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Design of Beam-Columns Using Artificial Neural Networks

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ABSTRACT

In this paper, manual design of beam-columns, based on the procedure adopted by american society of steel construction, is described. an attempt has been taken to apply artificial neural network to the design of steel beam-columns of hot-rolled shapes. for this purpose, a set of data have been generated using the software package staad pro, and then used in training and testing the neural network. the results showed that artificial neural network after successful learning could specify the proper sections with relatively high accuracy.

Keywords: Neural Network, Design of Beam-Columns, Hot-Rolled Sections.

تصميم الاعمدة - العتبية باستخدام الشبكات العصبية الاصطناعية

الخلاصة

في هذا البحث تم وصف التصميم الاعتيادي للأعمدة – العتبية المستندة إلى الطريقة المتبناة من قبل المعهد الأمريكي للمنشآت الفولاذية. أجريت محاولة لتطبيق شبكة عصبية اصطناعية في تصميم الأعمدة – العتبية الفولاذية ذات المقاطع الجاهزة. لتحقيق هذا الغرض تم توليد بيانات باستخدام الحزمة البرمجية (Staad Pro), ثم استخدمت في تدريب واختبار الشبكة العصبية. أظهرت النتائج أنالشبكة العصبية الاصطناعية بعد تدريب ناجح تمكنت من تحديد المقاطع المناسبة بدقة عالية نسبياً .

NOTATIONS

Ann	Artificial Neural Network
Rcc	Reinforced Cement Concrete
Aisc	American Institute Of Steel Construction
Asd	Allowable Stress Design
F_a	AllowableAxial Compressive Stress If Only Axial Force Existed (Ksi)
F_b	Allowable Compressive

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	Bending Stress If Only Bending Moment Existed (Ksi)
F_a	Actual Axial Compressive Stress (Ksi)
F_b	Actual Compressive Bending Stress (Ksi)
F'_e	Euler Stress In (Ksi) Divided By Factor Of Safety = 1.92
F_y	Specified Minimum Yield Point/Stress Of The Steel Used (Ksi)
L_b	Unbraced Length In The Plane Of Bending (Ft)
R_b	Radius Of Gyration In The Plane Of Bending (In.)
K	Effective Length Factor In The Plane Of Bending
C_{mx}, C_{my}	Modification Factors, Less Than Or Equal To One, Which Reduce The Stresses Due To Bending About Major And Minor Axises, Respectively.
P_{eff}	An Axial Effective Force Replacing The Interaction Effect Of The Axial Load And Biaxial Moment (Kips)
P_o	The Applied Axial Force (Kips)
M_x, M_y	Bending Moments About Major And Minor Axises, Respectively (Kips-Ft)
M	A Factor The Value Of Which Is Obtained From Table (1)
U	A Factor The Value Of Which Is Obtained From Column "Allowable Axial Loads" Table In Aisc Manual, Initially Taken As 3.
Lrfd	Load And Resistance Factor Design
Ip	Input Vector
Op	Output Vector

D	Nominal Depth Of The Selected W-Shape (Inches).
W	Weight Per Unit Length (Lb/Ft)

INTRODUCTION

Structural engineering involves good understanding of material behavior, thorough knowledge of laws of mechanics, intuition, past accumulated experience or expertise and analysis techniques[1-5]. the design of structural elements is an iterative process [6,7]. the initial design is the first step. the efficiency of the design process depends heavily on initial guess. a good initial design reduces the number of subsequent analysis-design cycles or iterations and increases the efficiency of the design process. the need for human intuition in the initial design makes it extremely difficult to computerize it. this explain the growing tendency in recent years to computerize the initial design process using the new technology of artificial neural networks ann as they can learn from available designs during training process.

an artificial neural network (ann) is an informational system simulating the ability of a biological neural network by interconnecting many simple information-processing units – neurons [8, 9]. the main benefits in using a neural network are its ability to learning, operating in parallel, fault tolerance and distributed memory. neural networks can easily exploit the massively parallel local processing and distributed storage properties in the brain.

