Prediction of Ultimate Strength of Steel-Concrete Composite Beams with Metal Deck Slab Using Artificial Neural Network

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Abstract: This paper explores the potential of using artificial neural networks to predict the ultimate moment capacity of steel-concrete composite beam with metal deck slab. Basic information on artificial neural networks and parameters suitable for analysis of experimental results are given. A multilayer Backpropagation neural network is used for training and testing the experimental data. A comparison study between the experimental values and two models (neural network and AISC models) is also carried out. It was found that the neural network model provides better results. The proposed neural network is also used to explore the effect of the various parameters on the behaviour of beams.

تقدير المقاومة القصوى للعتبات ألمركبه حديد-كونكريت ذات الطابق الحديدي باستخدام الشبكات العصبية الصناعية

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الخلاصة: يستكشف هذا البحث أمكانية استخدام الشبكات العصبية في ايجاد العزم الأقصى للعتبات المركبة حديد و كونكريت ذات الصفائح الحديدية بالاعتماد على نتائج الفحص العملي. وضحت الدراسة الحالية المعلومات الأساسية عن مفهوم الشبكات العصبية الصناعية وكذلك بعض العوامل المناسبة لتحليل نتائج الفحص العملية. استخدمت الشبكات العصبية ذات الإرجاع العكسي في تدريب وفحص النتائج العملية. كذلك أجريت مقارنة مابين النتائج العملية وكلا من طريقتي الشبكات العصبية و AISC. أظهرت نتائج المقارنة أن الشبكات العصبية الصناعية توفر نتائج أفضل. استخدمت الشبكة المقترحة في دراسة تأثير العوامل المختلفة على سلوك العتبات المركبة.

1- Introduction:-

Composite construction using steel and concrete has been used since the early 1920 s. It gained wide spread use in bridges in the 1950 s and in buildings in the 1960 s [1]. In composite beams, the steel and concrete are joined by mechanical connections, the most popular form being welded headed shear studs. The shear studs are welded to the top flange of steel beam to transfer shear and normal forces between the two components, thereby sustaining the composite action. A composite beam which is shown in Fig.(1) has greater strength and stiffness than if the steel and concrete behaviour independently [2]. The concrete slab may be solid as shown in Fig.(1.a) or with metal deck known as "ribbed slab" as shown in Fig.(1.b) [2]. Because of the advantages of the ribbed slab it becomes common used on construction. Nowadays approximately 60% of all new multi-story building and bridge in the UK used metal deck slab in construction [4].

The ribbed slab consist of light-gage, ribbed metal deck forms which interact with structural concrete topping as a composite unit to resist floor loads Fig.(2). Special embossments, dimples or lugs cold-rolled into the decking increase bond and act as shear connectors. Uplift is prevented either by the shape of the profile or by inclining the lugs to the vertical in opposite directions, on the two sides of the rib. It is usual practice to design the slab as simply supported beam, for the ultimate limit state (with the metal decking acting as reinforcement steel in the span direction), even though the slab and the decking may be continuous over the floor beams. The slab is usually provided with square mesh steel reinforcement at, or above, mid depth of the slab to minimize cracking due to shrinkage and temperature effects and to help distribute concentrated loads.

The thickness of metal deck plate element usually various from 0.83 mm to 2.51 mm, so metal deck slab is economic which very thin decking is used. The effects of corrosion on steel sheets about 2 mm thick are more sever than on thicker sections, so the material is usually galvanized. There is evidence that the galvanizing process can increase the yield strength of steel sheet by as much as 20% [4].

