PRELIMINARY DESIGN OF A BLAST RESISTANT RCC ELEMENT USING ARTIFICIAL NEURAL NETWORK

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Abstract: In recent years, the increase in the number of terrorist attacks, blasts in oil rigs, explosion accidents in petrochemical industries have shown that the impact of blast loads on building and its components are a serious matter which should be kept in mind during the design of a building. Preliminary design phase is most important in blast resistant design process. It includes whether the building component will be safe or not with initial guess values of parameters such as steel diameter, size of element, allowable response, etc. This phase requires structural designer's intuition to predict the initial guess. Artificial Neural Network (ANN) has shown great potential in prediction of values even with nonlinear relationships between parameters. In this research, ANN is used for the preliminary design of a RCC front wall of a building. Parameters such as peak overpressure, the natural time period, stand-off distance of blast, dimensions of the Wall, Steel Diameter, boundary conditions of the wall, allowable response were considered as input. Ductility ratio, maximum deflection and rotations were considered as output parameters. Spreadsheet was used for simpler calculations to generate required data based on values calculated using formulas and methods provided by Codal provisions such as special report "Design of Blast Resistant Buildings in Petrochemical Facilities" published by ASCE, UFC-3-340-02, IS:4991-1968 and TM 5-1300. To reduce the tedious process of predicting different values of output parameters through statistical methods, ANN can be used to train and simulate the prediction of the data. MATLAB software was used for training and simulation of ANN. Based on trained values, output parameters can be generated within allowable error values as ANN can create relations between most of the parameters. Simulated outputs within the input range of trained ANN provides satisfactory results while values outside the input range, doesn't provide satisfactory results.

***Index Terms* - Artificial Neural Network, RCC front wall, Preliminary Blast Design, Ductility Ratio, Non-linear Prediction.**

[redacted] INTRODUCTION

Conventional structures usually are not designed to deprecate detonation loads and seeing the scales of raw material loads are considerably less than those created by most of the blasts. Public buildings cannot sustain the extreme attacks such as attacks happened on the World Trade Centre in the USA. Building owners and professionals together can produce steps to get the better understanding for possible threats and challenging environment. With this in notice developers, architects, and engineers are seeking solutions for potential blast situations, to protect building occupants and the structures.

Artificial Neural Network (ANN) displays features such as mapping abilities or pattern relationship, simplification, robustness or error tolerance as well as comparable and rapid data processing. ANN learns by cases, thus, it can be trained with identified examples of a problem to gain information about it. Once, properly trained, the network can be put to actual use of resolving unknown or untrained illustrations of the problem. Due to its multidisciplinary environment, ANN is becoming common among the investigators, planners, designers, engineers, etc., as an effective tool for the completion of their work. Therefore, ANN is being effectively used in many engineering areas as well as in research areas.

1. Artificial Neural Network

Artificial Neural Network (ANN) is a subfield of the artificial intelligence technology that has gained strong popularity in it rather large array of engineering applications where conventional analytical methods are difficult to pursue or show inferior performance. Specifically, ANNs have shown a good potential to successfully model complex input/output relationships where the presence of non-linearity and inconsistent / noisy data adversely affects other approaches. ANN model is robust and Fault tolerant. ANN can also work with qualitative, uncertain and incomplete information, making it highly promising for inverse problems in structural engineering.

An ANN consists of a large number of interconnected computational elements called "neurons", organized in a number of layers. The connection between each pair of neurons is called a link and is associated with a "weight" that is a numerical estimate of the connection strength. Each neuron in an exceedingly layer receives and processes weighted inputs from neurons within the previous layer and transmits its output to neurons within the following layer. The weighted summation of inputs to a neuron is converted to an output according to a transfer function (typically a sigmoid function).

1.1 Artificial Neuron

Processes inside the biological neural networks are very complex and they still cannot be completely studied and explained. There are hundreds of different types of biological neurons in human brain, so it is almost impossible to create a mathematical model that will be absolutely the same as the biological neural network. However, for practical application of artificial neural networks, it is not necessary to use complex neuron models.

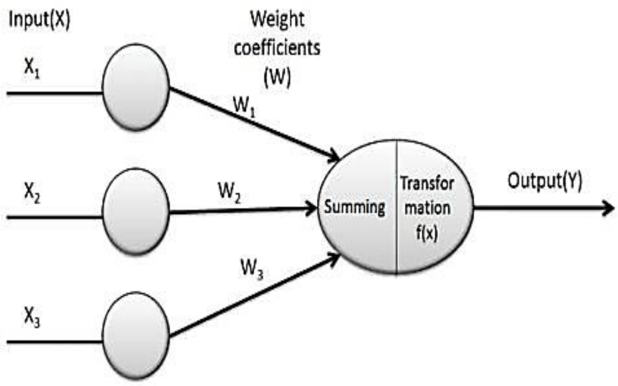


Figure 1 Model for Artificial Neuron

The artificial neuron receives the input signals and generates the output signals. Every data from the surrounding or an output from other neurons can be used as an input signal. The model for an artificial neuron is shown in Figure 1.

