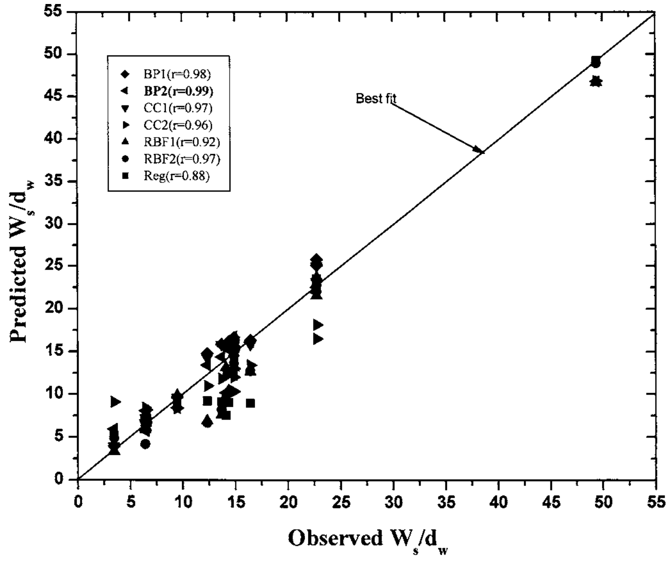

Fig. 4. Observed versus predicted relative scour width

"model-free" processing of data and a high degree of freedom associated with their architecture. Details of concepts involved in neural networks along with their applications in water resources can be seen in the ASCE Task Committee (2000), Dawson and Wilby (2001) and Maier and Dandy (2000). The text books of Kosko (1992), Wasserman (1993), and Wu (1994) also give details of the network theory. Typical problems tackled by the networks in hydraulic engineering include: estimation of pier scour and sediment transport in open channels (Trent et al. 1993a,b, 1999); prediction of flow conditions when the interfacial mixing in stratified estuaries commences (Grubert 1995); prediction of the scour depth at culvert outlets (Liriano and Day 2001); and prediction of sediment load concentration in rivers using neural networks (Nagy et al. 2002).

Before actual application the network has to be trained from examples. Training comprises presentation of input and output pairs to the network and fixing the values of connection weights, bias or centers. The training may require many epochs (presentation of complete data sets once to the network). Generally, the network is presented with the input and output pairs untill the training sum-square error reaches the error goal in order to give the desired network performance.

In the present study the usual feed forward type of network was considered. It was trained using both back propagation as well as cascade correlation algorithms with a view to ensure that proper training is imparted. Further, in order to see if advanced training schemes provide better learning than the basic back propagation, a radial basis function network was also used. Concepts involved behind these training schemes are outlined in the ASCE Task Committee (2000). The resulting neural network models are thus called FFBP, feed forward cascade correlation (FFCC), and RBF.

In order to map the causal relationship related to the scour two separate input–output schemes (called Model 1 and Model 2) were employed, where the first took the input of raw causal parameters while the second utilized their nondimensional groupings. This was done in order to see if use of the grouped variables produced better results. Model 1 (Fig. 5) thus takes the input in the form of causative factors, namely, q, H_1, R, d_{50}, d_w, and ϕ and yields the output of corresponding scour hole depth, length, and width, while Model 2 (Fig. 6) employs the input of grouped as

Table 2. Comparison of Predicted and True Scour

Parameter	r	AE	d	RMSE
FFBP-Model 1				
d_s/d_w	0.97	3.02	10.05	0.60
i_s/d_w	0.97	−11.39	13.53	2.72
w_s/d_w	0.98	−9.50	11.36	2.74
FFBP-Model 2				
d_s/d_w	0.97	−6.68	13.85	0.58
I_s/d_w	0.99	−2.87	3.72	0.72
w_s/d_w	0.99	−2.34	9.11	1.67
FFCC-Model 1				
d_s/d_w	0.98	2.00	7.58	0.54
i_s/d_w	0.97	1.96	8.13	1.84
w_s/d_w	0.97	−7.80	8.41	1.85
FFCC-Model 2				
d_s/d_w	0.95	−16.74	19.11	0.84
i_s/d_w	0.97	−5.29	10.13	1.74
w_s/d_w	0.96	−3.63	18.17	3.05
RBF-Model 1				
d_s/d_w	0.98	5.474	9.59	0.45
l_s/d_w	0.95	6.319	12.18	2.43
w_s/d_w	0.92	−5.26	18.87	4.53
RBF-Model 2				
d_s/d_w	0.97	2.39	15.13	0.66
l_s/d_w	0.94	8.80	11.92	2.72
w_s/d_w	0.97	7.66	12.98	2.62
Regression equations				
d_s/d_w	0.84	−1.43	22.79	1.34
l_s/d_w	0.93	3.90	13.55	3.57
w_s/d_w	0.88	−19.57	20.15	5.61

