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## **The Use of Artificial Neural Network (ANN) for Design of Beam-to-Column Rigid Connection**

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### **Abstract**

The Artificial Neural Network is one of the branches of Artificial Intelligence that is inspired by human nervous system. In neural networks, data processing is done through an interconnected network of little processors that act in parallel with each other. To solve rigid connection design, in welded metal structure building that has numerous stages, these networks were used because of their high speed processing and to show whether or not design speed is affected by processing speed. After writing network using MATLAB software and introducing all of design formulas, initially, 80% of data was used for network training and after the network got familiar with the pattern, by using 20% remaining data, the network was tested. Full analysis of design of some options, such as welding electrode material and weld size based on tenth subject of National Building Regulations, should be selected in designing, but since the choice of these variables is done mainly through the maximum 3 different types, and also they are constant in much of the designs, so it was not used in this article. All of connections should be considered rigid and web-flange connection should be full penetration diffusion welding. The thickness of reinforcing fillet welds on each side of web was considered thicker than 8 mm. the used neural network was perceptron network (MLP) with the back-propagation algorithm (BP), respectively.

**Keywords:** Artificial Neural Network, Rigid connection, Intermediate moment frame (IMF) design.



## Introduction

In the design of moment frames, connection details including the dimensions of top plate and bottom plate, and other factors such as the length of weld size and thickness of plates are highly regarded, especially in the design of spans with the size over 7 or 8m that it is essential to use plate beam in this moment frames. Nowadays, structural calculators for the design of moment frames and examine the dimensions and details of these connections use metal connection books or computational softwares, available on the market including programs that are written with Excel and are easily accessible on the Internet. According to calculator skill and availability of designation defaults, the design of each connection to Excel takes at least 10 minutes, due to the high number of procedures and control of them. In most of design steps, defaults are not sufficient and designer has to change them and it takes more time. For example may be the thickness of selected plate for beam cannot tolerate the acting forces on it and should be changed as a default.

However in this research, for better use of time and speed up the design process, a program was written, using the artificial neural network, to take less time and have high accuracy in design. The purpose of this study is to design an intermediate moment frame and with minor modifications in programing, the type of frame can be changed to the ordinary or special moment frame. All the used computational methods and formulas were collected from tenth subject of National Building Regulations edited in 2013. At the beginning, stages of design was written and the required formulas to obtain the desired items were extracted, then these formulas were written by using MATLAB software and Neural Network coding.

## Artificial Neural Networks method

Using Artificial Neural Network modeling brain function as a part of Artificial Intelligence had a significant growth in the decade of 1990s. The use of a Neural Network is to create an output pattern based on input pattern that presented to the network. This work is done by setting and training the network using previous experiences and information. An Artificial Neural Network (ANN), is made up of units call Neurons that shown in following figure. The input of this neuron is multiplied by the weighted coefficients and then adds to a fixed number that is called Bias. The result passes from a linear or non-linear function to make the output.

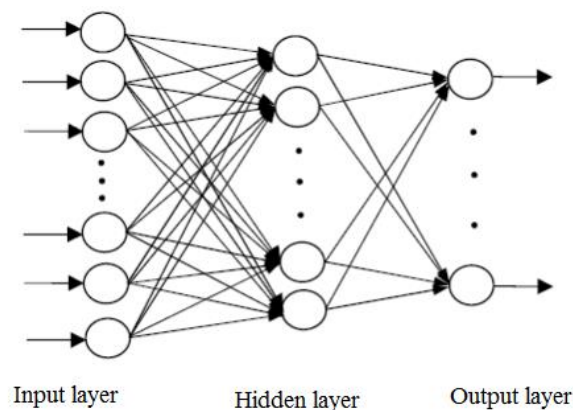


Fig. 1: schematic of a neuron in an Artificial Neural Network [1, 2, 10].



One of the most common types of neural networks is perceptron network (MLP), using the back-propagation algorithm (BP) (Fig. 2).

If number of layers and neural cells for multilayer perceptron, be selected properly then a nonlinear mapping can be performed with good accuracy.

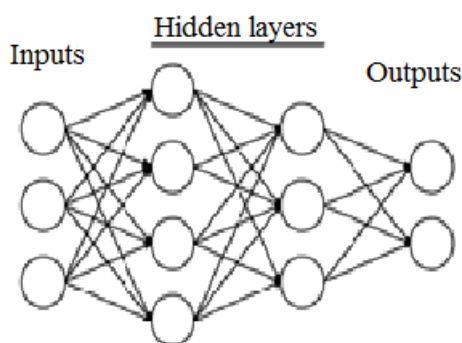


Fig. 2: The structure of neural network of MLP [1, 10].