1.2 Neural Network

Neural network is composed of numerous mutually connected neurons grouped in layers. The complicity of the network is determinate by the number of layers. Beside the input (first) and the output (last) layer, network can have one or few hidden layers (Figure 2).

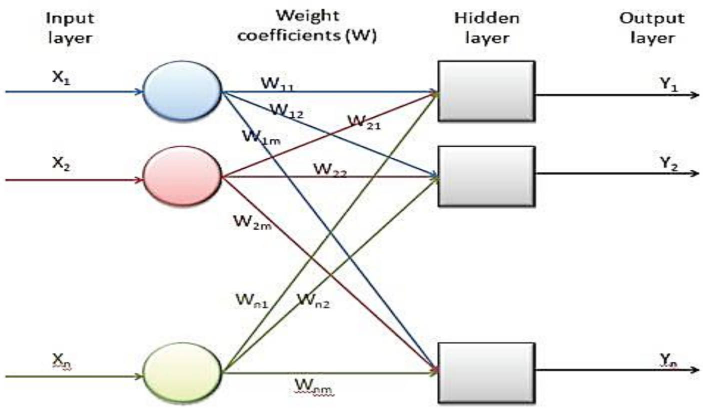


Figure 2 Model of one layered Artificial Neural Network

The purpose of the input layer is to accept data from the surroundings. Those data are processed in the hidden layers and sent into the output layer. The final results from the network are the outputs of the neurons from the last network layer and that is actually the solution for the analysed problem.

1.3 Weight Coefficients

Weight coefficients are the key elements of every neural network. They express the relative importance of each neuron's input and determine the input's capability for stimulation of the neurons. Every input neuron has its own weight coefficient. By multiplying those weight coefficients with the input signals and by summing that, we calculate the input signal from each neuron.

In Figure 2, the input data are marked as X1, X2 and X3, and the appropriate weight coefficients are W1, W2 and W3. The input neuron impulses are W1X1, W2X2 and W3X3. Neuron registers the totalled input impulse that is adequate the sum of all input impulses:

$$X = W_1X_1 + W_2X_2 + W_3X_3 \tag{1.1}$$

The received impulse is processed through an appropriate transformation function (activation function), f(x), and the output signal from the neuron will be:

$$\mathrm{Y} = \mathrm{f(x)} = f(W_1X_1 + W_2X_2 + W_3X_3) \tag{1.2}$$

Weight coefficients are parts of the matrix W that has n rows and m columns. For example, the weight coefficient W_{nm} is actually the m^{th} output of the n^{th} neuron (Figure 2).

1.4 Activation function

The main purpose of the activation (transformation) function is to determine whether the result from the summary impulse $X = W_1X_1 + W_2X_2 + \cdots + W_nX_m$can generate an output. This function is associated with the neurons from the hidden layers and it is mostly some nonlinear function. Almost every non-linear function can be used as an activation function, but a common practice is to use the sigmoid function (hyperbolic tangent and logistic) with the following form:

$$Y_t = \frac{1}{1 + e^{-Y}} \tag{1.3}$$

Where, Y_t is normalized value of the result of the summary function.

The normalization means that the output's value, after the transformation, will be in reasonable limits, between 0 and 1. If there is no activation function and no transformation, the output value might be too large, especially for complex networks that have few hidden layers.

1.5 Network's training process

The artificial neural networks have several basic characteristics, among which their learning capability takes an important place (this capability brings them closer to the real world and human thinking), together with their capability of discovering connection between chaotic and incomprehensible data and their generalizing capability (the network will give quality outputs even though the input data are not completed).

In many cases it is shown that the neural networks are a better calculation method compared to the classic methods, mostly because of their capability to analyse data that contain errors, or to solve problems that have no reasonable solution and to learn from the past data. The training (learning) process of neural networks consists of periodic data transmission through the network and compartment of the received input values with the expected ones. If there is a difference between those values, then a weight coefficient's adjustment (modification of the neuron connections) has to be made. This process is repeated a few times until the network reacts the way we want it to react, or until all the weight coefficients from all the training data are being adjusted.