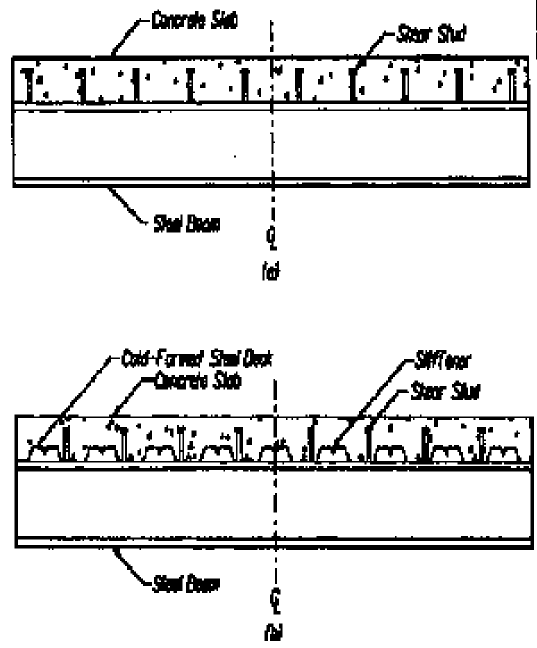

Fig.(1) Composite beam

a- composite beam with solid concrete slab

b- composite beam with metal deck slab

The advantage of the metal deck slab system is the elimination of the formwork, increase in speed of construction, act as slab reinforcement, save up till 30% concrete material, accommodate service ducks, and ease transportation and installation. Also, it acts as a diaphragm to help stabilize the steel skeleton by integrating all members into a system.

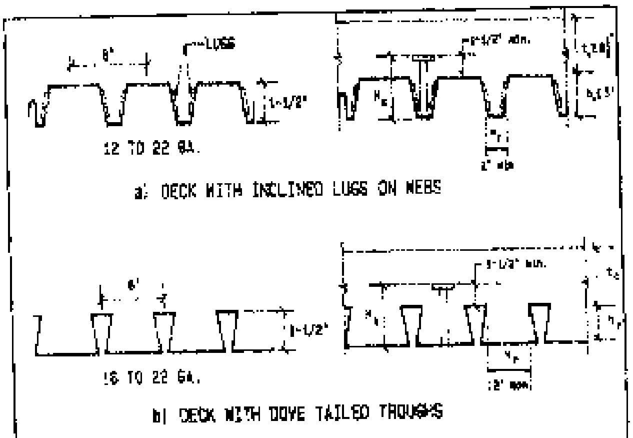

Fig.(2) Types of metal deck slab

2- Design of composite Beam with Ribbed Slab:-

For design purpose, a single steel beam is assumed to act compositely with an effective width of concrete slab, which is limited by the influence of shear lug. According to AISC the procedure for calculation ultimate moment capacity based on rectangular stress block for both full and partial interaction. This procedure gives three equations for the ultimate moment capacity, based on the location of plastic neutral axis (PNA). When the PNA is in steel web the ultimate moment capacity is given by:

$M=M_p-(C/P_{yw})^2M_{pw}+Ce$ ....(1)

where; M_p: steel section plastic moment, C: compressive force in concrete slab, P_{yw}: web yield force, M_{pw}: web plastic moment, e: distance from center of steel section to the center of compressive stress block in the slab. The force C is given by:

$C=\min[C^*, T, S]$ .... (2)

$C^*=0.85\ f_c\ b\ t$ ... . (3)

$T=A_s\ f_y$ .... (4)

$S=N\ Q$ .... (5)

where, f_c: cylinder compressive strength of concrete, b: width of concrete slab, t: thickness of concrete slab, A_s: area of steel beam, f_y: yielding strength of steel beam, N: number of connectors over half span length, Q: shear capacity of one connector. The distance e is given by:

$E=0.5d+h_r+t_c-0.5a$ .... (6)

where; d: depth of steel section, t_c: slab thickness above the steel deck, a: depth of compressive stress block, h_r: depth of steel deck.

Many research programs, both experimental and analytical have led to an understanding of the behaviour of composite beams with metal deck slab and evaluating of the ultimate moment capacity of them. These research programs were based on mathematical models which are complex for practical use. In this paper an attempt is made to use an alternative approach known as Artificial Neural Network in which no mathematical model is required to analyse composite beam with metal deck slab.

