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ASSESSMENT OF LONGITUDINAL SHEAR STRENGTH PARAMETERS OF COMPOSITE SLAB BY ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Longitudinal shear strength is considered as a major constraint in the design of composite slab and it can be assessed by expensive and time consuming experimental techniques. The objective of the present work is to provide a numerical tool to minimize hurdles in the design process and to reduce the dependency on expensive and time-consuming experiments. In this article, Artificial Neural Networks model has been developed for finding the *m* and *k* values for determination of the horizontal shear resistance. It is demonstrated that, with proper training of the neural network using the ratio of pitch length to width of top flange and depth of profile as input values, the proposed neural network model can generate the values of *m* and *k* quite accurately. Inherently the Artificial Neural Network is computationally efficient tool and hence the developed Artificial Neural Network will be very useful in optimization procedures of the composite slab.

Keywords: profiled deck slab, horizontal shear strength, m-k method, artificial neural network (ann)

1. INTRODUCTION

Steel-concrete composite slab is a structurally efficient combination of constituents as it exploits the tensile resistance of the steel and compressive resistance of the concrete in effective manner. Some of the important benefits are: it acts as slab reinforcement; offers an immediate working platform; saves up to 30% material; and the most important benefit from practical consideration is easy and fast construction (Figure 1).

2. COMPOSITE FLOOR SYSTEM-MODES OF FAILURE

The capacity of the composite slab should be sufficient to resist the factored load for the

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ultimate limit state. In a profiled steel deck, there are three possible modes of failure;

- Flexural failure at section 1 – 1
- Longitudinal shear failure at section 2 – 2
- Vertical shear failure at section 3 – 3.

Figure 2(a) shows the location of failure planes. Figure 2(b) shows the three modes in a plot of $\frac{V_t}{b\,d_p}$ vs $\frac{A_p}{b\,L_s}$. Here Vt is the external shear force at the support section and the other notations are explained after the equation 1. The most usual one is the longitudinal shear failure. For determining the longitudinal shear failure, the Eurocode 4 [1] suggested the following two methods;

- m - k test
- Partial Interaction method

In both of them, the shear resistance has to be determined by full scale slab tests.

In the m – k method, the maximum design vertical shear V (causing longitudinal shear failure) for a width of slab b should not exceed the design shear resistance $V_{\ell\,Rd}$ which is determined from the following semi-empirical relation (EC 4, Cl. 7.6.1.3.2):

$$V_{\ell\,Rd} = \frac{b\ d_P}{\gamma_{vs}} \left(\frac{m\,A_P}{b\,L_S} + k \right) \tag{1}$$

