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DESIGN OF COLD FORMED STEEL COMPRESSION MEMBERS USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT
The main aim of this study is to demonstrate the usefulness of Artificial Neural Network (ANN) in the creation of knowledge base available in the form of design standards. As an example, in this study, ANN is used for designing of cold- formed steel compression members. A new methodology is developed for selection of cold formed steel compression members using ANN simulation. This methodology facilitates in quick selection of the cold formed section with minimum weight and adequate load carrying capacity is possible for column design from the available sections.

Keywords: Artificial Neural Network (ANN); Cold formed steel; Back Propagation (BP); Permissible stress; Allowable Load.

INTRODUCTION
Artificial Neural Network
A neural network is a non-linear system consisting of a large number of highly interconnected processing units, nodes or artificial neurons (Figure1.1). Each input signal is multiplied by the associated weight value w_i and summed at a neuron. The result is put through an activation function to generate a level of activity for the neuron. This activity is the output of the neuron. When the weight value at each link and the connection pattern are determined, the neural network is trained. This process is accomplished by learning from the training set and by applying for certain learning rule. The trained network can be used to generalize for those inputs that are not including in the training set.

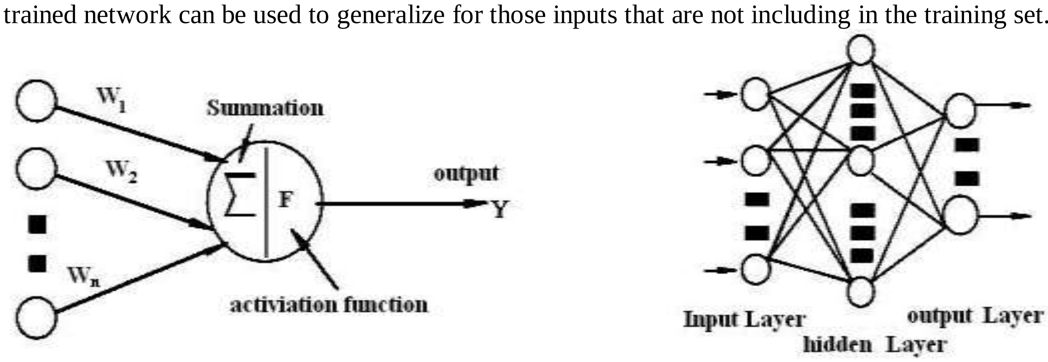

Figure 1.1 Architecture of a Neural Network.

Compared to conventional digital computing techniques, neural networks are advantageous because of their special features,

1. The massively parallel processing,
2. Distributed storing of information,
3. Low sensitivity to error, their very robust operation after training, generalization and Plasticity (adaptability) to new information.

The first structural engineering applications of neural network go back only to the end of 1980s. Since then, a wide range of applications has emerged. These applications includes,

1. Mapping of input-output data of non-linear relation for materials and structures;
2. Damage identification of structure and structural control against dynamic loads;
3. Preliminary design of structure;

4. Optimum design and analysis;
5. New generation of expert systems associated with fuzzy neural logic networks for Construction project planning, estimation of costs, management and maintenance of Structures, etc.
6. Used to compute structural response of a structural system

These applications have shown the robustness of the neural network in solving complex mechanic and engineering problems and its promising future development.

Cold Formed Steel Section

The light gauge steel members are defined as structural members cold formed to shape in rolls from carbon or low alloy steel sheets, generally not greater than 12.5mm. Cold-formed steel is a steel product that is formed by a steel strip or sheet of uniform thickness, in cold state.

The cold-formed steel section, which is regarded as steel strip with uniform profile along its length, is usually used in load bearing application. The use of cold-formed steel section can be found in automobile industry, shipbuilding, rail transport, and construction industry. In building construction, the cold formed steel utilized in both non structural and structural members. As non-structural members, the advantages are more on rust resistance and aesthetic purposes. It is used as non-structural member for wall paneling, doorframes, window frames, and services. As structural members, the usage includes roof sheeting, purlins, truss members, beams, columns, and floor decking in steel concrete composite construction.

