

Scour Depth Prediction for Asa Dam Bridge, Ilorin, Using Artificial Neural Network

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Abstract. Bridge Scour is the localized loss of the geomaterials around the foundation of a bridge as a result of the movement of water around it. Scour is a great risk to the stability of a bridge's foundation, thus leading to collapse, loss of lives and setback in a nation's socio-economic life. Artificial Neural Networks (ANN) are collections of simple, highly connected processing elements that learn according to sets of input parameters and use that to simulate the networks of nerve cells of humans or animal central nervous system. The Asa Dam Bridge, one of the longest bridges in Ilorin, Kwara State, Nigeria, has five (5) spans of 20m each. The bridge connects Ilorin to the Ogbomosho Express way (leading to the western part of the country) and the Eyenkorin-Jebba road (leading to the north). Thus, the bridge has a high economic value. In this research, factors such as flow depth, average flow velocity of the river and median sediment size were investigated to show how they affect the depth of scour around the bridge pile foundation. Data were taken for a period of 48 weeks and ANN was applied to predict and generate a model that shows how these factors relate to the scour depth of the riverbed. The model revealed that the hydraulic parameters and soil grading around the pile cap of Asa River Bridge bears significant influence on the scour depth of its foundation. The model was compared with five (5) other established scour equations.

Introduction

Civil engineering is concerned with the design of structures for stability and economy in order to improve the state of living of human beings. Bridges are structures constructed over water bodies, valleys, and roads to allow for passage of vehicles, humans and goods across the span of the bridge. When an obstruction such as a bridge abutment are placed over a bed in a river stream, it leads to a three-dimensional change of the flow due to the development of a spiral flow in the area of the obstruction [1]. In abutments, the flow separates at the upstream face of the abutment as it travels by its side, creating a vortex trail that run downstream leading to the scouring of the sediment bed in the area of the abutment foundation, hence, predisposing the bridge to failure. Scour is the process of removing underwater sediment from the base of a structure by waves and currents [2–7]. Due to the scouring action of water, bridge failures occur [8]. Failure of bridges due to scour at the foundation of abutments and piers is a common occurrence. This is a serious threat to the safety of a bridge as scour weakens the foundations of a bridge by removing the soils around them [9–15]. Maddison [16] highlighted several bridges that collapsed due to scouring. The Oko bridge, constructed in 2005, linking Oro-Ago in Ifelodun Local Government Area of Kwara State, Nigeria, with the other parts of the state collapsed on 2nd October 2010, due to scouring.

Scour could be categorized as local, contraction and general [11, 13, 17-18]. Melville [19] opined that upstream flow depth, flow intensity, upstream flow velocity, Euler number, sediment size and

shape, floating debris, time, pier width, pier alignment, pier shape and submergence of superstructure are factors that influences scour at bridges.

Extensive experimental investigations have been conducted to determine a method of predicting scour depth for various abutment situations [20]. Some models generated from some of these research works are shown in Eq. 1 to Eq. 5.

$$\frac{d_{se}}{b} = 2 \left[2 \frac{U}{U_c} - 1 \right] \tanh \left(\frac{h}{b} \right) K_s K_\theta \quad (1)$$

Where d_{se} = maximum scour depth in equilibrium condition; b = pier width; U = approaching flow velocity; U_c = critical velocity for sediment motion; h = approaching flow depth; θ = Shields mobility parameter calculated based on sediment size; K_s = pier shape factor; K_θ = pier alignment factor [21].

$$d_{se} = 1.84b \left[\frac{h}{b} \right]^{0.3} Fr_c^{0.25} \quad (2)$$

Where d_{se} = maximum scour depth in equilibrium condition; b = pier width; h = approaching flow depth; Fr = Froude number; Fr_c = Critical Froude number; [22].