nowadays, find applications of ann can virtually in every field where the solution of encountered problem involves mapping a given set of inputs to a specified set of target outputs. as is the case with most neural networks, the aim is to train the net to achieve a balance between the ability to respond correctly to the input patterns that are used for training (memorization) and the ability to give reasonable (good) responses to input that is similar, but not identical, to that used in training (generalization).

lot of researches and studies were addressed to applications of ann in the field of civil engineering in general, and in structural engineering, particularly [10-13].

h. s. rao and b. r. babu (2007) developed a hybrid neural network model which combines the features of feed forward neural network and genetic algorithms for the design of beam subjected to moment and shear [14].

j. b. alam et al. (2007) attempted to determine the optimum thickness of edge-supported slabs by using ann with different numbers of hidden layers and hidden nodes [15].

a set of experimental data for the training and testing of neural network was conducted by j. hola and k. schabowicz to determine concrete compressive strength [16]. they concluded that anns are highly suitable for assessing the compressive strength of concrete.

the work of t. m. m. pillai and p. i. karthekeyan [17] demonstrated the application of a feed forward network and backpropagation training algorithm in the design of rcc short and long columns subjected to combined axial load and biaxial moments.

in most of these works, the traditional well-known backpropagation algorithm has been used in training neural networks.

properly trained backpropagation networks tend to give reasonable answers when presented with inputs that they have never seen. typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. this generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs[18].

the training of a network by backpropagation involves three stages: the feedforward of the input training pattern, the calculation and backpropagation of the associated error, and the adjust of the feedforward phase. even if training is slow, a trained net can produce its output very rapidly. numerous variations of backpropagation have been developed to improve the speed of the training process.

although a single-layer net is severely limited in the mappings it can learn, a multilayer net (with one or more hidden layers) can learn many continuous mapping to an arbitrary accuracy. more than one hidden layer may be beneficial for some applications, but one hidden layer is sufficient [9].

in this work an attempt has been made to use a backpropagation neural network with one hidden layer for the design of beam-columns with hot-rolled wide flange sections.

DESIGN OF COLUMNS SUBJECTED TO AXIAL LOAD AND BIAXIAL BENDING

the load carrying capacity of columns subject to axial load and biaxial bending, or so-called beam-columns, depends upon the size and geometry of the section, the grade of the steel, which determines the yield limit, the magnitude of the eccentricities of the applied load, the unbraced length of the column and finally the type of end connections.

in general, the design of beam-columns manually is somewhat a cumbersome work. it requires a great deal of effort and time.

according to the american institute of steel construction (aisc) allowable stress design (asd) manual[19], members subjected to combined axial force and bending shall be proportioned to satisfy the following equations:

$$for\ \frac{f_a}{F_a} > 0.15:$$

$$\frac{f_a}{F_a} + \frac{C_{mx}\, f_{bx}}{(1 - f_a/F'_{ex})F_{bx}} + \frac{C_{my}\, f_{by}}{\left(1 - f_a/F'_{ey}\right)F_{by}} \le 1 \quad \ldots..(1)$$

$$(\mathrm{eq.\ HI - 1\ AISC\ Manual})$$

$$\frac{f_a}{0.6F_y} + \frac{f_{bx}}{F_{bx}} + \frac{f_{by}}{F_{by}} \le 1 \qquad \ldots..(2)$$

$$(\mathrm{eq.\ HI - 2\ AISC\ Manual})$$

$$for\ \frac{f_a}{F_a} \le 0.15:$$

$$\frac{f_a}{F_a} + \frac{f_{bx}}{F_{bx}} + \frac{f_{by}}{F_{by}} \le 1 \qquad \ldots..(3)$$

$$(\text{eq. HI} - 3\ \text{AISC Manual})$$

where:
f_a = allowable axial compressive stress if only axial force existed (ksi).
f_b = allowable compressive bending stress if only bending moment existed (ksi).
f_a = actual axial compressive stress (ksi).
f_b = actual compressive bending stress (ksi).
$f'_e = \frac{12\pi^2 e}{23(kl_b/r_b)^2}$: (ksi):
euler stress divided by a factor of safty

$$(23/12 = 1.92)$$

f_y = specified minimum yield point/stress of the steel used (ksi).
l_b = unbraced length in the plane of bending (ft).
r_b = radius of gyration in the plane of bending (in.).
k = effective length factor in the plane of bending.
c_{mx}, c_{my} = modification factors, less than or equal to one, which reduce the stresses due to bending about major and minor axises, respectively.