Note: r=Corr. coeff; AE=average error; d=average absolute deviation; RMSE=root mean square error; FFBP=feed forward back propagation; FFCC=feed forward cascade correlation; RBF=radial basis functions; d_s=scour depth; d_w=scour width; and l_s=scour length.

well as raw dimensionless variables namely, F_0, H_1/d_w, R/d_w, d_{50}/d_w, and ϕ [F_0 being the Froude number$=q/(gd_w^3)^{1/2}$] and also the output of relative scour depth, length, and width, i.e., d_s/d_w, l_s/d_w, and w_s/d_w, respectively.

Use of the neural network toolbox contained within the *MATLAB* as well as *SNNS* software packages was made. Similar to the regression exercise described earlier, out of the total of 95 input–output pairs, 80%, selected randomly, were used for training and the remaining 20% were employed for testing or validation. As dictated by the use of Gaussian function all patterns were normal-

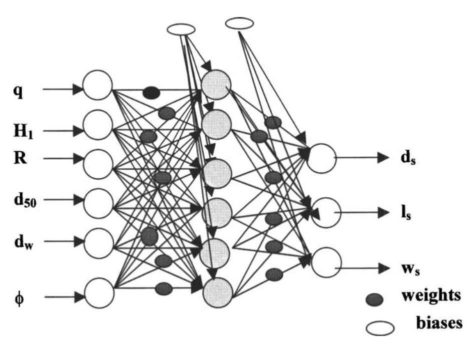

Fig. 5. Model 1: use of raw variables

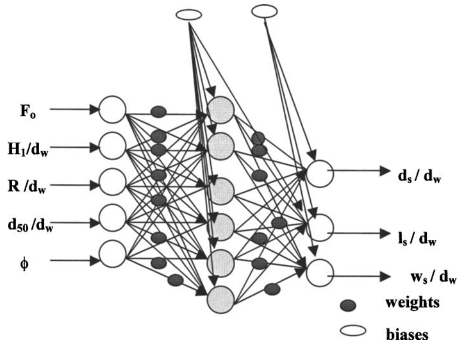

Fig. 6. Model 2: use of grouped variables

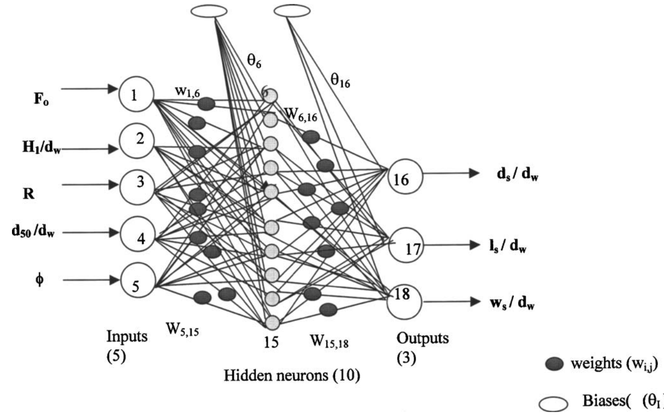

Fig. 7. Feed forward back propagation model 2: use of dimensionless parameters

ized within the range of (0.0, 1.0) before their use. Similarly all weights and bias values were initialized to random numbers. While the numbers of input and output nodes are fixed, the hidden nodes in the case of FFBP were subjected to trials and the one producing the most accurate results (in terms of the correlation coefficient) was selected. The optimization of the training procedure automatically fixes the hidden nodes in the case of the FFCC. The trainings of these networks were stopped after reaching the minimum mean square error of 0.0015 between the network yield and the true output over all the training patterns. For the RBF network various values of spread (σ) between 0 and 1 were tried out and the one of 0.01 resulting in the best performance on both training and testing data was selected.