$$d_{se} = K_{hb} K_I K_d K_s K_\theta K_G \quad (3)$$

Where d_{se} = maximum scour depth in equilibrium condition; K_{hb} = depth scale coefficient; K_I = flow intensity coefficient; K_d = sediment size coefficient; K_s = pier shape coefficient; K_θ = pier alignment coefficient; and K_G = channel geometry effects on scour depth; [23].

$$\frac{d_{se}}{b} = 2K_1 K_2 K_3 K_4 K_w \left(\frac{h}{b} \right)^{0.35} Fr^{0.43} \quad (4)$$

Where d_{se} = maximum scour depth in equilibrium condition; K_1 = pier nose shape correction factor; K_2 = flow angle of attack correction factor; K_3 = presence of bed forms correction factor; K_4 = bed armouring correction factor; and K_w = wide piers in shallow flows correction factor; [24].

$$\frac{d_{se}}{D_e} = \left(\frac{d_{se}}{D_e} \right)_{max} g_1 g_2 g_3 \quad (5)$$

where g_1 and g_3 represent the effect of shallowness and sediment coarseness, and g_2 represents the effect of flow intensity that is independent of the pier design; [8].

However, the various approaches used do not always give realistic results for scour predictions [25]. The use of artificial intelligence in modelling complex problems in Civil Engineering has brought solutions to this challenge. One of such artificial intelligence is the ANN [26-27]. ANN which consists of several interconnected neurons is an alternative method to overcome the variation of physical modeling and it is a good function approximator.

Neural networks can map a random input pattern to a random output pattern [26]. A typical ANN consists of several nodes that are organized according to a particular arrangement. In a feed forward network, the nodes are generally arranged in layers, with each layer having one or more nodes. Information passes from the input to the output side [28-29]. In most networks, the input layer receives the input variables from the problem at hand. This consists of all the quantities that can influence the output. The input layer is thus transparent, and it is a means of providing information to the network. The output layer consists of values predicted by the network and thus represents nodal output. Some researchers [29-32] have used ANN in predicting scour for different bridge piles.

This research aims at predicting the scour depth for the Asa Dam Bridge, Ilorin, with ANN using onsite data collected from the bridge site for a period of forty (48) weeks. The onsite data collected gave the actual scenario that occurs at the pier being considered.

Description of Study Area

The Asa- Dam Bridge is located between latitude $8^{\circ} 27' 6.23''$ North and longitudes $4^{\circ} 33' 36.04''$ East, in Ilorin, Kwara state. The bridge which connects the Ilorin metropolis to the Ogbomosho express road is 100 m long having five (5) spans of 20 m each. A picture of the bridge with exposed piles is shown in Fig 1.



Fig. 1 Asa-Dam Bridge showing signs of scouring

Materials and Methods

Determination of the Bridge profile

The profile section of the bridge riverbed was obtained using an electronic surveying instrument (Total station). The vertical profile of the riverbed was plotted from the data collected using the instrument.

Flow and Scour depth assessment at the Bridge

In determining the flow and scour depths at the Asa river bridge area, a weekly record was taken for forty-eight (48) weeks. Due to the high volume of the flowing water at some periods of this research, data were taken from the deck of the bridge to get the values for the flow depth. Improvisation of a measuring device was adopted by fabricating a long rod which was lowered into the river very close to the pile until it touched the bottom of the river after which it was pulled out and the depth of flow and scour were determined from the height of water on the rod as shown in Fig. 2. This procedure was repeated for the forty-eight (48) weeks being reported.



Fig. 2 Flow and scour depths determination at the Bridge location

Determination of flow velocity

A 75 cl plastic bottle was used to determine the flow velocity of the Asa river under the bridge. A stopwatch was used to determine the time-taken for the floating object to cover a predetermined distance from a known point along the river course. The velocity was determined by calculating the ratio of distance covered with the time taken for the bottle to cover the distance. The process was repeated three times to get the average velocity. This process was done weekly and recorded for the forty-eight (48) weeks being reported.