An artificial neural network has found wide application in all fields of science including structural engineering. The first application of neural network in structural engineering goes back only to the end 1980. Since then wide range of application have emerged. Vanluchen and Sun [1990] [5] used neural network to model simple reinforced concrete beam behaviour subject to bending moment. Jankins [1997] [6] applied a neural network based method to the approximate analysis of grillage structure. Guang and Wang [2000] [7] used artificial neural network to predict the compressive strength of concrete. Hadi [2002] [8] using neural network to design of reinforced concrete beam. Pathak and Gupta [2006] [9] used neural networks for preliminary design of tubular girder bridge deck.

3- Artificial Neural Network (ANN):-

Neural networks are problem solving programs modeled on the human brain. Neural network technology mimics the brain's own problem solving process. Similar to how humans apply knowledge gained from past experience to new problems or situations. A neural network takes previously solved examples to build a system of 'neurons' that make new decisions, classification, and forecasts [10].

Neural networks are networks of many simple processes which are called units, nodes, or neurons, with dense parallel interconnections. The connections between the neurons are called synapses or weight. Each neuron receives weighted input from other neurons and communicates its outputs to other neurons by using an activation function. Thus, information is represented by massive cross-weighted interconnections. Neural networks might be single or multilayer. The connection weights of the neural network are adjusted through the training process, while the training effect is referred to as learning. Training of neural networks usually involves modifying connection weights by means of learning rule. The learning process is done by giving weights and biases computed. In other words, neural networks learn from examples and exhibit some capability for generalization beyond the training data. Then, other testing data are used to check the generalization. The initial weights and biases joining nodes of an input layer, hidden layer, and an output layer are commonly assigned randomly. The weights and biases are changed for the output of networks to match required data values. As input data are passed through hidden layer, (tansigmoid, logsigmoid, purelin) activation functions are generally used. Figure (3) present simple architectural layout of the backpropagation networks that consist of an input layer, one hidden layer, an output layer, and connections between them.

The corresponding architecture for the backpropagation learning incorporates both the forward and backward phases of the computations involved in the learning process. The learning mechanism of the backpropagation networks is a generalized delta rule that performs a gradient descent on the error space to minimize the total error between the calculated and the desired one of an output layer during modification of connection weight. In other words, a least mean square error is carried out to find the values of the connection weights that minimize the error function by using Resilient backpropagation method.

4- Neural Network-Based Modeling of Ultimate Moment Capacity of Composite Beam with Metal Deck Slab

In this study, a Resilient backpropagation neural network was used to product the ultimate moment capacity of composite beam with metal deck slab. During the process of learning the mean square error (MSE) is monitored the network instantaneously to achieve better understanding of the network performance [11]. Details on the establishment of neural network models for composite beam, a longwith sources of the data that are used in development, are described below.

5-Generation of Data and System Model:-

In general, a good training data set should include comprehensive information about the characteristics of material behaviour. In this study, the experimental data include 90 results, which are taken from the test carried out by Grant etal.[13],Robinson and Wallace [14],