The information on number of nodes, number of epochs (or, passes through the training patterns) required to achieve the error goal as well as the CPU time taken in the case of each training scheme used [namely back propagation (BP), cascade correlation (CC), and radial basis function (RBF)] is shown in Table 3 for Models 1 and 2, respectively. As a matter of general information, which is not of real significance in this study, it can be seen that the cascade correlation algorithm, designed for efficient training, trained the network with fewer epochs than the BP network and in a very low amount of time, but the RBF network was trained in a significantly less number of epochs and in a fraction of the time compared with BP and CC algorithms, indicating its training efficiency.

After completion of training as above the networks were tested for unseen input. Figs. 2–4, as well as Table 2 show the degree of match between the network-yielded and the "true" scour depth,

Table 3. Network Architecture

Algorithm	Network configuration			Epochs	CPU time (s)
	I	*H*	*O*		
Model 1					
BP	6	10	3	25,000	900
CC	6	82	3	1,200	300
RBF	6	19	3	19	3
Model 2					
BP	5	10	3	15,000	600
CC	5	20	3	700	200
RBF	5	13	3	13	2

Note: *I*, *H*, *O* indicate number of input, hidden, and output nodes, respectively; BP=back propagation; CC=cascade correlation; and RBF=radial basis function.

width, and length, respectively, in each scheme of training for both Models 1 and 2.

It may be seen from Figs. 2–4, as well as Table 2 that when the scour depth alone is considered, AE and d do exhibit considerable variation across various networks, while r and RMSE do not. There is no single method, which produces the highest r and the lowest AE, d, and RMSE values simultaneously. Hence the FFCC Model 1 would probably be the most acceptable model showing highest correlation (r=0.97) and lowest (AE=2.0%, and d=7.59% and second lowest RMSE=0.54).

When it comes to length of the scour hole considerable variation in error measures across various networks may be noticed. In this case the FFBP Model 2 comes out as the most acceptable network in terms of accuracy as it involves the highest r (=0.99) and second lowest AE (=2.9%), and lowest d (=3.73) and RMSE (=0.72) values.

Examination of Table 2 for the case of width of the scour hole suggests that there is a large variation in magnitudes of error measures across the neural networks and that the most suitable network is again FFBP Model 2, which has the highest r of 0.99 and lowest AE, second lowest d, and lowest RMSE values of −2.34%, 9.11%, and 1.67, respectively.

The above observations thus show that when it comes to overall accuracy of predicting depth, width, and length, all error criteria viewed together point out that the simple FF network trained using the common BP algorithm is either as good as or even slightly better than more sophisticated networks. It also shows that use of grouped variables as input (Model 2) may be more beneficial than that of the raw variables (Model 1), provided an appropriate training scheme is chosen, where perhaps grouping of variables had resulted in evening out their scale effects.

In the end therefore the network configuration (FFBP, Model 2) shown in Fig. 7 along with corresponding weight and bias matrix given in Table 6 is recommended for general use in order to predict the depth, the location of the maximum scour from the bucket tip, as well as the width of the scour hole. The procedure for its use is also indicated in Appendix II. A package named *SKI-SCOUR* is prepared for general use by anyone, to get predicted values of scour depth, length, and geometry from an input of q, H_1, R, d_{50}, d_w, and ϕ parameters. (This could be made available by an e-mail request to the first writer.)

Table 6. Connection Weights and Biases (Refer to Fig. 7)