Particle Size Distribution Test on Samples

Sieve analysis was carried out at the Soil Laboratory of the Federal Polytechnic Offa using standard B.S. sieves to determine the soil grading around the pile cap to determine the soil's erodibility. Samples were taken from the riverbed for the period being reported very close to the pile cap. The samples were dried and weighed to the nearest 0.1g. The weights of the samples were recorded. The set of sieves were placed in a pan, with the largest opening on top plus cover, and the samples poured into the top sieve. The material was separated into a series of particle sizes using the sieves. The entire samples were sieved by lateral and vertical motion of the sieves with a "jarring" action that keeps the material moving continuously over the surface of the sieves. The sieving continued until no material passed through the sieve. Particles clinging to each sieve was brushed into the next lower sieve with a bristle brush. It was ensured that no material was lost. The individual weights were determined to the nearest 0.1g of aggregate retained on each sieve and the weights were recorded. An empty pan was placed on the scale and its weight was tared (zeroed out). The retained aggregate was poured into the empty pan and the weight recorded. The pan was re-tared for the next sieve size. This process was repeated until the weight of the materials on each sieve and the retaining pan (typically the material passing the No. 200 sieve) were recorded. The percentages were reported to the nearest 0.1% for each size of aggregate retained on each sieve. The percentage passing was plotted against the particle diameter and the average diameter of the particles (d_{50}) was obtained for the period being reported.

Artificial Neural Network Training

The processing ability of ANN is stored in the inter-unit connection strengths or weights obtained by a process of learning from a set of training patterns. The multilayered perceptron equation used is given in Eq. 6:

$$g(x) = f(w_0 + \sum_{i=1}^n w_i x_i) \quad (6)$$

Where w_0 denotes the intercept, $w_i = (w_1, w_2, \dots, w_n)$ the vectors consisting of all synaptic weight without the intercept, and $x = (x_1, x_2, \dots, x_n)$ the vector of all independents variable [28]. In this research, $g(x)$ is the scour depth, while $x = (x_1, x_2, x_3)$ are sediment size, average velocity and flow depth respectively.

The common measures of comparing two or more continuous predictions based on the model performance are: absolute mean deviation (Error Rate), mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and root mean absolute error (RMAE). If $Y = \text{Actual(observe) value}$, $\hat{Y} = \text{Predicted value}$ and $n = \text{sample size}$, the corresponding formulas are: $\text{Deviation (D)} = \frac{Y - \hat{Y}}{Y}$; $\text{Error Rate} = \frac{\sum_{i=1}^n |D|}{n}$; $\text{MSE} = \frac{\sum_{i=1}^n (Y - \hat{Y})^2}{n}$; $\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (Y - \hat{Y})^2}{n}}$; $\text{MAE} = \frac{\sum_{i=1}^n |Y - \hat{Y}|}{n}$ and $\text{RMAE} = \sqrt{\frac{\sum_{i=1}^n |Y - \hat{Y}|}{n}}$.

The structural architecture of the adopted ANN model is shown in Fig. 3. The Figure revealed the training learning rate of the ANN with best hidden layers of 2, the input learning rate include flow depth, average velocity and sediment size as contained in the analysis. These inputs were learning by optimizing the weighted value contained in the loss function for proper updating of the optimization to produce the best output variable (scour depth). In general, this structure displays the movement of

input variables (flow depth, average velocity and sediment size) to the weighted value and finally producing the output variable (scour depth).