where: b = width of the slab in mm
d_p = Depth of the profile in mm

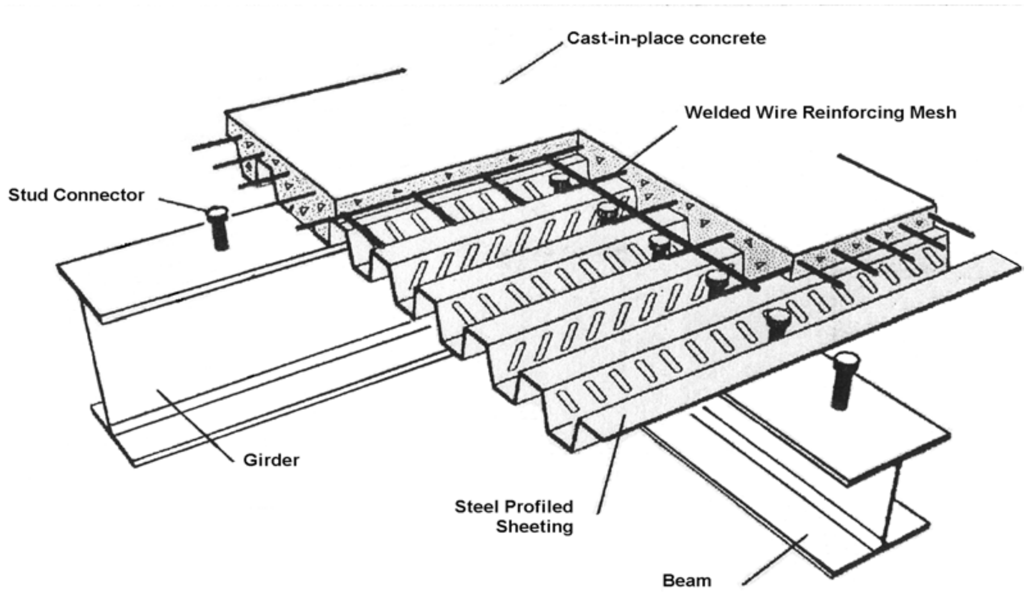

Figure 1. Details of composite profiled deck slab

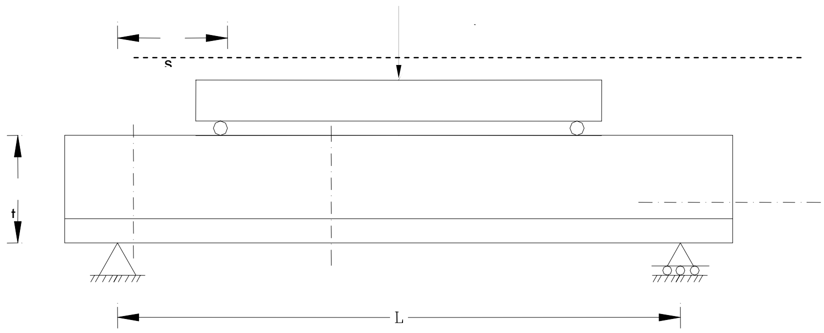

Figure 2(a). Modes of failure of composite slab

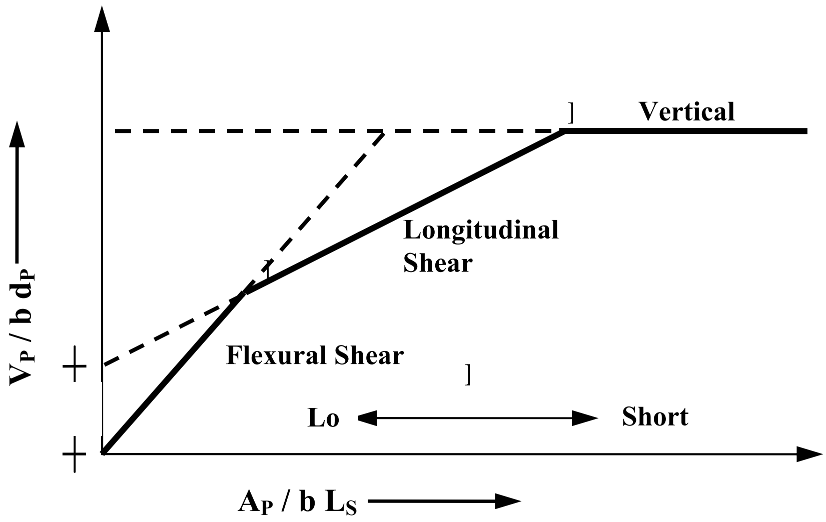

Figure 2 (b). Three modes of failure of composite slab

L_s = Length of the shear span in mm

A_p = Area of cross section the profile in sq. mm

m & *k* = design values for the empirical factors obtained from tests carried out in accordance with clause 10.3.1 of EC 4, in N/mm^2 [1.2]

γ_{vs} = Partial safety factor for shear connection (1.25)

h_t = Depth of the concrete slab

W = Applied Load

Normally, fabricators of steel sheeting provide engineers and builders with design tables for commonly used spans and thicknesses in order to facilitate the design of composite slabs. However, engineers who need to justify their calculations, or design slabs with non-standard dimensions generally will not have the necessary information required to carry out the calculations on which these design tables are based. This is because the information in the tables is determined by using the experimental values. Similarly, a fabricator wanting to develop a new sheeting profile currently does not have the means necessary to predict the degree to which it will be able to act compositely with the cast-in- place concrete [3, 4].

Nagy and Szatmari [5] presented the behavior of profiled decks as well as a review of ongoing research approaches. A clear mention was made of the need of an alternative approach to get best profiled sheet cross-sectional geometries satisfying strength and stability constraints at the construction stage. According to the authors, questions including horizontal shear resistance and independence from test data are still to be answered. Literature review clearly indicates the need of design approaches free from the expensive and time-consuming experiments (Mohan Ganesh et al.[6, 7], Nagy and Szatmari [5], Crisinel et al. [3,4]).

By considering the above points, the researchers are motivated to find the alternative solutions;

- that can reduce the number of performance tests required or replace them with smaller elemental tests that are less expensive.
- In the form of the numerical model to predict the composite slab strength.