Recently, permissible stresses and allowable load has attracted the attention of a number of researchers. Firstly, Finite Strip (FS) analysis has been used as a numerical method to investigate permissible stresses and allowable load of thin-walled steel sections. However, designers may not gain access to such computer programs and therefore several analytical methods have been formulated for estimating the permissible stress and allowable load of steel members under a number of simplified assumptions. At present in India IS code method is used to find out the permissible stresses and allowable load as an analytical method.

BASICS OF NEURAL NETWORKS

Biological Neurons

A biological neuron, which exists as a basic component in the nervous system, consists of dendrites, synapses, cell body and axon, as shown in Figure 2.1.

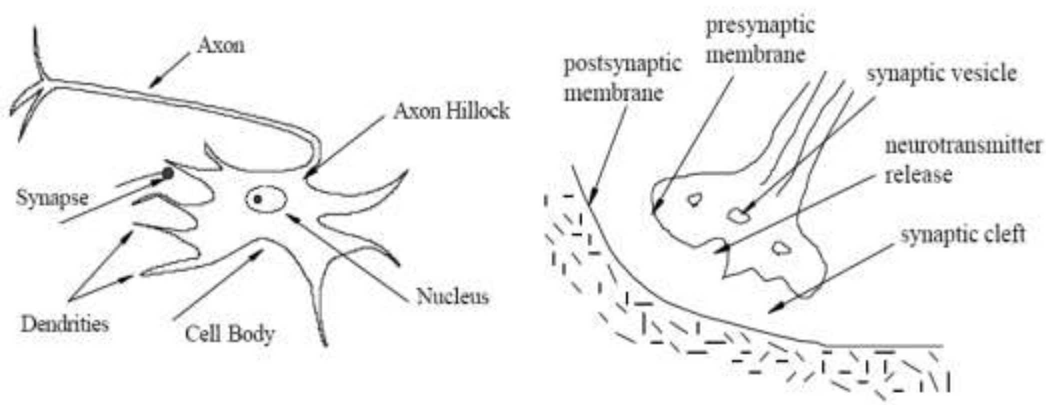

Figure 2.1 Biological Neuron and Chemical Signal at the Synapse

The information-processing abilities of biological neurons can be described by the following three aspects: transmission of information, information process at the neurons and synapses, and storage of information.

Transmission of information

Neurons transmit information using electrical signals. The semi-permeable membrane separates the intracellular plasma from the extra cellular liquid. On the two sides of this membrane, potassium, sodium, chloride and negative organic ions are mainly contained. This membrane is more selectively permeable to potassium ions than to sodium ions. Thus, a resting potential exists across the membrane. When an excitatory input is provided to the cell, an action potential is produced so as to reduce the potential difference across the membrane due to the potassium sodium pump effects. This action potential travels along the axon in a discontinuous manner.

Information processing at the neurons and synapses

The information is processed by the chemical signal. The synapses appearing as a thickening of the axon contain synaptic vesicles that can release chemical transmitter. The small gap between a synapse and the cell to which it is attached is known as the synaptic cleft (shown in Figure 3.1). With the arrival of an electric signal, the synaptic vesicles fuse with the pre-synaptic membrane and the transmitter flows into the synaptic cleft. These transmitters diffuse across the junction and join with the postsynaptic membrane at certain receptor sites, thus leading to changes in the permeability of the postsynaptic membrane to certain ions. An influx of positive ions into the cell will tend to depolarize the resting potential; this effect is excitatory. If negative ions enter, a hyper polarization effect occurs, this effect is inhibitory. Both effects are local effects that spread a short distance into the cell body and are summed at the axon hillock. If the sum is greater than a certain threshold, an action potential is generated.