Weights (w)					Biases
$w_{1,6}=3.49$	$w_{2,6}=-0.08$	$w_{3,6}=0.16$	$w_{4,6}=1.90$	$w_{5,6}=0.26$	$\theta_6=-0.45$
$w_{1,7}=3.49$	$w_{2,7}=-0.09$	$w_{3,7}=0.22$	$w_{4,7}=2.09$	$w_{5,7}=0.18$	$\theta_7=-0.47$
$w_{1,8}=2.63$	$w_{2,8}=0.86$	$w_{3,8}=0.24$	$w_{4,8}=-1.55$	$w_{5,8}=0.93$	$\theta_8=-2.91$
$w_{1,9}=2.19$	$w_{2,9}=0.33$	$w_{3,9}=0.19$	$w_{4,9}=-0.28$	$w_{5,9}=1.08$	$\theta_9=-2.23$
$w_{1,10}=2.93$	$w_{2,10}=-1.70$	$w_{3,10}=-1.29$	$w_{4,10}=-0.77$	$w_{5,10}=0.13$	$\theta_{10}=-1.19$
$w_{1,11}=1.95$	$w_{2,11}=-0.08$	$w_{3,11}=0.29$	$w_{4,11}=0.58$	$w_{5,11}=0.98$	$\theta_{11}=-1.36$
$w_{1,12}=3.08$	$w_{2,12}=-0.04$	$w_{3,12}=0.42$	$w_{4,12}=1.97$	$w_{5,12}=0.55$	$\theta_{12}=-0.53$
$w_{1,13}=2.96$	$w_{2,13}=-1.84$	$w_{3,13}=-1.32$	$w_{4,13}=-0.69$	$w_{5,13}=0.0001$	$\theta_{13}=-1.18$
$w_{1,14}=1.96$	$w_{2,14}=-0.09$	$w_{3,14}=0.29$	$w_{4,14}=0.61$	$w_{5,14}=0.98$	$\theta_{14}=-1.33$
$w_{1,15}=3.76$	$w_{2,15}=-3.04$	$w_{3,15}=-1.34$	$w_{4,15}=0.42$	$w_{5,15}=-1.09$	$\theta_{15}=-0.75$
$w_{6,16}=1.57$	$w_{7,16}=1.55$	$w_{8,16}=-0.11$	$w_{9,16}=0.02$	$w_{10,16}=2.70$	$\theta_{16}=-7.18$
$w_{11,16}=0.43$	$w_{12,16}=1.11$	$w_{13,16}=2.79$	$w_{14,16}=0.45$	$w_{15,16}=3.67$	$\theta_{17}=-5.79$
$w_{6,17}=0.87$	$w_{7,17}=0.83$	$w_{8,17}=3.05$	$w_{9,17}=2.68$	$w_{10,17}=0.45$	$\theta_{18}=-5.92$
$w_{11,17}=2.06$	$w_{12,17}=1.28$	$w_{13,17}=0.24$	$w_{14,17}=2.04$	$w_{15,17}=-1.63$	
$w_{6,18}=1.53$	$w_{7,18}=1.71$	$w_{8,18}=2.52$	$w_{9,18}=1.16$	$w_{10,18}=-0.52$	
$w_{11,18}=0.81$	$w_{12,18}=1.55$	$w_{13,18}=-0.65$	$w_{14,18}=0.81$	$w_{15,18}=-1.92$	

Note: $w_{i,j}$=connection weight between nodes i and j; and θ_k=bias in node k.

Significance of Input Parameters

An attempt was made to ascertain the importance or influence of different input parameters of q, H_1, d_{50}, R, d_w, and ϕ on the scour dimensions (namely d_s, l_s, and w_s). Various input combinations as in Tables 4 and 5 were considered by adding input variables one by one and their influence on testing the data sets was evaluated in terms of the RMSE and r criteria. Table 4 shows the outcome in terms of raw variables while Table 5 shows the same for their groupings. These tables give the impression that bucket geometry (R and ϕ) has only marginal influence on resulting scour compared to other site conditions. However considering the limitations and uncertainties in the data a full-fledged network involving all inputs variables would be desirable.

An alternative to the above analysis is to work out the "relative importance" of input quantities by multiplying connection weights between different neuron layers (Garson 1991; Goh 1994). This was done for raw variables input as well as for that of the grouped variables. This scheme of assessment again indicates a smaller influence of bucket radius, (but not lip angle ϕ) and head H_1 on the scour hole formation.

In view of the variability in the outcome resulting from application of different analytical schemes and in light of the fact that the bucket radius and the lip angle are most easily available with the designer it is felt that the network which requires all input quantities may be followed for generality.