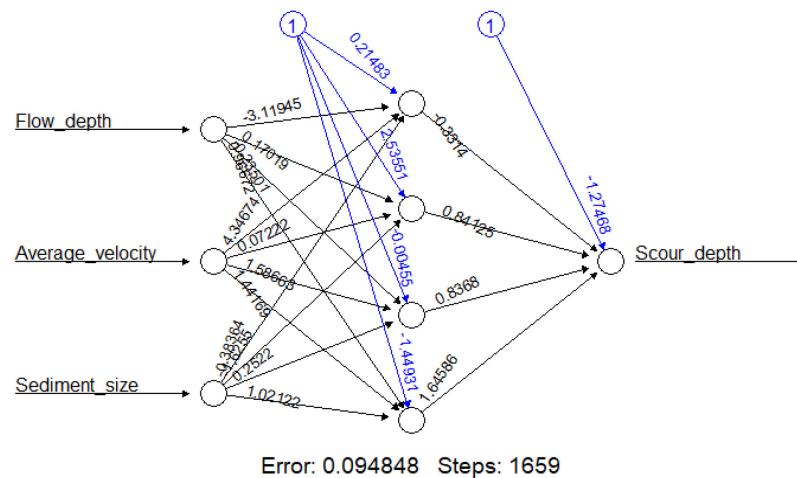


Fig. 3 Structural Architecture of the adopted ANN Model

Results and Discussions

The vertical profile of the river bed plotted from the data obtained using the Total station is shown in Fig. 4. The comparison of the ANN results and the existing models are presented in Table 1.

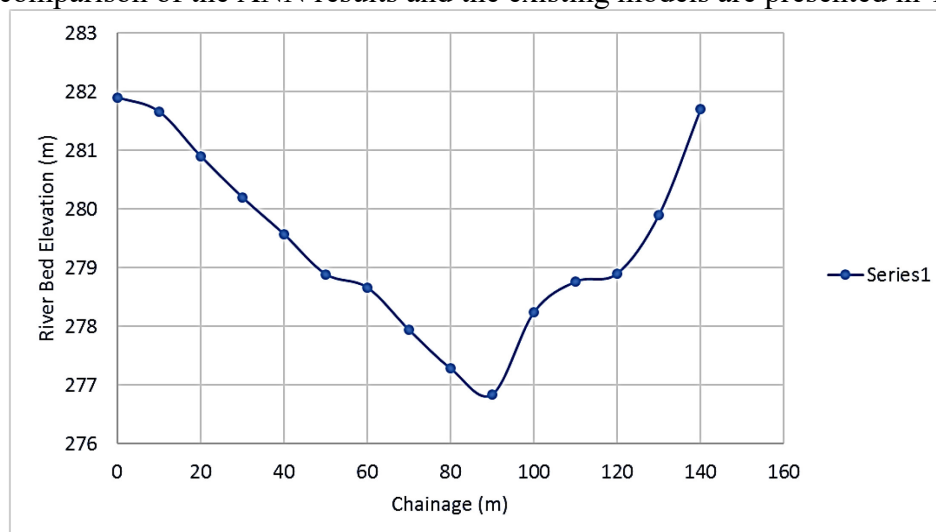


Fig. 4 Vertical profile of the Asa Bridge riverbed

Table 1 Comparison between the proposed and the existing models using model validation

Model**	ANN	[21]	[22]	[23]	[24]	[8]
Validation	Predicted (Proposed)					
Error Rate	0.5065	4.9739	5.8402	0.6202	31.54	1.3292
MSE	0.1145	82.855	2.2747	0.1856	90.9798	0.3001
RMSE	0.3384	9.1025	1.5082	0.4309	9.5383	0.5479
MAE	0.2776	5.2238	1.4722	0.3796	4.2649	0.5011
RMAE	0.5269	2.2856	1.2134	0.6162	2.0652	0.7079

** the lower the indices the better the model

From Table 1, the various results of ANN and the existing model were presented based on earlier explained measures of indices. The results reveal that the ANN adopted model performed better than any of the existing models irrespective of the indices, since it is the only model with minimum measures of indices across the existing methods. Moreover, the next performing model after the ANN model is the model used by [8] which also shows a reasonable improvement over other methods, followed by the model developed by Jain and Fischer [22] and Melville [23]. However, other methods apart from these three methods shows a poor prediction of the scour depth and drastically showcase a higher deviation from the original experimental results of the scour depth.

To further strengthen the comparison between these models, the results of the experiments based on observed scour depth and predicted value of all the models were plotted for easy assessment. It was observed that the ANN model predicted a value that is smoothly aligning and close to the observed scour depth than any other values predicted by the other models as shown in Fig. 5.