Storage of information—learning

In neural networks, information is stored at the synapses. When the circumstance is changed, the ion's permeable capacity of membrane will be changed thus producing a durable change of the threshold level of cell. Therefore, the efficiency of the synapses is changed as well. When this kind of information storage is used in an artificial neural network, synaptic efficiency can be modeled as a property of the edges of the network. The networks of neurons are thus connected through edges with different transmission efficiencies. Information flowing through the edges is multiplied by a constant that reflects their efficiency.

Types of Neural Networks

The computational capacity of one node may have some limitations. However, when many nodes are put together to form NNs, a complex computational task can be performed. The arrangement of nodes and the pattern of connections between them are called the architecture of NN (type or structure or topology of NN). There are mainly three types of architecture: feed forward, recurrent, and cellular NN, as shown in Figure 3.1.

In the feed forward NN, signals are transmitted in one direction, only from inputs to outputs. The standard feed forward architecture consists of layers of nodes that are not connected in the same layer but connected between one layer to the subsequent layer. In the usual terminology, the set of input nodes is called the input layer, and the set of Output nodes is called output layer. All other layers with no direct connections from or to the outside are called hidden layers.

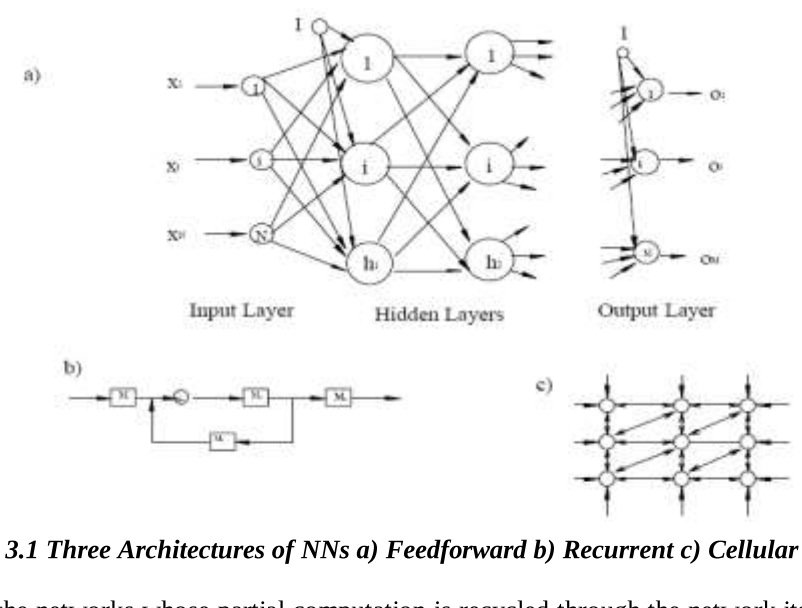

Figure 3.1 Three Architectures of NNs a) Feedforward b) Recurrent c) Cellular

Recurrent networks are the networks whose partial computation is recycled through the network itself. The cycle in the topology of the network makes the storage and reuse of signals possible for a certain amount of time after they are produced.

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Learning

A major concern in the development of the neural network is to determine an appropriate set of weights. The computational capacity of the neural network is realized by adjusting trainable weights using different learning methods, which can be classified as supervised and unsupervised learning methods (Rojas, 1996). In supervised learning, the outputs of the neural network are compared with the desired outputs or target outputs, and the error is calculated. The weights are adjusted so as to minimize this error. In unsupervised learning though, the weights are determined as a result of a self-organizing process, i.e. the connections to the network weights are not performed by an external agent. The network itself decides what output is best for a given input and reorganizes accordingly. Mainly, there are two types of unsupervised learning: reinforcement and competitive learning. In the first method, each input produces a reinforcement of the network weights to enhance the reproduction of the desired output. In competitive learning, the elements of the network compete with each other for the “right” to provide the output associated with an input vector. Only one element is allowed to answer the query and this element simultaneously inhibits all other competitors.