Neural networks may be used as a substitute for auto correlation, multivariable regression, linear regression, trigonometric and other arithmetical analysis techniques. A particular network can be defined using three vital components: transfer function, network design and learning rule. One has to define these components, depending upon the problem to be resolved.

1.6 Application of ANN in structural engineering

Over the past few years, neural computing has attracted researchers from many areas of structural engineering. Neural computing offers an attractive package of computational flexibility in terms of increased processing speed, machine learning, reduced knowledge engineering, easy implementation, capabilities for postulating complicated material and human behaviour, inherent parallel processing capacity, etc. Therefore, researchers have found this computing technique very useful in fields such as structural optimization, preliminary design, approximate analysis, earthquake characterization, damage detection, construction management, material modelling, inverse problems, capturing human behaviour and so forth.

[redacted] ASSUMPTIONS FOR THE STUDY

1. Rectangular diffraction type structure is considered.
2. Preliminary design optimization is considered only for RC front wall of a building.
3. The material of the wall is considered as homogeneous and isotropic.
4. Here element wise approach is used.
5. Single stage loading is considered.
6. Doors and windows are considered as blast resistant.
7. In this unconfined explosion - Surface burst explosion is considered.
8. Positive phase pressure is only considered for this study.
9. In this the blast loading is considered to act on the member which is above the ground level.

[redacted] STEP BY STEP PROCEDURE

2.1 Spreadsheet Calculations

After the step by step process for the design of blast resistant building component RC front wall, spreadsheets were prepared for quick calculations. Design calculations is important for comparison between output changes in dataset preparation. All the important parameters were being considered to create a database for input and output values.

Spreadsheet calculations were done based on the formulas of Standard Codal Provisions.

2.2 VBA Programming

In this step, iterative process takes place. VBA programming can be helpful in generating data for different input values which are directly independent from output values. Following parameters were used as input parameters:

1. Weight of TNT
2. Stand-off distance
3. Peak overpressure
4. Width of the building or Panel
5. Height of the building or Panel
6. Length of the building or Panel
7. Steel Diameter
8. Wall thickness

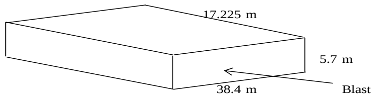
9. Boundary Conditions
10. Allowable Response
11. Peak dynamic pressure, etc.

Blast Load Calculation

1.0 General

Building dimensions are as follows:

Building Height H: 5.70 m (Above Ground)
Building width B : 38.4 m
Building Length L: 17.225 m



1.1 Blast wave parameter:

The blast wave parameters are as follows:

Peak over pressure P_{so} : 65.0 kPa
Time duration t_d: 0.15 sec

Clearing distance , S
S=H or B/2 whichever minimum= 5.70 m
Ambient Pressure P_o = 100.0 kPa
U = Shock velocity = 345 * ((1+0.0083*Ps_o)^0.5) (As per ASCE Equ 3.5)
= 345 * (1 +0.0083 * 65) ^ 0.5
= 428.06 m/sec
Length of Wave L_w = U * t_d
= 428.07 * 0.15
= 64.21 m
Peak Dynamic Wind Press. q_o= 0.0032*Pso^2 (As per ASCE Equ 3.4)
= 0.0032*65^2
= 13.5 kPa

1.2 Front Wall Loading:

The front wall is asssumed to span vertically from foundation to roof.
The design will be typical wall segment 1 m wide.

Peak reflected pressure P_r = (2+0.0073*Pso)*P_{so} (As per ASCE Equ 3.3)
= (2+0.0073*65)*65
= 160.84 kPa
Clearing time t_c = 4S/(1+R)Cr Where, R= S/G= 0.30
G= 19.2 G=H or B/2, whichever is greter
= 0.0425 sec Cr=sound velocity from Fig.2-192= 1.26
Drag Coefficient C_d = 1
Stagnation Pressure P_s = P_{so} + C_d * q_o
= 65 + 1 * 13.52
= 78.52 kPa
Front wall Impulse I_w = 0.5*(P_r-P_s)*t_c+0.5*P_s*t_d
= 0.5*(160.8425 - 78.52) * 0.0426 + 0.5 * 78.52 * 0.15
= 7.64 kPa-sec
Effective Duration t_e = 2 * I_w / P_r
= 2* 7.64 / 160.8425
= 0.095 sec

Figure 3 Sample of Spreadsheet Calculations

But since blast resistant design is mostly for industrial purposes safety inspection done by third party will provide values of peak overpressure and time duration. Thus weight of TNT and stand-off distances are not important for input parameters.
As ANN needs raw input data in the format of array (variables assigned to certain set of values), it is important to generate a data with row-column pattern.