Table 4. Sensitivity Analysis of Raw Variables (Case: Feed Forward Back Propagation 1)

Input variables	Root mean square error (RMSE)/ r (correlation coefficient) d_s	l_s	w_s
q, H_1	RMSE=0.54 r=0.86	RMSE=0.35 r=0.96	RMSE=0.37 r=0.89
q, H_1, d_{50}	RMSE=0.34 r=0.93	RMSE=0.34 r=0.97	RMSE=0.30 r=0.91
q, H_1, d_{50}, d_w	RMSE=0.33 r=0.9	RMSE=0.36 r=0.99	RMSE=0.21 r=0.97
q, H_1, d_{50}, R, ϕ	RMSE=0.42 r=0.91	RMSE=0.34 r=0.99	RMSE=0.68 r=0.85
q, H_1, d_{50}, R, d_w, ϕ	RMSE=0.32 r=0.96	RMSE=0.35 r=0.99	RMSE=0.20 r=0.98

Note: d_s=scour depth; l_s=scour length; w_s=scour width; q=unit discharge; H_1=head; d_{50}=median diameter; R=bucket radius; and ϕ=lip angle.

Parametric Study

In order to know if the trained network is able to reproduce the physical phenomenon of scour satisfactorilya parametric study was made. Keeping all input parameters but one as constants (at their average magnitudes) at a time, the variation of the scour depth with respect to different causative variables was drawn. Fig. 8 shows such a variation of scour hole depth d_s with q, H_1, R, d_{50}, d_w, and ϕ, respectively. From this figure it is clear that higher discharge results in a deepening of the scour; the corresponding depth of scour is very high in the beginning and much lower after

Table 5. Sensitivity Analysis of Grouped Variables (Case: Feed Forward Back Propagation 2)

Input variables	Root mean square error (RMSE)/ r (correlation coefficient) d_s/d_w	l_s/d_w	w_s/d_w
F_0, H_1/d_w	RMSE=1.78 r=0.89	RMSE=1.80 r=0.97	RMSE=4.25 r=0.91
F_0, H_1/d_w, d_{50}/d_w	RMSE=0.43 r=0.98	RMSE=0.66 r=0.99	RMSE=1.4 r=0.99
F_0, H_1/d_w, d_{50}/d_w, R/d_w	RMSE=0.53 r=0.98	RMSE=0.85 r=0.99	RMSE=1.36 r=0.99
F_0, H_1/d_w, d_{50}/d_w, R/d_w, ϕ	RMSE=0.57 r=0.97	RMSE=0.72 r=0.99	RMSE=1.67 r=0.99

Note: d_s=scour depth; d_w=water depth; l_s=scour length; w_s=scour width; F_0=Froud number; H_1=head; d_{50}=median diameter; R=bucket radius; and ϕ=lip angle.