Hence, all the above problems are put together, the objective of the present work is to provide an Artificial Neural Network based numerical tool that can minimize hurdles in the design process and reduce the dependency on expensive and time-consuming experiments.

3. NEURAL NETWORKS

Artificial neural networks have been used recently to recognize complicated patterns and solution of problems too complex to be modeled accurately by traditional computing methods. Civil engineering applications of neural networks have increased in recent years and continue to increase. A state of the art review of journal articles on civil engineering applications of neural networks is presented in a recent article by Adeli [8, 9, 10].

Neural Networks are simplified models of the biological nervous system and, therefore, have drawn their motivation from the kind of computing performed by a human brain. Neural Networks exhibit characteristics such as mapping capabilities or pattern association, generalization, robustness and high speed information processing. ANN can be trained with the known values from collected data or from the test data and they can recall full patterns from incomplete, partial, or noisy patterns. The main advantages of the Artificial Neural Networks are:

- Once appropriately trained, ANN works as model free estimator and it can be effectively used in solving the unknown or untrained instances of the problem.
- ANN has more fault tolerance capabilities.
- In future, whenever more data are available, further training can be done without starting from scratch.
- Okabe et al. [11] have developed the neural network to estimate the joint stiffness values at the beginning stage of the structure. Sirca, G.F. and Adeli [10] have used Artificial Neural network model for finding the uplift load capacity of Cold-formed Metal Roof Panels. The neural network is a very effective tool and solved a large

number of structural engineering problems.

In the present work Artificial Neural Network is used in the assessment of longitudinal shear strength parameters *m* and *k* of composite slab. The required design values of shear strength parameters are interpreted from the available *m* and *k* values by the neural network. For this, the sectional properties of the profiled deck and the corresponding *m* and *k* values are collected from various leading profiled deck manufacturers [12, 13, 14, 15] and the data are used to train an ANN which can over-ride the present practical difficulties and constraints. With proper training of the neural network, the proposed neural network model generates the values of *m* and *k* quite accurately.

4. DEVELOPMENT OF ANN NETWORK FOR PROFILED DECK SYSTEM

Most neural network applications are based on the back-propagation paradigm, which uses the gradient-descent method to minimize the error function [16]. Back-propagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors or classify input vectors in an appropriate way as defined. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities [17].

The back-propagation neural network is given its name due to its learning rule, where errors at the output nodes are back-propagated through the connections to update the weights of the connections. The back-propagation neural network and its variants are currently the most widely used networks in applications.

Properly trained back-propagation networks tend to give reasonable answers when presented with inputs that they have never seen. This generalization property makes it possible to train a network on a representative set of input and target pairs and get good results without training the network on all possible input and output pairs [17].

There are generally four steps in the training process:

- Determination of the training set
- ANN Architecture
- Training of the network
- Generalization Capabilities

5. DETERMINATION OF THE TRAINING SET

The training data of *m-k* values and profiled deck properties are obtained from the various multinational manufactures; Precision Metal Forming Ltd., Cheltenham, UK [12]; Richard Lee Steel Decking Ltd., Ashbourne, UK [13]; Structural Metal Decks, Ltd., Ringwood, UK [14] and Ward Building Components, Malton, UK [15].

The data sets like width of top flange, width of bottom flange, width of flange per pitch, thickness of profile, depth of profile are extracted from the design tables and manufacturers manual. All the parameters of the profiled decks from the collected data are listed in Table 1 (Figure 3) and compared with each other. The collected data are analyzed to obtain the minimum number of key parameters, having a substantial influence on the horizontal shear strength parameters of the deck. All the above data sets are critically compared with respect to the *m* and *k* values. Based on this, the following points are observed;