According to the investigated cases, the data space is required to use in neural network algorithm is provided. Neural Network with the following characteristics is used, in order to create an appropriate relationship between the data used by the code. This network is multilayer and use the model of Group Modeling Data Handling (GMDH). Maximum four-layer neural network with up to 15 neurons in each layer is considered. 80% of data that sent to the code are used to train the network and the remaining 20% are used for testing.

### Assessment indicators of neural network models

To evaluate the performance of neural network models some indicators are needed to judge functioning of models compared with the collection of data and empirical results. Therefore, the following indicators are used to evaluate the models and compare their performance relative to each other:

- The correlation coefficient (R): the association between two variables is shown by this parameter. Correlation coefficient between x and y as two variables is defined as follows:

$$R = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}} \quad (1)$$

- Mean Absolute Error (MAE): this parameter represents the average error in the intended set of data. This indicator is expressed by the following equation:

$$MAE = \frac{1}{N} \sum_{i=1}^N |E_i| \quad (2)$$

- Root-Mean-Square Error (RMSE): this indicator also expresses the average error value and it shows the difference between obtained value from experiments and models.



$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (E_i)^2} \quad (3)$$

The results for 15 designed variables are given below and contains tow sets of chart for each one of them.

### Design method

Based on the proposed approach for the design a number of input variable and a number of output variable was set. Input variables or in other words design parameters include of: the length of designed beam, dead loads and live loads, the width of the load beam and the geometric characteristics of the beam consist of cross-section, length of web and its thickness, upper part of section, width of column section (the attached side). In this article column section was given to the software as a main default by a constant value. This 9 variables was considered as basic variables in the design. However in full analysis of design some options, such as welding electrode material and weld size based on tenth subject of National Building Regulations, should be selected in designing, but since the choice of this variables is done mainly through the maximum 3 different types, also they are constant in much of the designs, therefore hadn't been used in this article. In order to train the neural network, 100 different variables were specified as training data and according to the mentioned method for formulation, beam and column design was done for this input variables.

Based on the design, all the 15 needed parameters were extracted. This 15 variables were the bases in neural network algorithm and the mentioned algorithm was used to design all of them.

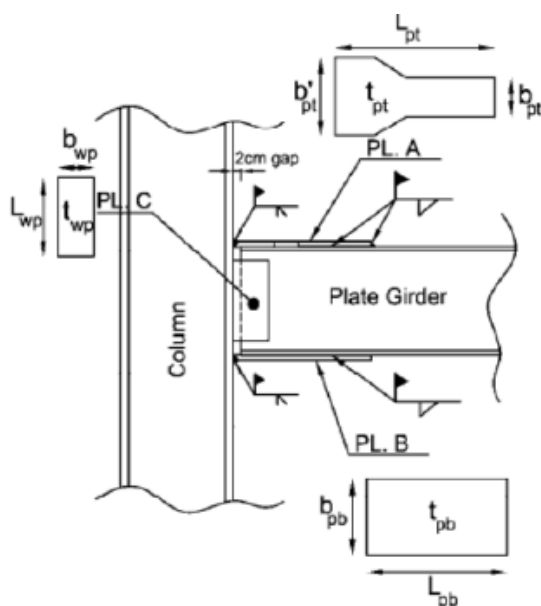


Fig. 3: details of rigid connection [11].





Table 1: Maximum and minimum of used variables

min	max	Design variable	number
3	7	Length of designed beam (m)	1
300	800	Dead load (kg/m <sup>2</sup> )	2
100	400	Live load (kg/m <sup>2</sup> )	3
1.5	2.5	Width of load beam (m)	4
10	20	Width of beam section (cm)	5
0.8	1.3	Thickness of upper part of beam section (mm)	6
18	24	Length of beam web (cm)	7
0.5	0.7	Thickness of beam web (mm)	8

This variables consist of bellow items:

The length, width and thickness of top and bottom plate, total weld length for both top and bottom plate, web plate thickness and x parameter related to the web welding,  $a_1$  and  $a_2$  parameters related to welding plate to beam web and column web, the minimum flange thickness for lack of need for stiffener in H shaped columns and box columns and finally the thickness of continuity plate.