in eqs. (1) through (3), subscripts x and y indicate the axis of bending. coefficient $1/(1- f_a/f'_e)$ is an amplification factor which takes into account

The increased moments caused by lateral displacements. depending on the actual slenderness ratios, axial load, lateral loads, and end restraint conditions, this amplification factor may become excessively conservative. to offset this situation, a modification or reduction factor c_m is introduced. the value of c_m is less than or equal to one.

The design procedure of beam-columns is a trial and error process in which a trial section is checked for compliance with the adopted design criteria.

The aisc manual of steel construction suggests a fast method for selecting an economical hot-rolled w- or s-shape section in which, an equivalent (effective) axial force (p_{eff}) replaces the interaction effect of the axial load and biaxial moment. the value of p_{eff} can be calculated from the following formula:

$$p_{eff} = p_\circ + mm_x + mm_y u \qquad \ldots\ldots(4)$$

where:
p_{eff} = an axial effective force replacing the interaction effect of the axial load and biaxial moment (kips).
p_o = the applied axial force (kips).
m_x = bending moment about major axis (kips-ft).
m_y = bending moment about minor axis (kips-ft).
m = a factor the value of which is obtained from table (1).
u = a factor the value of which is obtained from column "allowable axial loads" table in aisc manual, initially taken as 3.

The subsequent values of the factor m are obtained from table 1 (table b of the aisc manual [19]) based on the effective length (kl). the value of u in the first iteration is taken three and the subsequent values are listed in column allowable axial load tables.

From appropriate column load table, a tentative section is selected to support the calculated equivalent load p_{eff}. based on the selected section new values are found for m and u, and hence new value of p_{eff} is calculated from equation (4). the procedure continues until the values of m and u (and hence the section) settle. as the trial tentative section has been selected the remaining will be a pure analysis job where the selected section is checked for compliance with equations (1) through (3). the design procedure is considered accomplished when the selected section is found to be the most economical (lightest) one among the available sections.

The essential features of this design procedure have been kept unchanged in the later editions of aisc manual that adopted the new design approach of load and resistance factor design (lrfd) [20].

It is clear that the design procedure described above is effort- and time consuming. this is true even for the more recent approach and design aids developed using the aisc-lrfd specifications for design of steel beam-columns [21, 22].

The objective of this work is to demonstrate the applicability of ann, as alternate, more direct and time conserving approach, for the design of standard hot-rolled wide flange columns subjected to compressive & bending stresses. the target goal has been reached through various stages, which are addressed in the following sections.

APPLICATION OF ANN IN DESIGN OF BEAM-COLUMN SELECTION OF INPUT AND OUTPUT VECTORS

Input set must cover various parameters influencing the design of beam-columns. these are axial load p_o, bending moment about major axis mx, bending moment about minor axis my and effective length of the column kl. the output of the design procedure is the lightest section, selected from the table of standard american wide flange sections. the range of available sections was limited to those listed in the tables of allowable axial loads on columns[19]. each section is represented by two output variables, the first denotes the nominal depth of the section in inches (d), while the second one (w) represents the weight of unit length in ib/ft. thus, the input and output vectors will be:

$$\mathrm{ip} = \{\mathrm{p}, \mathrm{m}_x, \mathrm{m}_y, \mathrm{kl}\} \qquad \text{…....(5)}$$

$$\mathrm{op} = \{\mathrm{d}, \mathrm{w}\} \qquad \text{…....(6)}$$

where:
ip = input vector.
op = output vector.
d = nominal depth of the selected w-shape (inches).
w = weight per unit length (lb/ft).
the ranges of values of input parameters were chosen as given in table 2. this will yield a total number of 3200 input/output sets.