Table 1. Dimensions of the collected profiled decks

S. No.	**Specification**	**b_1 'mm'**	**b_2 'mm'**	**b 'mm'**	**b/b2**	**d_p 'mm'**	**t 'mm'**
1	Profile 1	130	38	152.5	4.01	51	0.9
2	Profile 2	130	38	152.5	4.01	51	1
3	Profile 3	130	38	152.5	4.01	51	1.1
4	Profile 4	130	38	152.5	4.01	51	1.2
5	Profile 5	130	40	150	3.75	51	0.9
6	Profile 6	130	40	150	3.75	51	1
7	Profile 7	130	40	150	3.75	51	1.2
8	Profile 8	112.5	40	152.5	3.81	51	0.9
9	Profile 9	112.5	40	152.5	3.81	51	1
10	Profile 10	112.5	40	152.5	3.81	51	1.1
11	Profile 11	112.5	40	152.5	3.81	51	1.2
12	Profile 12	105	67	225	3.36	46	0.9
13	Profile 13	105	67	225	3.36	46	1.2
14	Profile 14	136	112	300	2.68	55	0.9
15	Profile 15	136	112	300	2.68	55	1
16	Profile 16	136	112	300	2.68	55	1.1
17	Profile 17	136	112	300	2.68	55	1.2
18	Profile 18	135	115	300	2.61	80	1.2
19	Profile 19	140	120	300	2.50	50	0.9
20	Profile 20	140	120	300	2.50	50	1
21	Profile 21	140	120	300	2.50	50	1.1
22	Profile 22	140	120	300	2.50	50	1.2
23	Profile 23	119	129	300	2.33	80	0.9
24	Profile 24	119	129	300	2.33	80	1.2
25	Profile 25	133	140	333	2.38	60	0.9
26	Profile 26	133	140	333	2.38	60	1
27	Profile 27	133	140	333	2.38	60	1.2
28	Profile 28	110	153	333	2.18	60	0.9
29	Profile 29	110	153	333	2.18	60	1
30	Profile 30	110	153	333	2.18	60	1.1
31	Profile 31	110	153	333	2.18	60	1.2

- Contribution of *k* value in comparison to that of m value is less towards final horizontal shear resistance and is in the range of 20 % to 30 % only (Eq. 1). It is giving minimum effects.
- Thickness of profiled sheet has less or no impact on the *m* and *k* values because the *m* and *k* values are same for all the thickness of profiled sheets (t) that varying from 0.9mm to 1.2mm (the collected data of the 3 companies).
- Shear stress intensity is more at the neutral axis of the deck; hence width of the top flange of the profiled sheet and dimples provided at this level are more effective. This will improve the value of frictional resistance of the profiled deck (*m*).
- The depth of the profiled deck (d_p) also has substantial influence on the horizontal shear resistance.

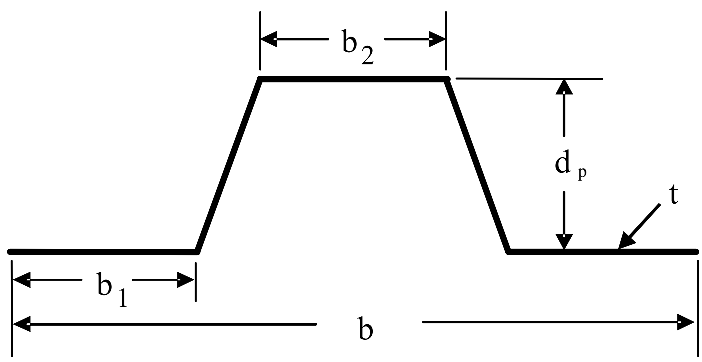

Figure 3. Cross section of trapezoidal profile (pitch length)