Generalization

After learning, the network should extract “regularities” or “rules” from the training data and be able to generalize, i.e. to give the right answers for input not belonging to the training sets. When the network is trained with a randomly selected set of examples and tested with another set of inputs, the expected number of correct results is called generalization capability. Generalization capability can be used to evaluate the behaviour of the NN. The neural networks have extensive applications in civil engineering.

CONFIGURATION OF BACK PROPAGATION NEURAL NETWORK

Input and output layer

The nodes in the input layer and output layer are usually determined by the nature of the problem. In this research, the depth of the web, *bw*, the width of the flange, *bf* and the depth of the lip, *bl*, are chosen as the components of the input vector. The output vector is composed of the elastic local and distortional buckling stress of the uniform compression member. Therefore, the nodes in the input layer and output layer are three and two, respectively.

Training of the Neural Network

Pre-process and post-process of the training patterns the training patterns should be normalized before they are applied to the neural network so as to limit the input and output values within a specified range. This is due to the large difference in the values of the data provided to the neural network. Besides, the activation function used in the back propagation neural network is a sigmoid function. The lower and upper limits of this function are 0 and 1, respectively. The following formula is used to pre-process the input data sets whose values are between -1 and 1.

$$V = 2.\ \frac{x - xmin}{xmax - xmin} - 1$$

Since the output value of the sigmoid function is between 0 and 1, the following function might be used

$$0 = 2.\ \frac{Y - Ymin}{Ymax - Ymin}$$

However, using this formula, the normalized value of the output usually approaches 0 and 1.

This makes the training process more difficult. Even the generalization of the neural network will be affected. Therefore, the following formula suggested by Rafiq is used:

$$o = \sqrt{\frac{Y}{10^{n}}} + c$$

Where c is a constant between –0.25 and 0.25 to ensure that the output values are in the range of 0.2 to 0.8, and n is a constant that reduces y to a number between 0 and 1. In this analysis, n = □4 and c =□0.2 are used.

The effects of the two formulas for normalizing the output data on the convergence history are shown in Figure 3.2. In the figure, the solid line is the formula provided by Rafiq and the dashed line is the other formula mentioned above.

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It can be seen that the way in which the data is provided for the neural network critically affects the performance and training of the neural network.

Each net was trained using the back-propagation algorithm, which tries to minimize the mean square error between the network output and the corresponding target values. Each training iteration is normally called an epoch. The training was limited on 10,000 epochs. After each iteration, the network explores the error surface searching for the greater gradient of reduction in the mean square error.

The weights and biases are then adjusted to decrease the error. The initial weights and biases for each neural network were generated automatically by the program. This strategy allowed the exploration of different regions of the error surface.

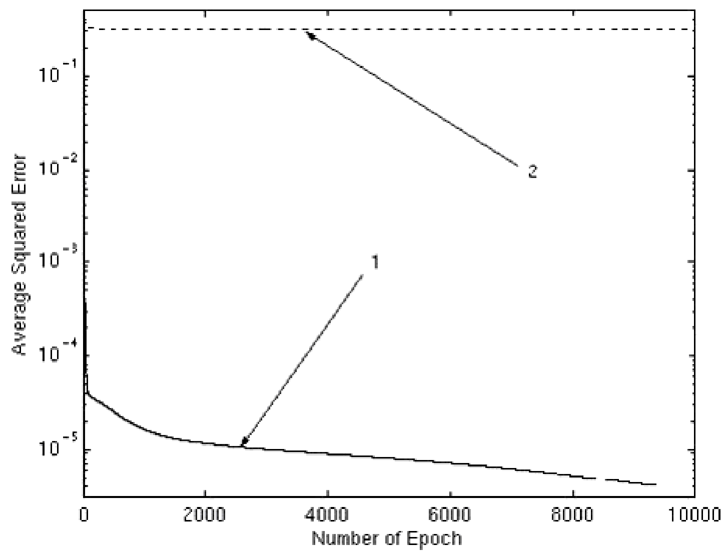

Figure 3.2 Effect of the Normalizing Formula for the Output Patterns on the Behaviour of Neural Network