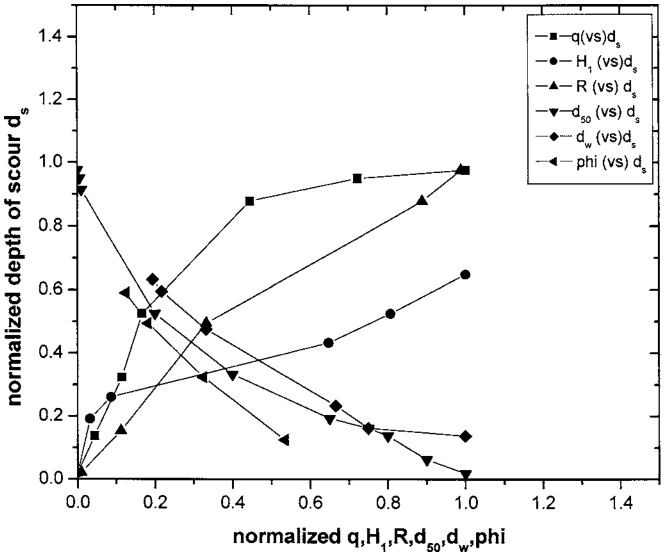

Fig. 8. Variation of d_s with q, H_1, R, d_{50}, d_w, and ϕ

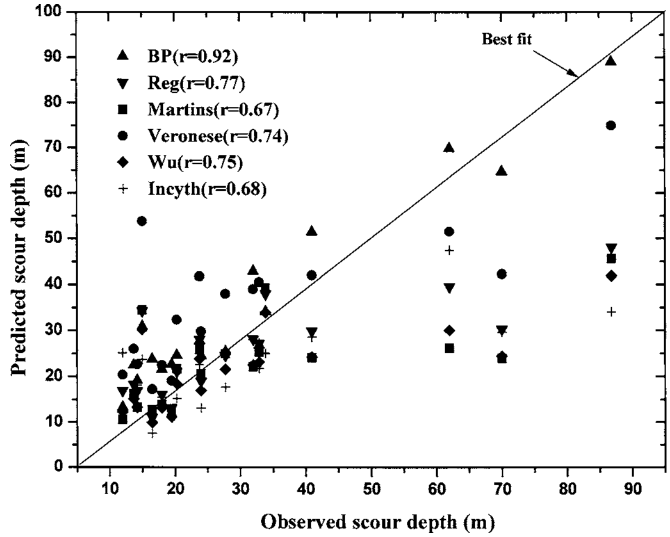

Fig. 10. Performance of neural networks, traditional scour predictors, and regression model

around the middle of the discharge range. Increase in scour depth with the available head could be noted from Fig. 8. The rate of increase is nonuniform, indicating underlying nonlinearity. As expected, higher values of the bucket radius, the sediment size, and the tail water depth produce smaller scour as seen in Fig. 8. Increase in the lip angle may result in higher depth of scour due to increasing height of the jet while total momentum remains almost the same. It may thus be seen that the trained network produced physically consistent output.

Network Based on Prototype Data

Another study to estimate the scour based on past prototype measurements rather than against the above-described case of scale-model observations was also conducted. A survey of available publications reporting such observations was done. This indicated that only three types of information, namely, scour depth below tail water level t, discharge intensity q, and head drop H_1 are uniformly reported in all references. Further, considering that many traditional prediction formulas, including those due to Veronese (1937), Damle et al. (1966), Wu (1973), Martins (1975), and INCYTH-LHA (1982) are based only on q and H_1 a neural network with two input nodes (for q and H_1) and one output node (for the scour depth t) only was developed (see Fig. 9). In total there were 91 input–output pairs formed out of the published data. The training and testing of these data were done in a manner similar to the analysis of the hydraulic model observations reported in all previous sections. Details of this work are available in Azmathullah (2004). From this study it was found that similar to the experimental data considered in this paper the FFBP network provided the most satisfactory training and that the neural network predictions of d_s, l_s, and w_s based on the information of q and H_1 were much better than those obtained by the common formulas of Veronese (1937), Wu (1973), Martins (1975), and INCYTH-LHA (1982), as well as by the newly fitted regression equation ($d_s = 1.42q^{0.44}H_1^{0.3}$). The scour depths arrived at using the above four formulas (with respect to the validation data set) were compared with corresponding "true" or measured values. Fig. 10 shows the result in scatter plots of predictions against observations.

However the best network predictions in this case corresponded to $r=0.92$, AE$=-8.9\%$, and $d=13.27$ as against their values of 0.97, -6.7%, and 7.6, respectively in the present hydraulic model data case, indicating that if more accurate predictions are desired, use of parameters of R, d_{50}, d_w, and ϕ would be necessary in addition to those of q and H_1.

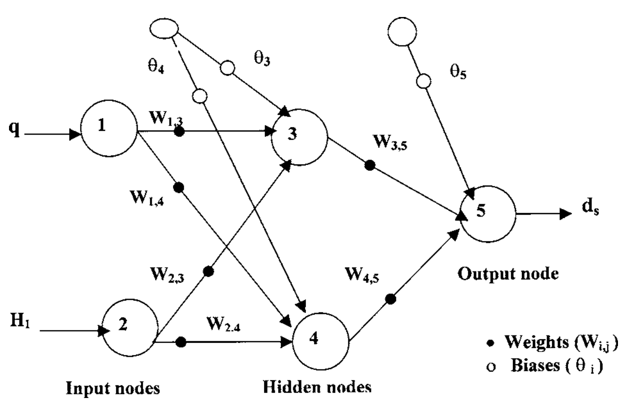

Fig. 9. Typical neural network architecture

Conclusions

An alternative approach to the traditional empirical formulas used to obtain scour downstream of the ski-jump bucket spillway is presented in this study. It is based on the approach of neural networks and it involved analysis of an extensive data base in order to obtain the depth, the location of maximum scour from the bucket lip, as well as the width of scour hole out of the given parameters of q, H_1, R, d_{50}, d_w, and ϕ.