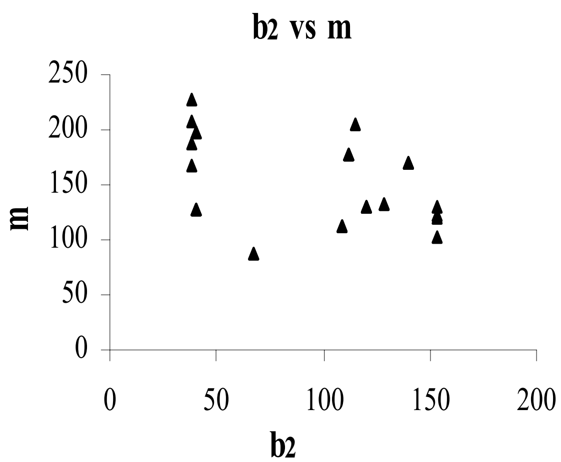

Figure 4. Comparison of b_2 vs *m*

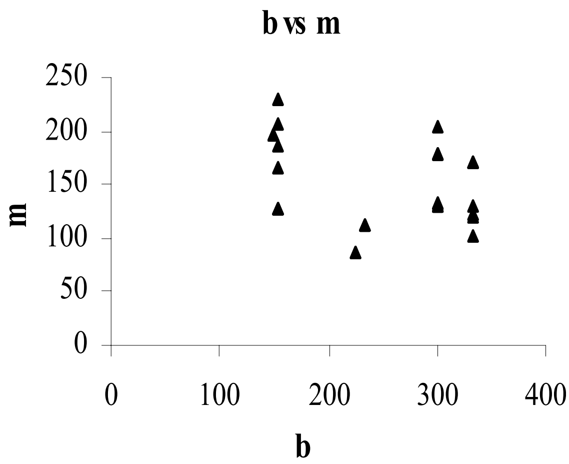

Figure 5. Comparison of b vs *m*

Width of top flange (b_2) vs *m*, pitch length (b) vs *m*, thickness of profile (t) vs *m* and width of bottom flange (b_1) vs *m* are plotted and is shown in Figure 4 to Figure 7. Based on this, the following points are observed from the plots (Figure 4 and Figure 5) that;

- In Figure 4 and figure 5, both the variations are similar except there is a horizontal shift between the two plots. It is decided that the ratio of top flange width and pitch length should be taken as an input parameter (I_1) in the ANN in place of two variables b & b_2.
- In figure 6 and Figure 7, the points in the plots are not having systematic patterns and hence are not included in the as input in ANN model.

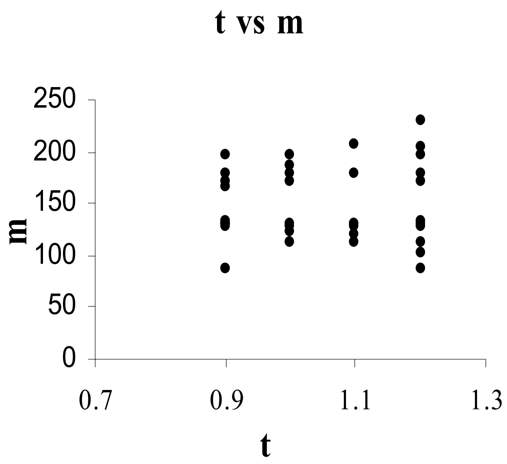

Figure 6. Comparison of t vs *m*

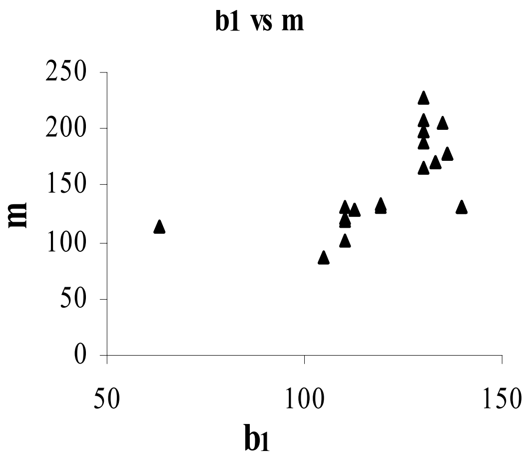

Figure 7. Comparison of b_1 vs *m*

This curtailment in the number of ineffective input nodes of ANN leads to a smaller size network, which can be trained easily and effectively with the help of less number of training data and accurate output values can be predicted. In addition, training time is reduced considerably. Hence, 'the ratio of top flange width to pitch length (I_1)' and 'the depth of the profiled deck (I_2)' are identified as the most critical parameters and hence included in the input layer (I_1, I_2) of the neural network, having two output nodes (O_1, O_2) giving m and k values for the deck (Figure 8).

6. ANN ARCHTECTURE

6.1 Network Size

As discussed above the network has 2 inputs and 2 outputs, the neural network architecture is developed based on the trial and error method in the Matlab programming language. For this, various sizes of networks have been tried out from 2–2–2 to 2–8–2 and finally 2–4–2 size networks is adopted and the performance value of the network is 0.130912. All the other networks gave less performance value than this 2–4–2 network and shown in figure 7. In this the following symbols are used to denote the various weights between the nodes; $W1_{hi}$–Weight between Hidden & Input layer; $W2_{oh}$–Weight between Output & Hidden layer; $W1_{3i}$, $W2_{5h}$–Bias Node in the Input, Hidden Layer respectively (Not shown in Figure 8). Figure 11 shows the performance function and convergence details.