Training Results

The backpropagation neural network with 3-8-2 nodes in input, hidden and output layers and the selected parameters mentioned above is trained to determine the Permissible stress and Allowable load of the I-section with lip. The output of the trained neural network for the inputs included in the training patterns and the error from the target values are shown in Table 3.1

Table 3.1 Output of the Trained Neural Network for the Training Patterns

Target Output		Output by Trained NN		Error	
σp (N/mm^2)	Pa (KN)	σp (N/mm^2)	Pa (KN)	σp (N/mm^2)	Pa (KN)
68.54	65.09	66.85	65.09	+1.69	+0.02
95.05	104.56	96.10	104.72	-1.04	-0.16
108.05	135.07	109.48	135.19	-1.42	-0.12
115.31	161.44	115.95	161.30	-0.63	+0.13
119.74	185.60	120.03	185.50	-0.29	+0.10
65.69	68.97	58.90	62.89	+6.79	+6.08
88.60	106.32	88.79	106.28	-0.19	+0.03
103.05	139.12	103.15	139.11	-0.09	+0.01
111.20	166.80	110.54	166.59	+0.66	+0.20
116.22	191.77	115.43	191.65	+0.79	+0.12
62.40	71.76	51.09	58.92	+11.31	+12.84

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81.23	105.61	81.51	105.61	-0.28	+0.00
96.91	140.52	96.80	140.60	+0.10	-0.07
105.87	169.39	105.06	169.32	+0.81	+0.06
111.48	195.09	110.71	195.11	+0.77	-0.02
58.91	73.64	53.96	15.29	+15.29	+19.67
73.97	103.57	74.44	103.56	-0.46	+0.00
90.64	140.49	90.61	140.58	+0.03	-0.08
100.28	170.49	99.68	170.46	+0.60	+0.02
106.42	196.88	106.04	196.92	+0.37	-0.04
55.37	74.75	36.58	48.51	+18.78	+26.23
67.15	100.73	67.66	100.69	-0.51	+0.03
84.61	139.60	84.65	139.65	-0.04	-0.04
94.82	170.69	94.50	170.64	+0.32	+0.04
101.41	197.75	101.53	197.72	-0.11	+0.02
52.52	76.15	30.05	42.87	+22.46	+33.28
60.86	97.37	61.23	97.32	-0.36	+0.05
78.95	138.16	78.99	138.17	-0.04	-0.01
89.63	170.31	89.56	170.24	+0.07	+0.06
96.60	198.03	97.21	197.93	-0.61	+0.09
49.56	76.82	24.07	37.21	+25.48	+39.60
55.10	93.67	55.14	93.65	-0.04	+0.01
73.69	136.34	73.63	136.37	+0.06	-0.03
84.77	169.54	84.89	169.52	-0.12	+0.01
92.04	197.89	93.12	197.80	-1.08	+0.09
47.15	77.81	18.67	31.67	+28.48	+46.13
49.84	89.71	49.42	89.80	+0.41	-0.08
68.84	134.24	68.58	134.38	+0.25	-0.13
80.23	168.48	80.49	168.61	-0.25	-0.13
87.76	197.47	89.27	197.49	-1.50	-0.01

Generalization of Neural Network

The Generalization of the neural network with 3-8-2 node in input, hidden and output layers is monitored by the test patterns. The results are shown in table 3.2