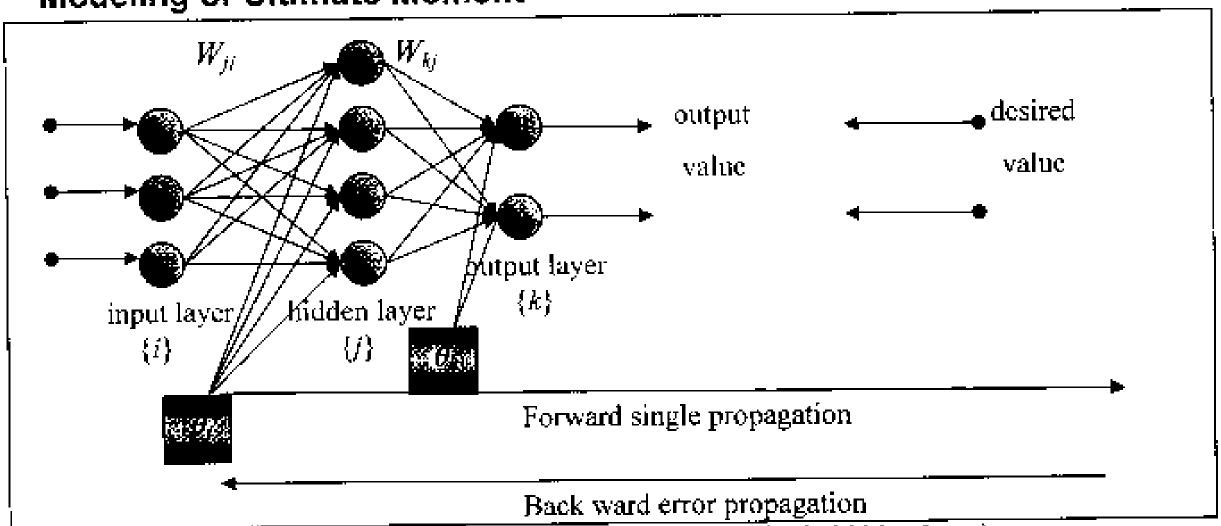

Fig.(3) Neural Network Architecture (with single hidden layer)

Fisher [15], Seek et al. [16], Errera [17], Fulong and Henderson [18], Allan etal.[19], Jones [20], Lacap [21], Robinson [22], Jayas and Hosain [23], and Gibbings etal. [24]. A mong the collected data 75 selected randomly are used as training data, and the remaining 15 are regarded as testing data.

From the previous studies eight major variables are adopted to model the behaviour of composite beam. These variables are as follows:-

b_c: concrete slab width.

t_c: concrete slab depth.

f_c: cylinder compressive strength of concrete.

i: moment of inertia of steel section.

f_y: yielding strength of steel section.

S: connectors strength.

h_r: steel deck height.

w_r: steel deck width.

So the input layer of the neural network consists of eight processing nodes (units) representing these eight variables, and the output layer includes one neuron representing the ultimate moment capacity of beams.

6- Training and Testing of Network:

As mentioned earlier, the network configuration is defined in terms of number, size, nodal properties, ect. of the input/output and intermediate hidden layers, once the input and output are decided to cater the present investigation requirements, the task of selecting a suitable configuration has been taken up. In this study, the network configuration was arrived after watching the performance of different configurations. Then, learning parameters were changed and learning process were repeated. In addition, to avoid over-training the convergence criterion adopted in this study depends on whether the MSE of testing data has reached its minimum. Before the neural networks are trained, to avoid the slow rate of learning near the end points of the range, the input and output data were scaled into the interval [-1,1] by using the minimum and maximum method (premnmx). After a number of trail, the values of the network parameters considered by this study are as follows:

Number of hidden layers= 2

Number of units in first hidden layer= 8

Number of units in second hidden layer= 6

Training cycles= 500

The MSE, as stated previously is adapted to provide a measure of the output network accuracy. For the above network the MSE for training and testing are 0.0015, 0.0021 respectively. Figure (4) shows convergence history of this network for both training and testing data.

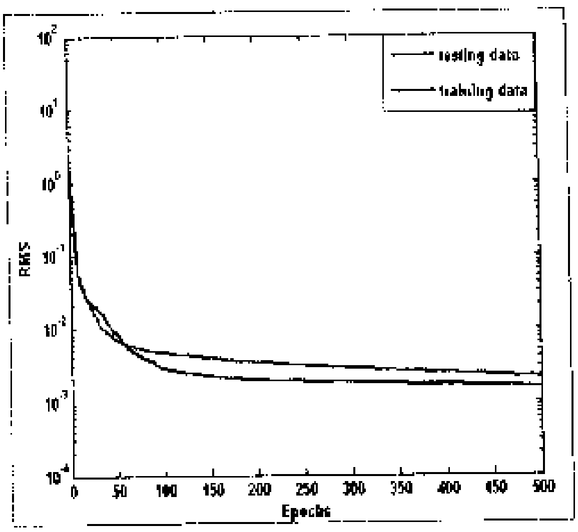

Fig.(4) Convergence history of network

7- Discussion and Comparison of Prediction Models:-

To compare the neural network results with other well-known existing models, the same training and testing data are used to calculate the ultimate moment capacity of composite beams. Regarding all 90 beams the measured ultimate moment capacities are plotted against the calculated values using the ANN and AISC models as shown in Fig.(5) for training data and Fig.(6) for testing data.