The data used for the ANN model predictions and predictions obtained from the model of [8, 21-24] are reported in Table 2.

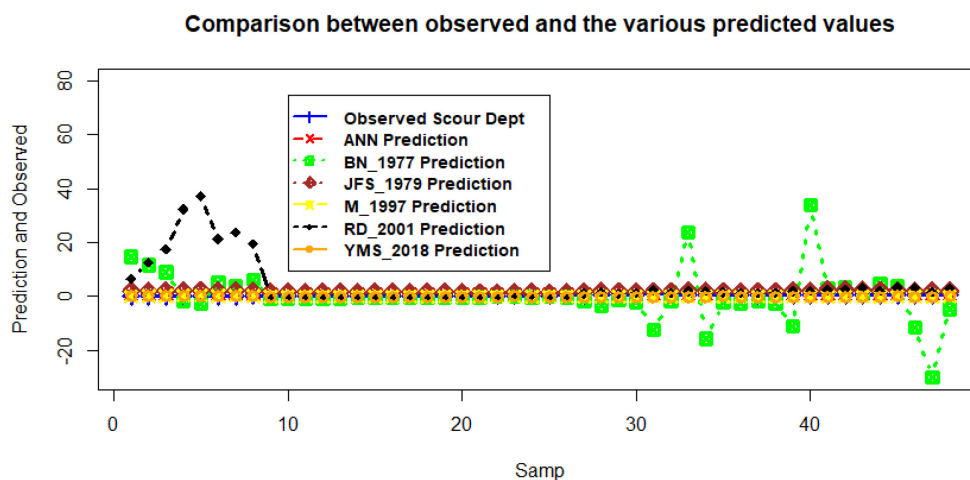


Fig. 5 Comparison between the observed and predicted values

Table 2 Observed and predicted scour parameters at the Asa river

Week	Date	Flow depth (m)	Average flow velocity (m/s)	Median Sediment size (mm)	Observed Scour depth (m)	ANN Predicted Scour depth (m)	[21] model scour prediction (m)	[22] model scour prediction (m)	[23] model scour prediction (m)	[24] model prediction (m)	[8] prediction (m)
1	29 th October, 2017	1.75	2	3.00	0	0.14	14.67	2.15	0.08	6.55	-0.02
2	5 th November, 2017	1.73	3.7	2.80	0.05	0.14	11.66	2.13	0.15	12.70	-0.01
3	12 th November, 2017	1.72	5	2.93	0.08	0.14	8.94	2.14	0.20	17.56	0.00
4	19 th November, 2017	1.74	8.8	2.85	0.09	0.14	-1.69	2.14	0.36	32.40	0.00
5	26 th November, 2017	1.78	10	3.30	0.12	0.14	-2.56	2.18	0.37	37.32	0.00
6	3 rd December, 2017	1.75	6	2.85	0.20	0.14	5.07	2.14	0.24	21.44	0.00
7	10 th December, 2017	1.73	6.6	2.80	0.20	0.14	3.90	2.13	0.27	23.73	0.00
8	17 th December, 2017	1.75	5.5	2.85	0.26	0.14	6.26	2.14	0.22	19.52	0.00
9	7 th January, 2018	0.58	0	2.85	0.26	0.14	-0.76	1.69	0.00	0.00	-0.26
10	14 th January, 2018	0.57	0	2.85	0.26	0.14	-0.73	1.68	0.00	0.00	-0.26