Table 3.2 Generalization of Neural Network for the Test Patterns

Test Patterns					Generalization (Permissible stress and allowable load)		Generalization Error	
Dimension of I-section			(permissible stress and allowable load)					
b_w	b_f	b_l	σp(N/mm^2)	Pa(KN)	σp(N/mm^2)	Pa(KN)	σp(N/mm^2)	Pa(KN)
90	55	15	83.76	92.13	76.79	93.36	+6.97	-1.22
90	75	20	109.33	141.59	105.80	149.57	+3.53	-1.97
90	105	25	121.30	206.22	103.07	208.73	+18.23	-2.50
130	55	15	68.03	88.45	63.59	88.13	+4.47	+0.31
130	75	20	97.91	151.77	100.18	150.31	-2.26	+1.46

130	105	25	112.69	214.12	100.95	212.50	+11.74	+1.61
170	55	15	54.61	81.91	49.20	81.19	+5.40	+0.72
170	75	20	86.32	151.06	93.76	150.332	-7.44	+0.73
170	105	25	103.23	216.80	98.70	216.17	+4.53	+0.62
210	55	15	49.16	83.58	34.13	72.36	+15.02	+11.21
210	75	20	76.09	148.39	86.43	149.43	-9.59	-15.61
210	105	25	94.51	217.38	96.28	219.69	-1.76	-2.30

COMPUTER PROGRAM FOR DESIGNING, TRAINING AND GENERALIZATION OF NEURAL NETWORK

Structure of the Program for BPNN

The computer program that is coded in MATLAB languages realizes the training and generalization processes of the backpropagation neural network. The structure of the computer program is shown in Figure 5.11. The main variables are stored using the cell arrays. The cell arrays in MATLAB are multidimensional arrays whose elements are copies of other arrays.