All the 100 investigated cases and results in connection design are given in the following. It should be noted that for this 100 cases to including a wide area and having a uniform distribution, the random distribution of data between maximum and minimum value of them (table 1), was used.

### Processing of neural network data

Initially conformity of obtained data from neural network, and input data into code, in a diagram is reported. In this part 100 input data are displayed, which include 80 data for network training and 20 data for testing. In the following the conformity of data will be discussed. Furthermore various types of criteria to determine the errors are mention in this section such as: RMSE and MAE. The data which must be correspond to the normal curve are presented too.

In the second part of each figure, the curve that passed through data is displayed. This curves are showed for testing data, training data and total data and R parameter that represents information processing precision is given in this section too.

As the first designed parameter, bottom plate thickness is considered. As it can be seen, there is an appropriate conformity between input data and neural network generated data so that the RMSE parameter is 0.48 in this case.

The relative value of error between data is consistent with the normal curve, with considerable accuracy. Also, R parameter for the second part of results are 98, 93 and 97 % for the training, testing and total data. This amount of compliance reflects adequacy of input data to the algorithm for training about this design parameter.



### Training and testing data for neural network with passed curve through data for bottom plate thickness

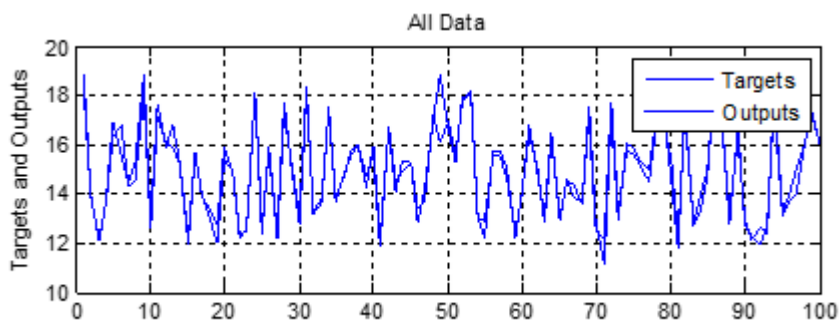


Fig. 4: diagram of desired data and software output data [9].

Fig.4 shows the matching of desired data and software output data, however in many points due to the high compliance, they are quiet consistent.

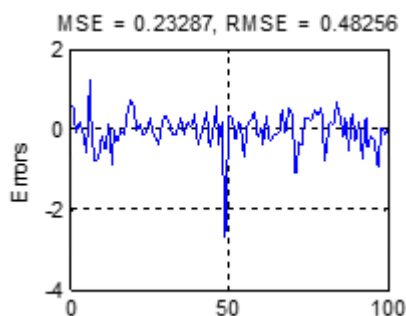


Fig. 5: error value between two sets of obtained data [9].

Fig. 5 displays the error value between two sets of obtained data in different conditions.

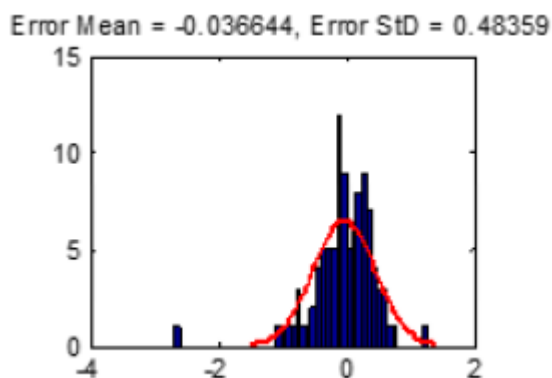


Fig. 6: statistic distribution of data associated with each error [9].

The statistical distribution of data associated with each error are displayed in Fig. 6.

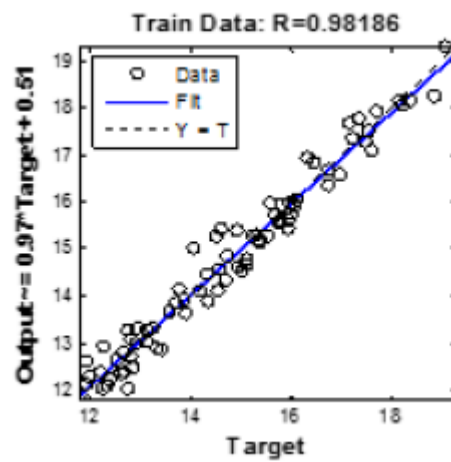


Fig. 7: relationship between input and output data for the training data [9].

The relationship between input and output data, for the training data is displayed in Fig. 7.