The network predictions were generally more satisfactory than those given by traditional regression equations because of low errors and high correlation coefficients.

Although the common and simple feed forward back propagation network took a very large time to train compared to some advanced schemes, it imparted equally reliable training as the latter.

Incorporation of causative variables in grouped form was found to be more rewarding than that of their raw or individual state.

The input of bucket radius, lip angle, sediment size, and tail water depth was found to be necessary in addition to that of unit discharge and height of fall (as practiced in traditional formulas), if accurate predictions are desired.

Further research based on the type of rock bed, classified as per rock quality designation, and rock mass rating by using artificial neural network (ANN) and adaptive network based inference system (ANFIS) is underway.

Acknowledgment

The writers are grateful to Dr. Masoud Ghodsian of Tarbiat Modarres University, Tehran, Iran for sparing his experimental data that enabled authors to considerably increase their database.

Appendix I. Error Measures Used

Correlation Coefficient

$$r = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \tag{11}$$

where $x = X - X'$; $y = Y - Y'$; X=observed scour values; X'=mean of X; Y=predicted scour values; and Y'=mean of Y.

Average Error

$$\mathrm{AE} = \frac{\sum \frac{X - Y}{X} \times 100}{n} \tag{12}$$

where n=total number of pairs of X and Y values.

Average Absolute Deviation

$$d = \frac{\sum |(Y - X)|}{\sum X} \times 100 \tag{13}$$

Root Mean Square Error

$$\mathrm{RMSE} = \left[\frac{\sum (X - Y)^2}{n}\right]^{1/2} \tag{14}$$

Appendix II: Weight and Bias Matrix for Feed Forward Back Propagation (Model 2)

Output of the network can be obtained as follows:

1. Sum up weighted inputs, i.e.

$$\mathrm{Nod}_j = \sum_{i=1}^{\mathrm{NIN}} (W_{ij} x_i) + \theta_j \tag{15}$$

where Nod_j=summation for the jth hidden node; NIN=total number of input nodes; W_{ij}=connection weight ith input and jth hidden node; x_i=normalized input at the ith input node; and θ_j=bias value at the jth hidden node.

2. Transform the weighted input

$$\mathrm{Out}_j = 1/[1 + e^{-\mathrm{nod}_j}] \tag{16}$$

where Out_j=output from the jth hidden node.

3. Sum up the hidden node outputs

$$\mathrm{Nod}_k = \sum_{j=1}^{\mathrm{NHN}} (W_{jk} \mathrm{Out}_j) + \theta_k \tag{17}$$

where Nod_k=summation for the kth output node; NHN=total number of hidden nodes; W_{ik}=connection weight between the jth hidden and kth output node; and θ_k=bias at the kth output node.

4. Transform the weighted sum

$$\mathrm{Out}_k = 1/[1 + e^{-\mathrm{nod}_j}] \tag{18}$$

where Out_k=output at the kth output node. Referring to Fig. 7 let nodes 1,2,3,4, and 5=top to bottom input nodes, respectively; nodes 6,7,8…. and 15=hidden nodes from top to bottom, respectively; and nodes 16,17, and 18=top to bottom output nodes, respectively. The weight and bias matrix of the trained network is given in Table 6.

Notation

The following symbols are used in this paper:

d = average absolute deviation;
d_s = maximum depth of scour below tail water level (m);
d_w = tail water depth (m);
d_{50} = mean sediment size (m);
F_0 = Froude number;
g = acceleration due to gravity (m^2/s);
H_1 = head between upper (reservoir) water level and tail water level (m);
l_s = distance of maximum scour depth from spillway bucket lip (m);
q = water discharge per unit width ($m^3/s/m$);
R = radius of bucket (m);
RMSE = root mean square error;
r = correlation coefficient;
w_s = maximum width of scour hole (m);
ρ_s = sediment density;
ρ_w = density of water; and
ϕ = lip angle of bucket (radians).

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