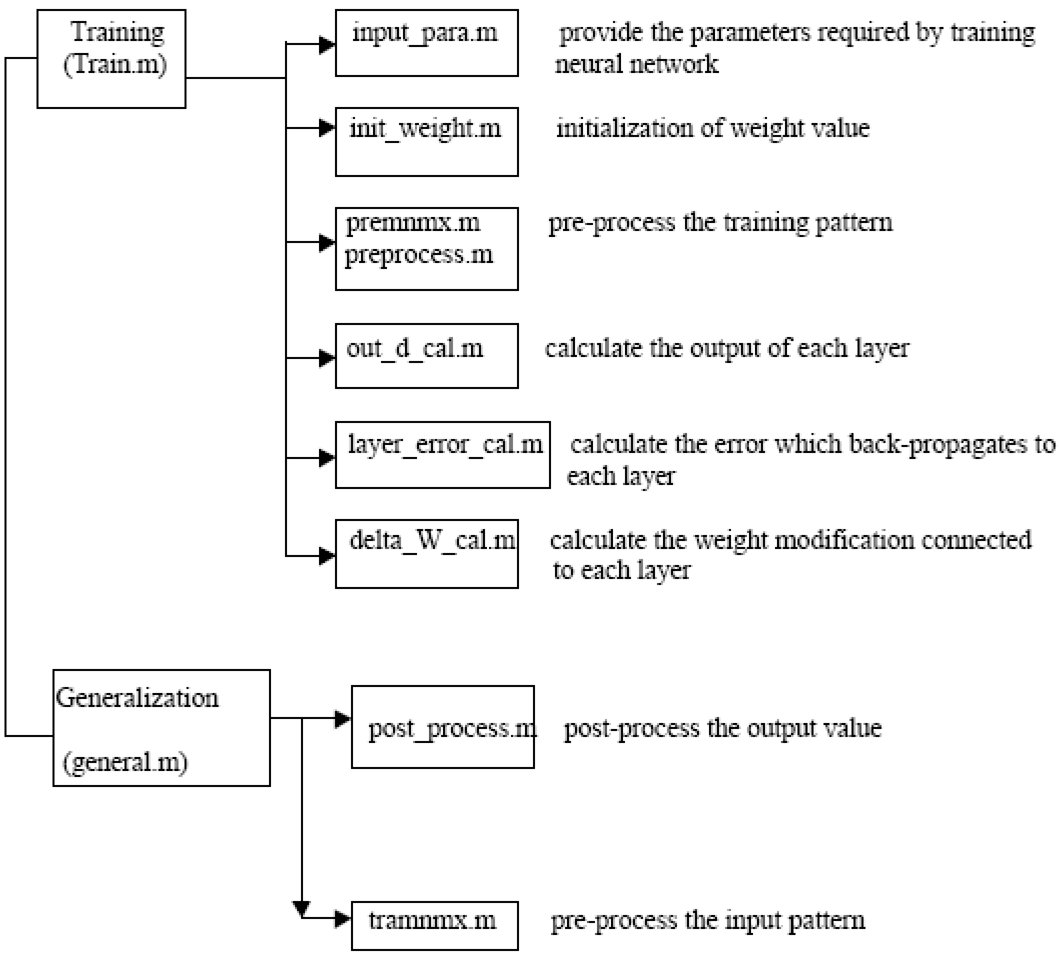

Figure 4.1 Modulus of the Training and Generalization Program

MATLAB Program for Training and Generalization:

MATLAB Program for Training is shown in blelow,

```
function net = train_net(bw_arr,bf_arr,bl_arr,le_arr,bw_norm, bf_norm, bl_norm, le_norm,ps_norm,al_norm)
        net = newff([minmax(bw_arr);minmax(bf_arr);minmax(bl_arr);minmax(le_arr)],[8 2],{'tansig' 'purelin'});
        Y = sim(net,[bw_norm; bf_norm; bl_norm; le_norm]);
        net.trainParam.epochs = 3000;
      net.trainParam.mu = 0.7;
      net = train(net,[bw_norm;bf_norm;bl_norm;le_norm],[ps_norm;al_norm]);
```

MATLAB Program for generalization is shown in below

```
function test_net(net,bw_test,bf_test,bl_test,le_test)
       index = 1; bw_index = 1; bf_index = 1; bl_index = 1;
        global bw_tarr bf_tarr bl_tarr le_tarr ps_out al_out;
        while (bw_index <= numel(bw_test))
      while (bf_index <= numel(bf_test))
        while (bl_index <= numel(bl_test))
            le_tarr(index) = le_test;
            bw_tarr(index) = bw_test(bw_index);
            bf_tarr(index) = bf_test(bf_index);
 bl_tarr(index) = bl_test(bl_index);
            index = index + 1;
  bl_index = bl_index + 1;
        end
          bl_index = 1;
          bf_index = bf_index + 1;
      end
      bf_index = 1;
      bw_index = bw_index + 1;
     end
     %normalize inputs
      [bw_norm bf_norm bl_norm le_norm] = normalize_inputs(bw_tarr,bf_tarr,bl_tarr,le_tarr);
      Y = sim(net,[bw_norm; bf_norm; bl_norm; le_norm]);
        %convert into actual value
      %display('------------- Test Report ----------------');
        %display(' bw(mm) --- bf(mm) --- bl(mm) --- le(mm) ------ ps(N/sq.mm) ------ al(kN) ----');
      for ii = 1:numel(bw_norm)
        ps_out(ii) = ((Y(1,ii)-0.2)^2)*10000; %in N/sq.mm
        al_out(ii) = ((Y(2,ii)-0.2)^2)*10; % in kN
        %display(sprintf('\n%d      %d      %d      %d     %f
%f',bw_arr(ii),bf_arr(ii),bl_arr(ii),le_arr(ii),ps_out,al_out));
End
```

CONCLUSION

In the process of training the neural network, the following conclusions can be drawn:

1. The input parameters are greatly influenced in the result of the artificial neural network model (BP). The target value of the training pattern was pre processed between 0.2 and 0.8.
2. The final value has been determined by synthesis consideration of the training time, the mapping of the neural network for the training pattern and generalization of the neural network monitored by the test patterns.
3. According to the objective of this study, the cold formed steel compression members are designed effectively and fast manner.
4. The neural network, which is trained by the BPNN algorithm showed good generalization and can be used for future research.

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