To illustrate the overall trend of correlation, the theoretical line with $M_e/M_c=1$ (where M_e: is experimental moment, M_c: is calculated moment) is drawn in Figs.(4) and (5) alongwith the data points. The nearer the points gather around the diagonal line, the better are the predicted values. Figures (5) and (6) clearly show that the least scatter of data around the diagonal line confirms the fact that ANN based model is an excellent predictor for the value of ultimate M. For comparison purpose, the values of MSE and R (where R is correlation coefficient) of the training and testing results for the models (ANN and AISC) are also listed in Table (1).

$$MSE=\frac{1}{n}\sum_{i=1}^{i=n}(t_i-y_i)^2 \quad \ldots\ldots\ldots\ldots\ldots (8)$$

$$R=\frac{\sum_{i=1}^{i=n}(y_i-y^-)(t_i-t^-)}{\sqrt{\sum_{i=1}^{i=n}(y_i-y^-)^2(t_i-t^-)^2}} \quad \ldots\ldots (9)$$

$$t^-=\frac{1}{n}\sum_{i=1}^{i=n}t_i\ ,\ y^-=\frac{1}{n}\sum_{i=1}^{i=n}y_i \quad \ldots\ldots\ (10)$$

where, t_i: actual value, y_i: predicted value, n: number of values, t^-: mean of actual values, y^-: mean of predicted values.

It can be seen that ANN model gives the smallest MSE and the largest R for both training and testing data. In addition, the two prediction models have been compared by means of the average value (AVG), Standard deviation (STD), and coefficient of variation (COV) of the ratio of M_e/M_c. Table (2) shows that for the ratio of M_e/M_c the ANN model possesses the least COV value of 0.0012 (with AVG= 1.005 and STD=0.035) and 0.0014 (with AVG=1.01 and STD=0.06) for training and testing set respectively.

This proves that the prediction of ANN model is better than those of the AISC model.

Table (1) summary of values of MSE and R

Models	MSE		R	
	Training	Testing	Training	Testing
ANN	0.0015	0.0021	0.992	0.980
ASIC	0.0083	0.0098	0.970	0.955

Table (2) summary of values of AVG, STD and COV

Models	AVG		STD		COV	
	Training	Testing	Training	Testing	Training	Testing
ANN	1.0050	1.010	0.0350	0.060	0.0012	0.0014
AISC	1.1035	1.135	0.0917	0.124	0.0832	0.1093

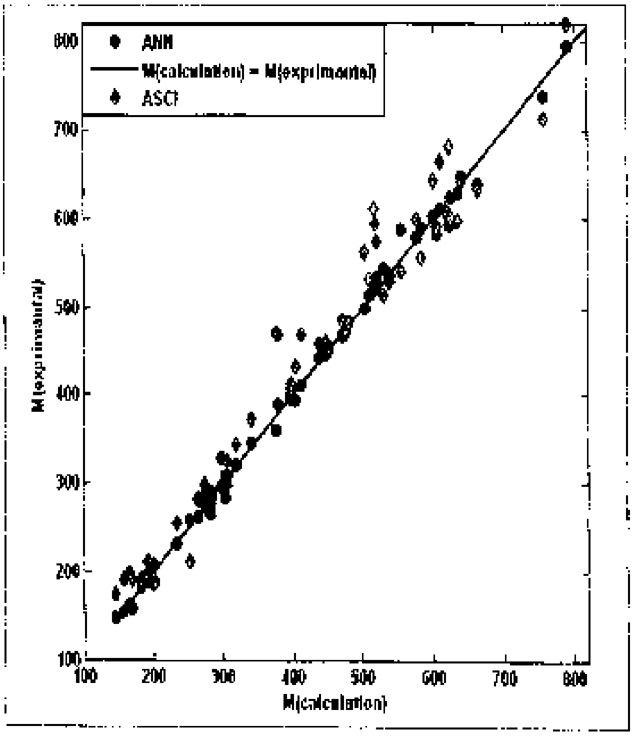

Fig.(5) Comparison of ultimate strength of composite beam obtained by various models for training data