11	21 st January, 2018	0.56	0	2.85	0.26	0.14	-0.70	1.67	0.00	0.00	-0.26
12	28 th January, 2018	0.56	0	2.85	0.26	0.14	-0.70	1.67	0.00	0.00	-0.26
13	4 th February, 2018	0.54	0	2.85	0.26	0.14	-0.65	1.66	0.00	0.00	-0.25
14	11 th February, 2018	0.53	0	2.85	0.26	0.14	-0.62	1.65	0.00	0.00	-0.25
15	18 th February, 2018	0.53	0	2.85	0.26	0.14	-0.62	1.65	0.00	0.00	-0.25
16	25 th February, 2018	0.5	0	2.85	0.26	0.14	-0.55	1.63	0.00	0.00	-0.25
17	4 th March, 2018	0.5	0	2.85	0.26	0.14	-0.55	1.63	0.00	0.00	-0.25
18	11 th March, 2018	0.49	0	2.85	0.26	0.14	-0.52	1.63	0.00	0.00	-0.24
19	18 th March, 2018	0.47	0	2.85	0.26	0.14	-0.48	1.61	0.00	0.00	-0.24
20	25 th March, 2018	0.44	0	2.85	0.26	0.14	-0.41	1.59	0.00	0.00	-0.23
21	2 nd May, 2018	0.34	0.16	1.30	0.34	0.08	-0.23	1.38	0.03	0.33	-0.18
22	8 th May, 2018	0.24	0.12	2.80	0.24	0.14	-0.12	1.39	0.02	0.23	-0.07
23	13 th May, 2018	0.28	0.34	3.30	0.34	0.15	-0.15	1.46	0.05	0.73	-0.04
24	20 th May, 2018	0.31	0.23	3.00	0.34	0.14	-0.19	1.48	0.03	0.49	-0.05
25	28 th May, 2018	0.20	0.12	3.00	0.398	0.14	-0.08	1.35	0.02	0.23	-0.06
26	4 th June, 2018	0.34	0.11	2.85	0.41	0.14	-0.24	1.50	0.01	0.22	-0.09
27	16 th June, 2018	0.81	0.42	2.93	0.44	0.14	-1.60	1.82	0.03	1.08	-0.06
28	23 rd June, 2018	1.05	0.62	2.62	0.46	0.13	-3.35	1.90	0.04	1.71	-0.06
29	29 th June, 2018	0.74	0.35	3.20	0.45	0.14	-1.29	1.80	0.03	0.88	-0.06
30	2 nd July, 2018	0.90	0.49	1.80	0.73	0.09	-2.08	1.77	0.04	1.30	-0.10
31	9 th July, 2018	1.38	0.80	1.36	1.145	0.25	-12.29	1.88	0.06	2.35	-0.11
32	16 th July, 2018	0.80	0.49	1.98	0.73	0.10	-1.52	1.74	0.05	1.27	-0.09
33	23 rd July, 2018	1.70	0.65	2.11	0.73	0.11	23.78	2.06	0.03	1.94	-0.09
34	30 th July, 2018	1.41	0.70	2.60	0.72	0.13	-15.77	2.02	0.04	2.04	-0.06
35	6 th August, 2018	0.94	0.55	2.98	0.64	0.14	-2.38	1.88	0.04	1.48	0.00
36	13 th August, 2018	0.94	0.48	3.15	0.45	0.14	-2.41	1.89	0.03	1.28	-0.06
37	20 th August, 2018	0.81	0.46	3.08	0.57	0.14	-1.60	1.83	0.04	1.19	-0.06
38	27 th August, 2018	0.94	0.52	3.11	0.6	0.14	-2.40	1.89	0.04	1.39	-0.06
39	3 rd September, 2018	1.35	0.67	2.96	0.53	0.14	-11.01	2.03	0.03	1.93	-0.06
40	10 th September, 2018	1.66	0.68	2.99	0.56	0.14	34.05	2.13	0.03	2.03	-0.06
41	20 th September, 2018	2.58	0.76	3.00	0.54	0.14	2.97	2.34	0.02	2.44	-0.06
42	24 th September, 2018	2.5	0.83	3.18	0.66	0.14	3.39	2.34	0.02	2.67	-0.05
43	2 nd October, 2018	2.89	0.97	3.21	0.52	0.14	1.33	2.42	0.02	3.23	-0.05