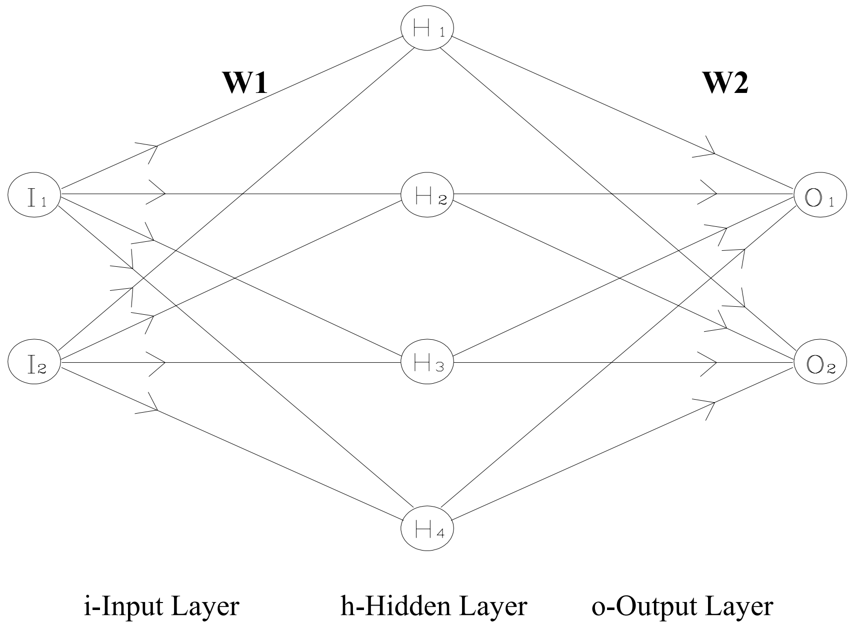

Figure 8. Architecture of neural network

6.2 Transfer Functions
The transfer function in the first layer of neural network is tan-sigmoid and defined as [17],

$$f(x) = \frac{1}{1+e^{-n}} \tag{2}$$

This transfer function maps the input to the interval (-1, 1) and the general plot is shown in Figure 9. The output layer transfer function is linear and plot is shown in figure 10.

6.3 Method of Training - Scaled Conjugate Gradient Algorithm
The conjugate gradient algorithm is chosen as the method of training the network because of the relative ease of implementation and quick learning convergence. Each of the conjugate gradient algorithms that has own methodology of a line search at each iterations. This line search is computationally expensive, since it requires that the network response to all training inputs be computed several times for each search. The scaled conjugate gradient algorithm (SCG), is designed to avoid the time-consuming line search developed by Moller. The basic idea of this algorithm is to combine the model-trust region approach (used in the Levenberg-Marquardt algorithm) with the conjugate gradient approach [17].

6.4 Performance Function - Mean Square Error
Mean square error (LMS) algorithm is a network performance function. It measures the network's performance according to the mean of squared errors. The least mean square error (LMS) algorithm is an example of supervised training, in which the learning rule is provided

with a set of examples (Eq.3) of desired network behavior:

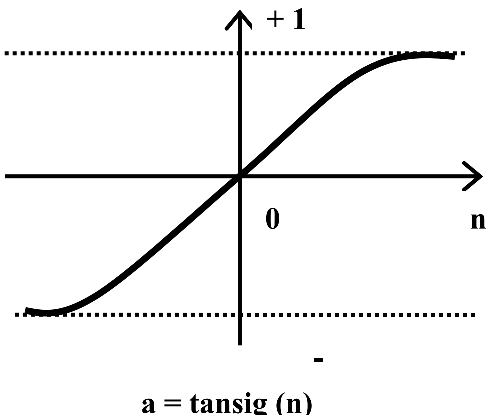

Figure 9. Sigmoid transfer function

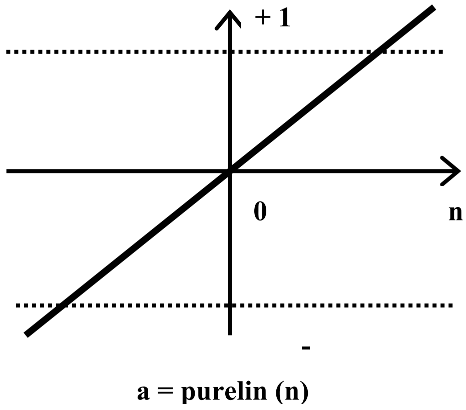

Figure 10. Linear transfer function

$$\{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_Q, t_Q\} \quad (3)$$

Here p_Q is an input to the network, and t_Q is the corresponding target output. As each input is applied to the network, the network output is compared to the target. The error is calculated as the difference between the target output and the network output (Eq. 4).

$$mse = \frac{1}{Q}\sum_{k=1}^{Q} e(k)^2 = \frac{1}{Q}\sum_{k=1}^{Q} (t(k) - a(k))^2 \quad (4)$$

The LMS algorithm adjusts the weights and biases of the network so as to minimize this mean square error.