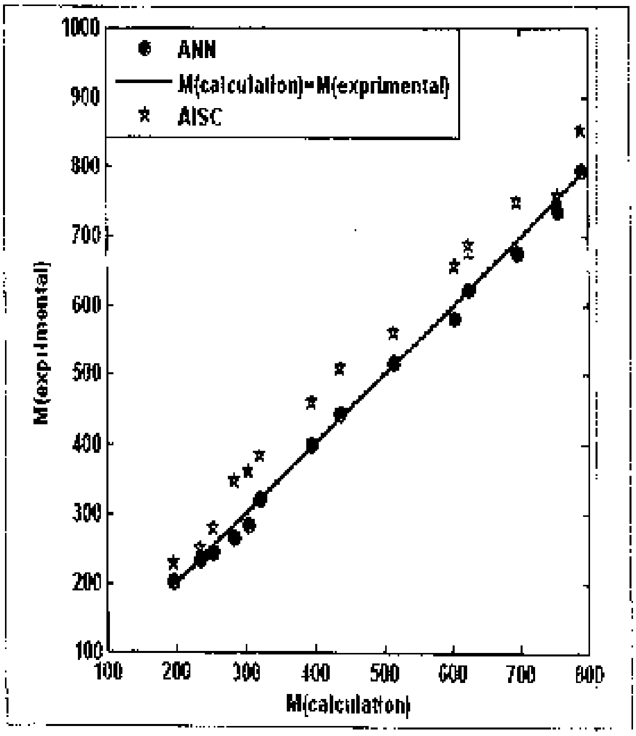

Fig.(6) Comparison of ultimate strength of composite beam obtained by various models for testing data

Also the above network was used to stud the effect of varies input parameter on the behaviour of composite beam with ribbed slab.

Figure (7) shows the variation of ultimate moment capacity of composite beam with concrete slab compressive strength. For an increase in compressive strength from 18 to 32 MPa, the increase in the ultimate moment capacity was 12%.

Figure (8) shows the variation of ultimate moment capacity with steel beam yielding stress, fy. This figure shows that an increase in yielding stress from 230 to 420 MPa, leads to increase in the ultimate moment capacity of 36%.

Slab dimensions also affect the beam behaviour. The slab thickness has a marked effect on strength but slab width is less effective. Figure (9) illustrates the effect of slab thickness on the ultimate moment capacity. Beam with deeper concrete slab have higher ultimate capacity. A small increase in ultimate moment capacity of composite beams occurs with the increase in width of concrete slab. This can be seen in Fig.(10).

Figure (11) shows how the ultimate moment capacity of beam varies with connector strength (degree of interaction). The ultimate moment capacity and connector strength are nonlinearly related. The increase in connecter strength causes increase of ultimate capacity, for example at 50% composite action, the ultimate strength is about 72% of fully composite ultimate strength. But with increase of connecter strength (degree of interaction) greater than 1.25 the increase in the ultimate moment capacity is small.

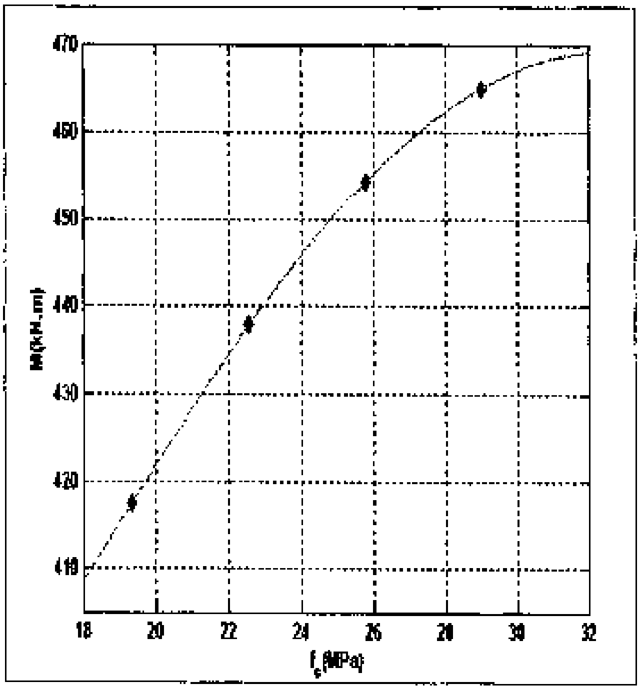

Fig.(7) Variation of ultimate moment capacity with variation of cylinder concrete compressive strength