Generating Input And Output Data

In this work, instead of making calculations manually, which is a time and effort consuming process, we used the software package staad.pro [23] for generating the input / output sets of data. by running the "analyze" command 3200 times, each time feeding the "editor" file with new set of inputs (ip vector), one can get the proper w-shape (op vector). table 3 presents part of input/output data obtained this way.

The value of modification factors c_{mx} and c_{my} in eq. (1) was taken 0.85, as recommended by section h1 of the aisc specifications for compression members in frames subject to joint translation. aisc specifications permits the use of this value in some conditions of end supports and bracing against joint translation. however, extending the use of this value to other conditions may yield somewhat preservative, yet safe sections. all the sections listed in table (3) are computed for f_y = 36 ksi.

Suggested Topology

In this work, a neural network with backpropagation algorithm has been adopted. as mentioned before, the backpropagation algorithms has been widely and efficiently used in solving civil engineering problems.

the suggested backpropagation network (figure 1) has four nodes in the input layer and two nodes in the output layer. the number of nodes in the hidden layer has been taken twenty. several preliminary trials, made with different numbers of nodes, showed that this number led to minimum error ($2.8x10^{-5}$) with reasonable training time. the activation functions used were tan-sigmoid activation function in the hidden layer and pure-linear activation function in the output layer. with this topology the backpropagation network is able to recognize a sample among different sections.

Training and Testing

The backpropagation ann algorithm developed in matlab7.0 [18] software package with the topology suggested above has been trained and tested in two stages.

In the first stage the total number of the generated data sets, which equals 3200, were divided into two groups, one consisting of sets with odd set numbers (sets in boldface in table 3) and the other consisting of even samples. the first group, with odd numbers, was used for training the net, where the group of even samples have been used for testing.

table 6 shows some examples of results obtained in both conventional and suggested method in the first stage.

In the second stage all the 3200 data sets were used for training the net. in order to test the validation of the ann model, the same training 3200 sets were used to generate several testing sets of data by altering the value of each input parameter individually, verbally by shifting their values by ± 20% and ± 40% of the increment, and this way we obtain new 16 times 3200 data sets as shown in table 5.

Some examples of results obtained in both conventional and suggested method in the second stage are shown in table 7.

Results and discussion

Results of training and testing in the first stage are presented in figure 2 and table 4, where those of second stage in figure 3 and table 5.

it is clear that splitting data into two groups, one for training and the other for testing, as done in the first stage, gave very good results. among 1600 data samples used in testing, only 7 failed, which means an error percentage of 0.4375% (table 4). figure 2 shows that it took only 27 epochs to reach the goal error $2.8x10^{-5}$. this means that the time required for training the net is reasonable.

In the second stage, the goal error has been reached after 53 of training epochs (twice of that in the first stage). testing results showed a good match between the sections obtained by calculations and those obtained by using nn, especially for the those values of input parameters which are close to training values table(5). relatively high error ratios are observed in the testing sets with input values farther from those of training values. this situation seems to be different of that of the first stage. the reason behind this may be explained by the data used for training and testing in each case. thus, the scenario used in the first stage seemed to be more efficient than that applied in the second stage. furthermore, the authors recommend to conduct further studies to cover ranges with smaller values than that specified in this work.

CONCLUSIONS

In this paper, the authors demonstrated the application of artificial neural network in the design of steel hot-rolled beam-columns. the neural network has been trained using 3200 sets of input/output data. the data was obtained from staad pro software. two scenarios have been tried in training and testing the network. in both cases, the network, after rapid and successful training, was able to specify the proper sections for new problem parameters. it was concluded that the first scenario of training and testing has better working for all values of the variables within the ranges specified.