7. TRAINING OF THE NETWORK

The training status is displayed for every 1000 iterations of the algorithm. The training of network is stopped if the number of iterations exceeded epochs, else if the performance function dropped below the goal, else if the magnitude of the gradient is less than the minimum gradient. But in most of the trials, the neural network has trained around 13000 epochs to 15000 epochs (Figure 9) and after that the minimum amount of training only takes place or even further training is stopped in some cases. In this the following parameters are selected;

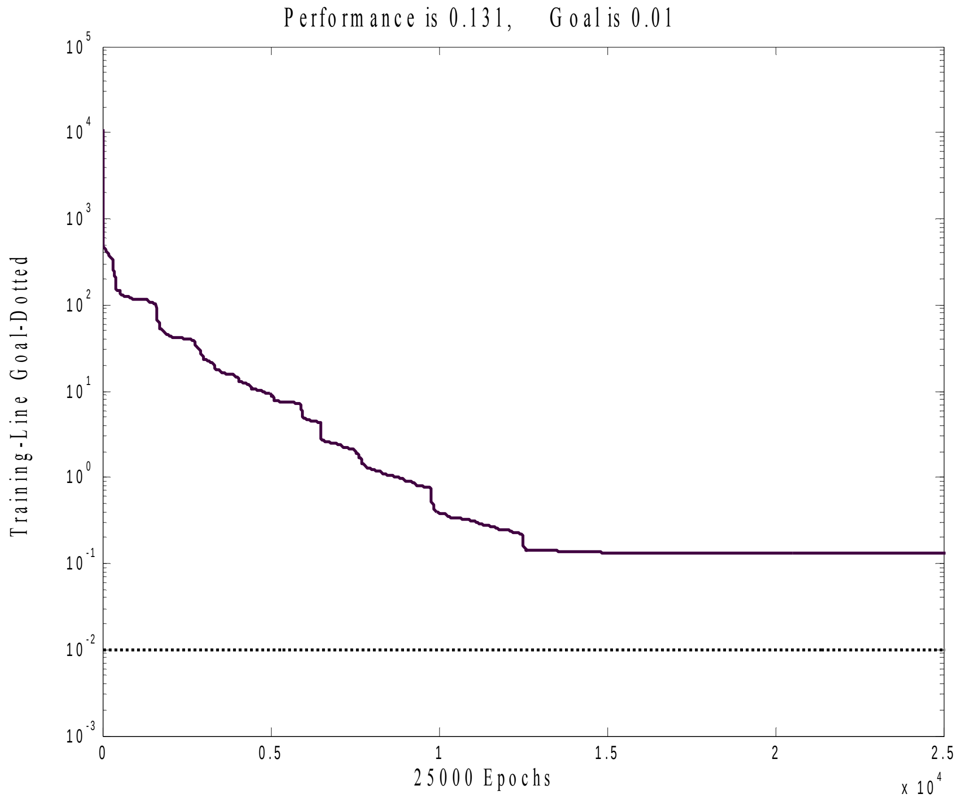

Figure 11. Convergenceof training data with goal

- The parameter – iteration or show is set to 1,000.
- The parameter – total iteration or epoch is set to 25,000.
- The value of the training parameter - goal is 0.01.