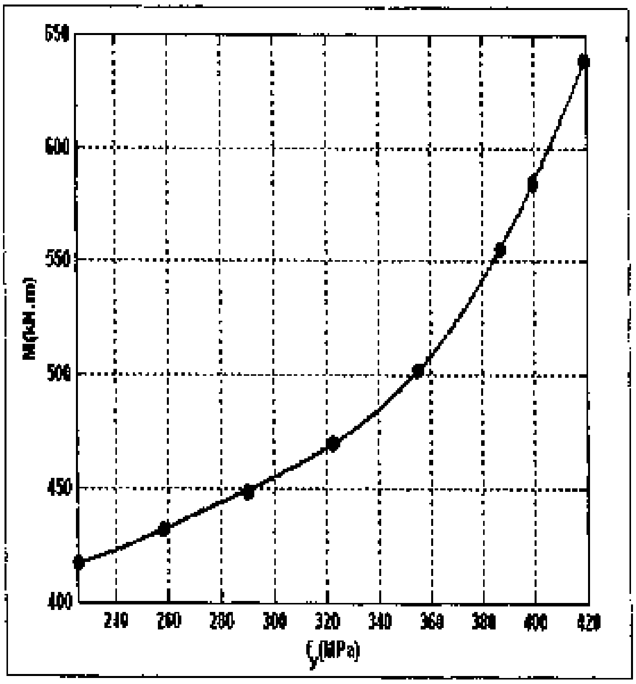

Fig.(8) Variation of ultimate moment capacity with variation of yielding strength of steel section

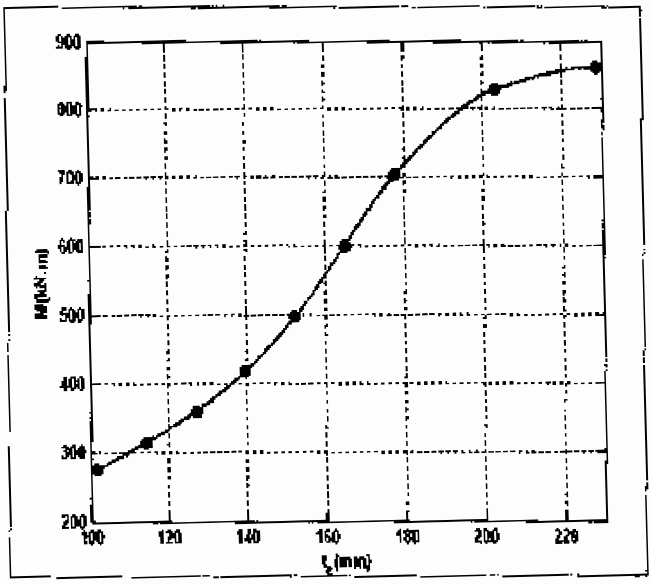

Fig.(9) Variation of ultimate moment capacity with variation of concrete slab thickness

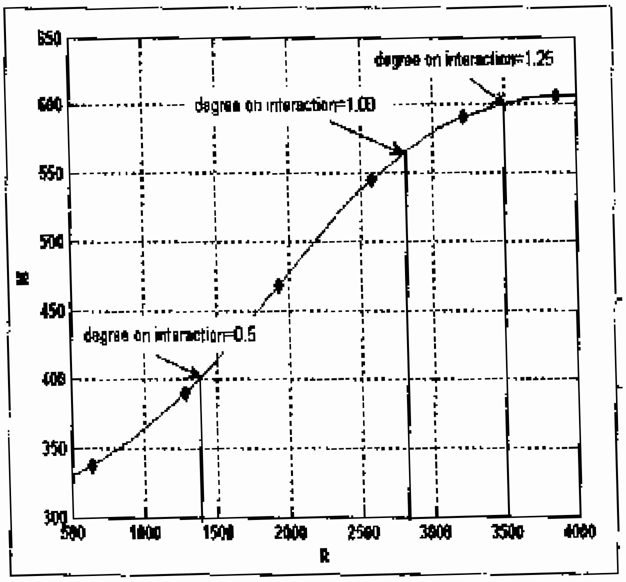

Fig.(11) Variation of ultimate moment capacity with variation of connectors strength