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Table (1) The values of m [19]

F_y	36 ksi							50 ksi						
KL (ft)	10	12	14	16	18	20	22 & over	10	12	14	16	18	20	22 & over
1st Approximation														
All shapes	2.4	2.3	2.2	2.2	2.1	2.0	1.9	2.4	2.3	2.2	2.0	1.9	1.8	1.7
Subsequent Approximations														
W, S 4	3.6	2.6	1.9	1.6	—	—	—	2.7	1.9	1.6	1.6	—	—	—
W, S 5	3.9	3.2	2.4	1.9	1.5	1.4	—	3.3	2.4	1.8	1.6	1.4	1.4	—
W, S 6	3.2	2.7	2.3	2.0	1.9	1.6	1.5	3.0	2.5	2.2	1.9	1.8	1.6	1.5
W 8	3.0	2.9	2.8	2.6	2.3	2.0	2.0	3.0	2.8	2.5	2.2	1.9	1.6	1.6
W 10	2.6	2.5	2.5	2.4	2.3	2.1	2.0	2.5	2.5	2.4	2.3	2.1	1.9	1.7
W 12	2.1	2.1	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	1.9	1.9	1.8	1.7
W 14	1.8	1.7	1.7	1.7	1.7	1.7	1.7	1.8	1.7	1.7	1.7	1.7	1.7	1.7

*Values of *m* are for C_m = 0.85. When C_m is other than 0.85, multiply the tabular value of *m* by $C_m/0.85$.

Table (2) the ranges of input variables

input variable	min. value	max. value	increment	variations
p_o (axial load) kips	50	1000	50	20
mx (moment about major axis) k-ft	50	400	50	8
my (moment about minor axis) k-ft	50	200	50	4
kl (effective length) ft	10	30	5	5
total variations (sets) 20*8*4*5 =				3200

Table (3). Some parts of the generated input/output data.

set no.	kl (m)	p_o (kips)	mx (kip-ft)	my (kip-ft)	section
1*	**10**	**50**	**50**	**50**	**w12x79**
2	15	50	50	50	w12x87
3	**20**	**50**	**50**	**50**	**w12x87**
4	25	50	50	50	w12x87
5	**30**	**50**	**50**	**50**	**w12x87**
6	10	100	50	50	w12x87
7	**15**	**100**	**50**	**50**	**w12x87**
8	20	100	50	50	w14x90
9	**25**	**100**	**50**	**50**	**w14x90**
10	30	100	50	50	w14x90
11	**10**	**150**	**50**	**50**	**w14x90**
. . .	. . .	. . .	. . .	. . .	. . .
15	**30**	**150**	**50**	**50**	**w14x109**
16	10	200	50	50	w14x90
. . .	. . .	. . .	. . .	. . .	. . .
100	30	1000	50	50	w14x311
101	**10**	**50**	**100**	**50**	**w14x90**
. . .	. . .	. . .	. . .	. . .	. . .
800	30	1000	400	50	w14x426
801	**10**	**50**	**50**	**100**	**w14x109**
. . .	. . .	. . .	. . .	. . .	. . .
1600	30	1000	400	100	w14x455
1601	**10**	**50**	**50**	**150**	**w14x145**
1602	15	50	50	150	w14x145
1603	**20**	**50**	**50**	**150**	**w14x145**
1604	25	50	50	150	w14x145
1605	**30**	**50**	**50**	**150**	**w14x145**
1606	10	100	50	150	w14x145
1607	**15**	**100**	**50**	**150**	**w14x145**
1608	20	100	50	150	w14x159
1609	**25**	**100**	**50**	**150**	**w14x159**
1610	30	100	50	150	w14x159
1611	**10**	**150**	**50**	**150**	**w14x159**
. . .	. . .	. . .	. . .	. . .	. . .
1615	**30**	**150**	**50**	**150**	**w14x176**
1616	10	200	50	150	w14x159

. . .	. . .	. . .	. . .	. . .	. . .
1700	30	1000	50	150	w14x398
1701	**10**	**50**	**100**	**150**	**w14x159**
. . .	. . .	. . .	. . .	. . .	. . .
2400	30	1000	400	150	w14x500
2401	**10**	**50**	**50**	**200**	**w14x176**
. . .	. . .	. . .	. . .	. . .	. . .
3200	30	1000	400	200	w14x550

***** data sets in boldface were used for training only in the first stage, while other sets, for testing the net.

Table (4) results of testing the network in the first stage.