44	7 th October, 2018	2.28	0.69	3.26	0.59	0.14	4.91	2.30	0.02	2.16	-0.05
45	15 th October, 2018	2.39	0.99	3.10	0.54	0.14	3.97	2.31	0.03	3.21	-0.04
46	22 nd October, 2018	1.37	1.08	2.50	0.47	0.13	-11.49	2.00	0.06	3.24	-0.05
47	29 th October, 2018	1.48	0.58	2.80	0.49	0.14	-30.11	2.06	0.03	1.68	-0.07
48	5 th November, 2018	1.16	1.02	3.30	0.45	0.14	-4.65	1.99	0.06	2.97	-0.03

The importance of the predictors used in the ANN Model is shown in Fig. 6. Consequently, the flow depth, average velocity and sediment size greatly influences the scour depth. Among these three variables, the flow depth is found to be the most influential in predicting the scour depth of the flow, followed by the average velocity and lastly the sediment size. Therefore, to reduce the scouring around the pier of the bridge, efforts must be made to reduce the flow velocity by increasing the cross section of the river channel around the bridge area. This will also result in the reduction of the flow velocity. Boulders can be used as rip-rap around the bridge foundation, thus increasing the sediment size and reducing the effect of scour.

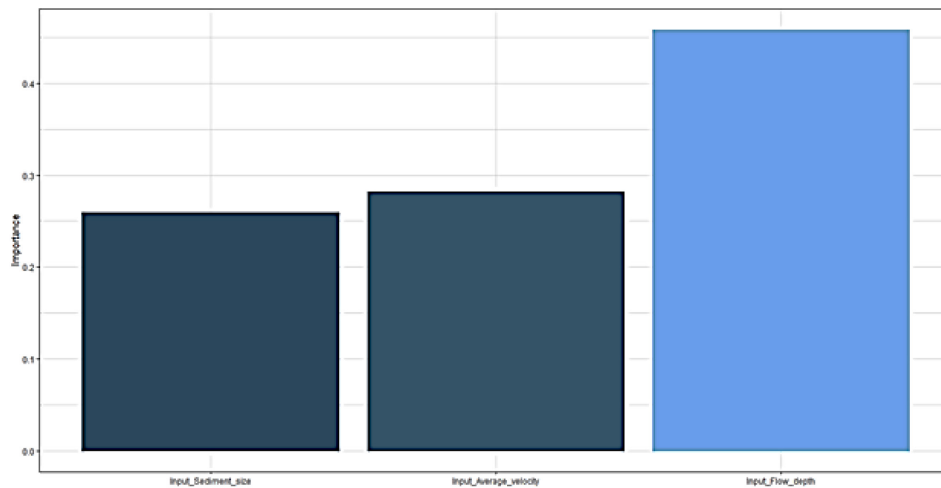


Fig 6 Importance of the predictors based on ANN Model

Conclusion

The local scour around Asa bridge foundation in Ilorin, Nigeria was evaluated using field estimated data. Hydraulic parameters, such as flow velocity, flow depth, sediment sizes and scour depth were obtained. ANN analysis was carried out to determine the significance level of the influence of these parameters on the scour depth of Asa bridge foundation. It was discovered that increase in the hydraulic parameters resulted in a corresponding increase in the local scour depth of the bridge foundation while increase in sediment sizes led to a decrease in the local scour depth. The generated model was validated by comparing the results obtained with established scour equations. The comparison revealed that scour equation models from [8, 22-23] were in good agreement with the field data while equation models from [21, 24] overestimated the scour depth. From this study, it can therefore be concluded that the influence of the flow velocity, flow depth of Asa River as well as particle sizes around the pile cap of the bridge have significant effect on the scour depth of the bridge.

Thus, efforts must be made to reduce the flow velocity by increasing the cross section of the river channel around the bridge area. This will result in the reduction flow depth and the flow velocity of the river. Boulders should be used as rip-rap around the bridge foundation, thus increasing the sediment size and reducing the effect of scour.

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