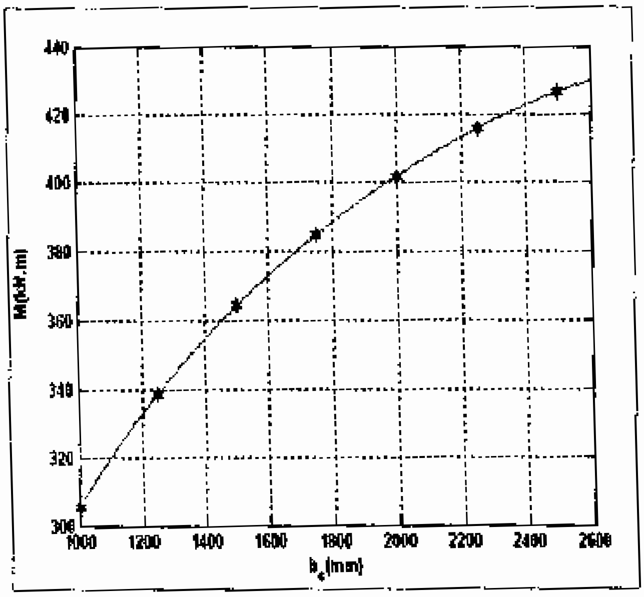

Fig.(10) Variation of ultimate moment capacity with variation of concrete slab width

9- Conclusions:-

In this study it is found that the neural network model is very effective in the analysis of composite beams with metal deck slab with incomplete between concrete slab and steel beam. The configuration 8-6 nodes in (first and second hidden layer) is proved to be very efficient for predicting the ultimate strength of such system which gives minimum mean square error for both training and testing data. The neural network model is proved to give results more accurate than those given by AISC method. The proposed network used to explor the effect of varation of input parameter on behaviour of composite beam with ribbed slab. The ultimate strength increases by an amount of 12% with increase of compressive strength from 18 t0 32. The an increase in yielding stress from 230 to 420 MPa, leads to increase in the ultimate moment capacity of 36%.

Slab dimensions also affect the beam behaviour. The slab thickness has a marked effect on strength but slab width is less effective. The increase in connecter strength causes increase of ultimate moment capacity, for example at 50% composite action, the ultimate strength is about 72% of fully composite ultimate strength.

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Notation

ANN	artificial neural network
A_s	area of steel beam

marked effect on strength but slab width is less effective. The increase in connecter strength causes increase of ultimate moment capacity, for example at 50% composite action, the ultimate strength is about 72% of fully composite ultimate strength.

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Notation

ANN	artificial neural network
A_s	area of steel beam
AVG	Average values
b_c	concrete slab width

C	compressive force in concrete slab
COV	coefficient of variation
d	depth of steel beam
e	distance from center of steel to the center of compressive stress block in the slab
E	error between the calculated and desired value
f_c	cylinder compressive strength of concrete
f_y	yielding strength of steel section
h_r	metal deck height
i	moment of inertia of steel section
N	number of connectors
M_c	calculated moment
M_e	experimental moment
M_p	steel section plastic moment
M_{pw}	steel web plastic moment
MSE	mean square error
P_{yw}	web yield force
R	correlation coefficient
S	connector strength
STD	standard deviation
t_c	concrete slab thickness
t_i	actual value
$\bar{t}$	mean of actual values
W_{ji}	weights between the input and hidden layer
W_{kj}	weights between the hidden and output layer
w_r	steel deck width
y_i	predicted value
$\bar{y}$	mean of predicted values
θ_j	biases for the hidden layer
θ_k	biases for output layer