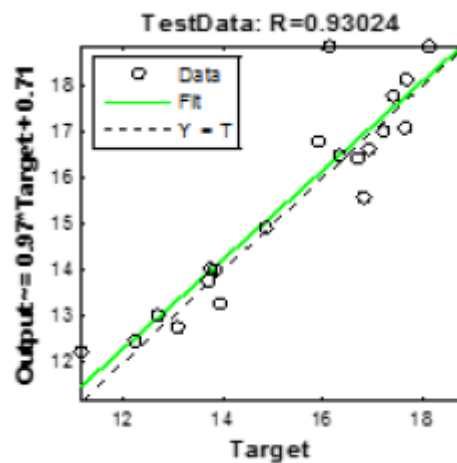


Fig. 8: relationship between input and output data for the testing data [9].

Figure 8, shows the relationship between input and output data for the testing data.

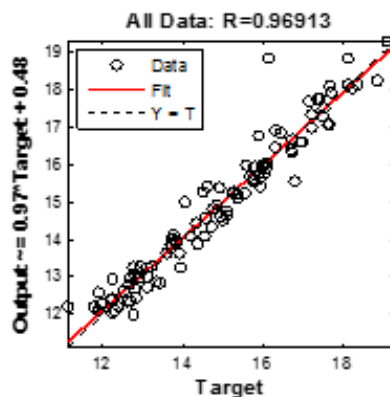


Fig. 9: relationship between input and output data for total data [9].

And fig. 9 displays the relationship between input and output data for total data that was given into code. In fig. 10 results of bottom plate width are represented. It is observed that the R parameter in this case is equal to 1. It is due to obtaining bottom plate width from sum of upper beam section width and a constant value. So the value of this parameter is influenced by input parameters and there is a direct and linear correlation between input and output data.

This is indicated by the Value of  $R=1$ , that the written code has recognized this problem so good and it can determine the bottom plate width certainty, by using input data. The trend of using the neural network code, written for other variables, is given below. It should be noted that for each of this chart, input variable mode should be constant and only target design variable change that has studied in 15 different mode.

Conformity between neural network output data and expected data was very high. Error value and r parameter in each case are written in figures [3].

In order to better investigation of the compliance, accuracy of algorithm for different variables are reported in a table at the last part of diagrams.

For better assessment of neural network algorithm performance, instead of 100 data, 30 input data was used and the results are given bellow.

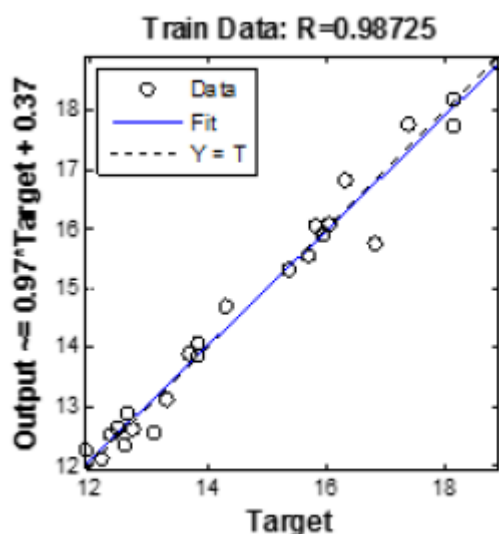


Fig. 10: bottom plate thickness and passed curve through the data [9].





Fig. 10 shows the results in using 30 input data, for bottom plate thickness and passed curve through the data.