training sets	testing sets	failing tested sets	error ratio
1600	1600	7	0.4375%

Table (5) results of testing the network in the second stage.

training sets *	testing sets	input 1 (kl) increment	input 2 (p_o) increment	input 3 (mx) increment	input 4 (my) increment	failing tested samples	error ratio
3200	3200	+2 #	-	-	-	144	4.5000%
3200	3200	+1	-	-	-	11	0.3438%
3200	3200	-1	-	-	-	10	0.3125%
3200	3200	-2	-	-	-	122	3.8125%
3200	3200	-	+20	-	-	20	0.6250%
3200	3200	-	+10	-	-	6	0.1875%
3200	3200	-	-10	-	-	6	0.1875%
3200	3200	-	-20	-	-	19	0.5938%
3200	3200	-	-	+20	-	79	2.4688%
3200	3200	-	-	+10	-	17	0.5313%
3200	3200	-	-	-10	-	16	0.5000%
3200	3200	-	-	-20	-	74	2.3125%
3200	3200	-	-	-	+20	865	27.0313%
3200	3200	-	-	-	+10	115	3.5937%
3200	3200	-	-	-	-10	115	3.5937%
3200	3200	-	-	-	-20	838	26.1875%

* here the whole 3200 sets listed in table 3 were used for training in each case.

this means that the same 3200 sets used for training are also used for testing, except that the values of (kl) are incremented by +2, so on for the other cases.

Table (6) some examples of results obtained in conventional and suggested method in the first stage.

design by using ann		conventional aisc design		my	mx	p_o	kl
d (in.)	unit weight (lb/ft)	d (in.)	unit weight (lb/ft)				
12	87	12	87	50	50	50	15
14	233	14	233	100	400	50	30
14	283	14	283	150	400	200	20
14	342	14	342	150	350	600	25
14	426	14	426	200	400	900	10

Table (7) some examples of results obtained in conventional and suggested method in the second stage.

design by using ann		conventional aisc design		my	mx	p_o	kl
d (in.)	unit weight (lb/ft)	d (in.)	unit weight (lb/ft)				
12	79	12	79	50	50	50	10
14	90	14	90	50	100	50	25
14	99	14	99	50	100	100	20
14	134	14	145	50	50	250	30
14	193	14	193	50	100	650	15
14	342	14	342	150	300	750	20
14	500	14	500	200	400	950	30

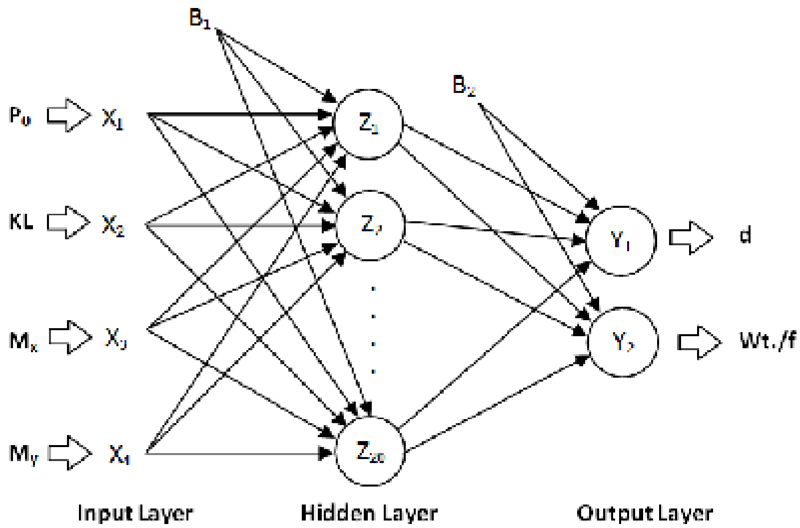

Figure (1). Architecture of the suggested ANN.