After the training of the neural network, all the weights of the nodes from input layer (I_1 & I_2) to hidden layer (H_1 to H_4) including the bias in the input layer (B_I) are listed in the following matrix form;

$$\begin{bmatrix} W1_{11} & W1_{21} & W1_{31} \\ W1_{12} & W1_{22} & W1_{32} \\ W1_{13} & W1_{23} & W1_{33} \\ W1_{14} & W1_{24} & W1_{34} \end{bmatrix} = \begin{bmatrix} 4.55916 & 0.235535 & -29.4635 \\ -22.9327 & -0.77255 & 125.977 \\ 6.51867 & -0.28074 & 2.75129 \\ -1.96507 & -0.70935 & 40.0482 \end{bmatrix}$$

All the weights of the nodes from the hidden layer (H_1 to H_4) to output layer (O_1 & O_2) including the bias in the hidden layer (B_{HL}) are listed in the following matrix form;

$$\begin{bmatrix} W2_{11} & W2_{21} & W2_{31} & W2_{41} & W2_{51} \\ W2_{12} & W2_{22} & W2_{32} & W2_{42} & W2_{52} \end{bmatrix} = \begin{bmatrix} 84.6588 & 76.8280 & 65.6493 & -70.0156 & 50.1730 \\ 0.0257 & 0.0443 & -0.0090 & 0.0206 & 0.0520 \end{bmatrix}$$

The feed-forward neural network is created and finally the whole network set is converted into simulink block set. Hence all the neural network details with input nodes; output nodes; bias nodes and the weights of each network connections from input layer to the hidden layer as well as the hidden layer to output layers including bias values are embedded in the simulink block set and simulink interface model diagram is shown Figure 12. From this simulink model, the input values are directly feed in the Input Block set and required *m* and *k* values are obtained in the output block by simulating the network very easily.

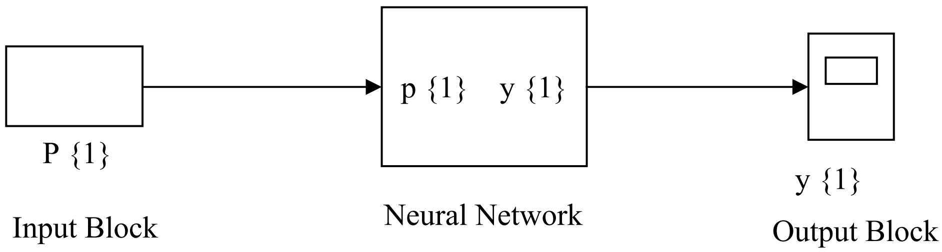

Figure 12. Simulink interface model

8. GENERALIZATION CAPABILITIES

The validation of ANN is done by cross checking its output with the available target data. Here all the *m* values are exactly matched without error and *k* values are also matched with errors. Due to the minimum number of data, one data is not considered for the training purpose and that data is used as a raw test data. A sample match on the one raw and one training data is shown in Table 2. The comparisons of the actual target output values and output from the neural network are given in Table 2.

Table 2. The comparison of target output & actual output values

S.No	**Profile**	**Target Output**		**Output from NN**	
		m	**k**	**m**	**k**
1.	Profile 1-training data	204.4	0.1562	204.4	0.107
2.	Profile 2-raw test data	121.3	0.01254	120.05	0.041

In the first case, the first output value *m* is perfectly matched with the target output data sets and second output value *k* is having 0.68 times of the target output value. For all other training sets also *m* values are exactly matched and *k* values are having some amount of errors. In comparison to the *m* value, the contribution of *k* value towards horizontal shear resistance is less (Eq. 1) and hence amount of error in the prediction of horizontal shear resistance will reduce. Hence, the total percentage of error in the neural network value is less than 10 % only.

In the second case, additionally to check the general interpolation ability of the neural network, the value of raw test data is given to the input block and the output is obtained and is shown in the Table 2.

However, because of the limited number of experimental values currently available, the neural network model needs to be further trained and validated with newly available data that can improve the performance of the network [18]. A trained network with additional training cases can be readily updated by means of adaptive training methods.

9. CONCLUSIONS

This study demonstrates the feasibility of using multilayer feed forward neural networks to learn the complicated nonlinear mapping between the input parameters associated with profiled deck and the output parameters m and k associated with horizontal shear resistance of the composite deck. The main observations of present study are as follows;

- With the aim to reduce the size of ANN and based on the available data, two parameters b/b2 and depth of profiled deck are identified as the most critical parameter for the assessment of horizontal shear resistance.
- With the constraints of less training data, 2–4–2 ANN architecture is found appropriate for the problem.
- The developed ANN is computationally efficient as well as it produces reasonably accurate results.
- Lack of training data is realized. By adding some more new data of profiled decks, the range and accuracy of the present network can be improved.

The neural network model can be useful in checking preliminary as well as routine designs because it provides reasonable results without demanding much computational effort. Preliminary studies using a limited data set of experimental tests showed promising results.

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