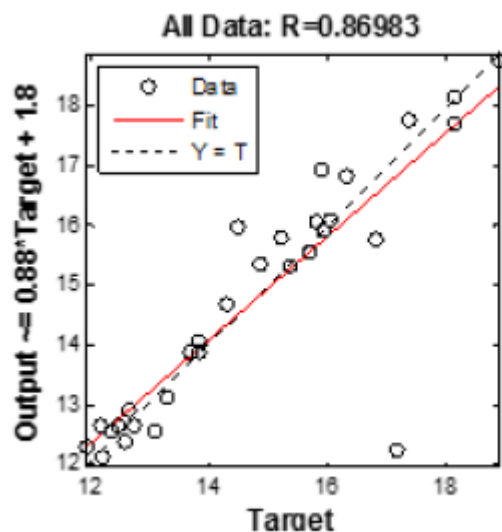


Fig. 11

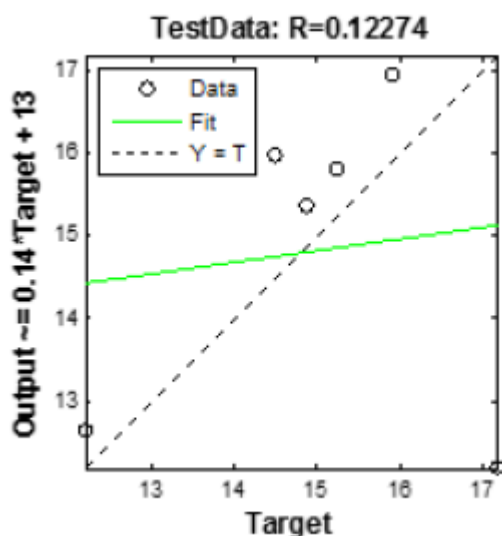


Fig. 12

In fig 12 “11” Using 30 input data rather than 100 data, has increased the algorithm error, so that in using 100 data passed curve has had a compliance rate of 97% and in using 30 data the compliance has reduced to 87%. So to get the proper results, input data should increase and using 100 data in this case can be suitable.

In order to manual control of neural network, for 5 input data, using neural network algorithm and manual method, the results are reported in table 2. In this 5 cases, it is attempted to covering the entire study area about design variables. Maximum error in manual and neural network solution, is less than 10% that shows the accuracy of written code in this study.



Table 2:

	L (m)	DL (kg/m <sup>2</sup> )	LL (kg/m <sup>2</sup> )	w (m)	bf (m)	tf (m)	hw (m)	tw (m)
1	4	750	350	1.8	12	0.9	18.5	0.55
2	4	350	150	2.3	18	1.2	23.5	0.65
3	5	600	250	2	15	1	20	0.6
4	6	750	350	1.8	18	1.2	23.5	0.65
5	6	350	150	2.3	12	0.9	18.5	0.55

	Bottom plate				Top plate			
	Plate width (cm)	Plate length (cm)	Plate thickness (mm)	Total weld length (cm)	Plate width (cm)	Plate length (cm)	Plate thickness (mm)	Total weld length (cm)
1	17	331	12.44874	621	9.333333	401.9497	30.23265	703.8994
2	23	612	17.5298	1183	17.333333	720.5191	31.01427	1341.038
3	20	434	14.10327	828	13.333333	519.09	28.20655	938.18
4	23	615	17.62279	1190	17.333333	724.0758	31.17878	1348.152
5	17	313	11.74592	586	9.333333	382.0796	28.52581	664.1593

	Web plate design		Design of plate to beam web welding size	Design of plate to column web welding size	Minimum of flange thickness for lack of stiffener in H shaped column (mm)	Minimum of flange thickness for lack of stiffener in box column (mm)	Continuity plate thickness (mm)
	twp	x	a <sub>1</sub> (mm)	a <sub>2</sub> (mm)			
1	4.79	3.80198	0.282573	1.050825	2	1.410906	15.11633
2	5.73	3.459459	0.366247	1.089779	3	1.745907	15.50713
3	4.99	3.692308	0.30272	1.043094	2.5	1.558846	14.10327
4	5.95	3.459459	0.38045	1.13204	3	1.745907	15.58939
5	3.66	3.80198	0.215601	0.801773	2	1.410906	14.2629



### **Result and discussion**

In design of welding rigid connection of plate beam to column for a structure with medium ductility (according to tenth subject of National Building Regulations edited in 2013), several steps of calculation and its control must be done for a complete design.

To obtain the desired optimum sections in this design, 9 parameters as the variable parameters should be changed by trial and error method to get the required value. Manual design and excel software can be used, (excel software has more computational speed than manual design). In any design and all of calculation steps from beginning to the end, a constant variable should be considered. Finally it will be clear that used variables give desired outputs or not and this process takes a lot of time.

In this study by using neural network design, the results will be obtained much faster. Neural network program gives automatically and so fast, required answers and appropriate sections value, by using trial and error method.

In order to measure the accuracy of obtained results from program written in MATLAB [6], results for the 5 input data, using manual design were compared with software outputs and observed that error value was negligible.

Input variables or in other words design parameters include of: the length of designed beam, dead loads and live loads, the width of the load beam and the geometric characteristics of the beam consist of cross-section, length of web and its thickness and upper part of section thickness. Using a combination of genetic algorithm and neural network to obtain the relationship between variables, optimizing the results, considering various types of beam to column connection and applying neural network to the design data can be so useful [7].



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