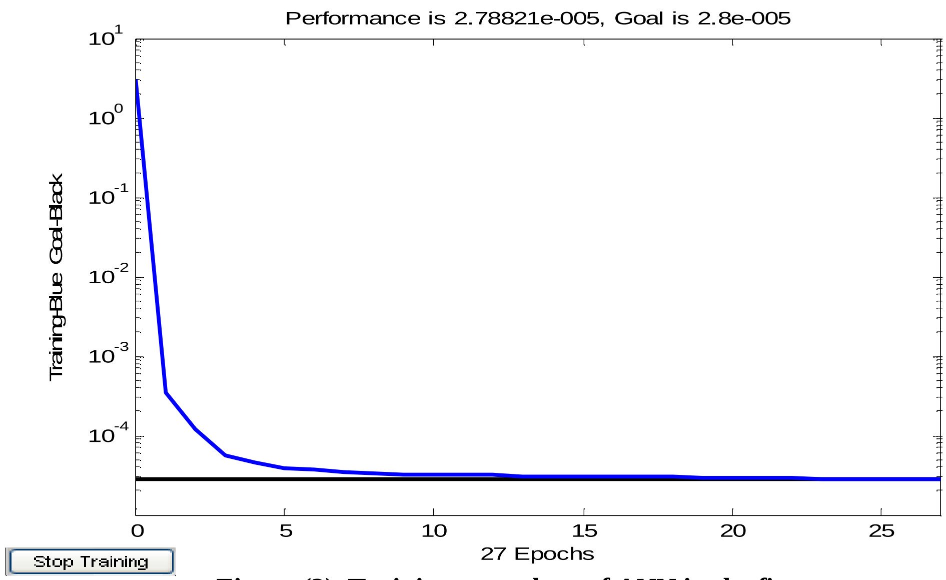

Figure (2). Training procedure of ANN in the first stage.

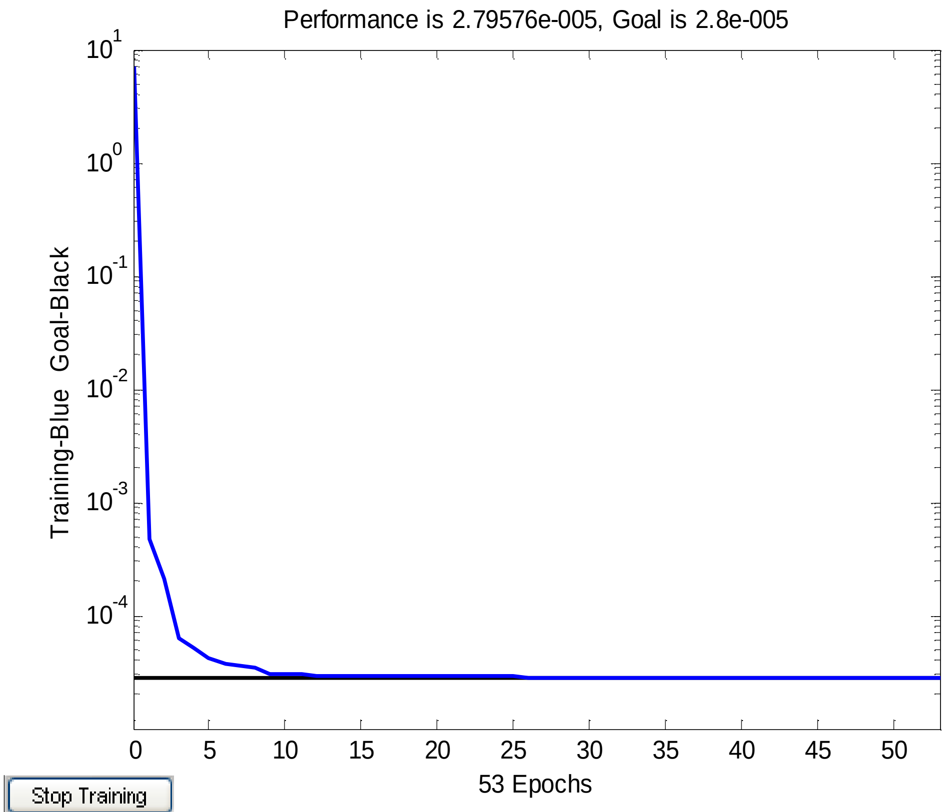

Figure (3). Training procedure of ANN in the second stage.