2.3 Dataset Preparation

As explained earlier that ANN needs array of input – output values. Thus it is important to have a database of input and output parameters in row-column format. Database of design parameters can be referred as “Dataset”. Using VBA programming iterative process can generate row by row data of different input values and output values as per formulas. ‘for…next’ and ‘Do...Until’ loop was used for the process of row by row iteration.

In this dataset columns also known as fields were named as parameters needed for input values which were Peak Overpressure, Time Duration of blast loading, Height of building or front wall, Width of building or front wall, and Length of front wall or building, Steel Diameter, boundary conditions, allowable rotation. For the array of output values following parameters were used:

1. Ductility Ratio
2. Deflection and
3. Support Rotation

A sample of the input and output dataset is shown below: Values of ductility ratio are determined by chart solution.

Table 1 Sample Input and Output Dataset

Peak Over pressure (kPa)	Time Duration (sec)	Height (m)	Width (m)	Length (m)	Wall Thick. (mm)	Steel Dia. (mm)	Boundary Condition	Allowable Response	Ductility Ratio μ	Deflection (mm)	Rotation (degree)
30.00	0.01	3	3	3	10	110	1	2	2.4807	25.8743	0.8017
30.00	0.012	3	3	3	10	110	1	2	2.7630	28.8182	0.8929
30.00	0.014	3	3	3	10	120	1	2	2.5650	24.4697	0.7582
45.00	0.032	12	37	37	32	320	3	4	2.9191	426.3891	3.8435
45.00	0.034	13	37	37	32	360	3	4	2.8949	422.9619	3.5351
45.00	0.036	14	37	37	32	400	3	4	2.9995	431.9504	3.3650
45.00	0.038	6	37	37	32	230	3	2	1.4848	89.9761	1.5393
45.00	0.04	3	37	37	20	140	3	2	2.6554	55.5420	1.7205
80.00	0.224	3	41	41	10	120	4	2	2.2196	21.1751	0.6561
80.00	0.226	4	41	41	32	230	4	2	2.0555	61.2397	1.4935

80.00	0.228	5	41	41	16	130	4	2	1.3910	59.0087	1.1867
80.00	0.23	6	41	41	32	330	4	2	2.6713	105.3813	1.8027
120.00	0.292	4	26	26	32	160	4	2	1.4328	55.4745	1.3530
120.00	0.294	5	26	26	32	390	4	2	2.8935	65.0418	1.3080

2.4 Artificial Neural Network Setup

Setting up ANN is the most important part in this process. Different types of networks are divided according to: number of layers, connection type between neurons, learning process, data type, course of information spreading, etc.

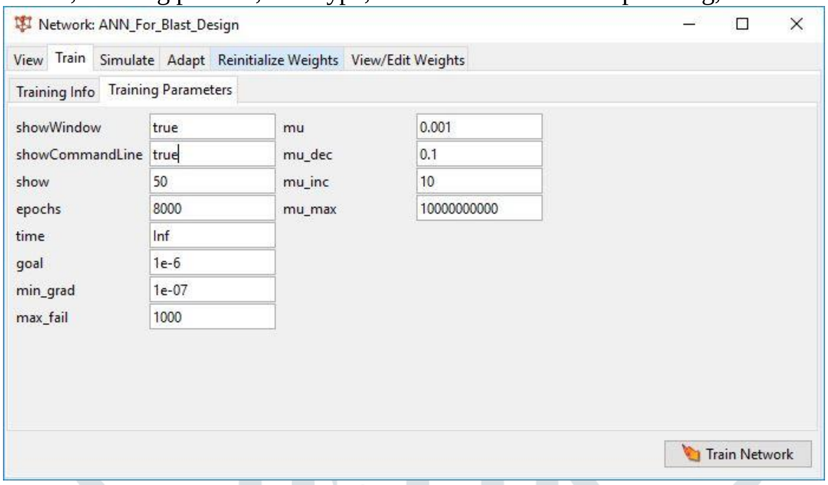


Figure 4 NN Training Parameters

For this project following configuration was used in ANN:

1. Algorithm used in ANN configuration:
   a. Data Division: Random.
   b. Training: Levenberg – Marquardt (Trainlm algorithm)
   c. Performance: Mean Squared Error (mse)
   d. Calculation: MEX
2. Validation Checks: Experimental from 100 to 1000.
3. One input layer and one output layer with 2-3 hidden layers.
4. Layered connection between neurons.
5. Back-propagation feed forward learning process.
6. Partly supervised and supervised course of information spreading.
7. Sigmoid function as activation function.
8. 1000 to 8000 epoch value.
9. Non linearity consideration.

2.5 Training and Simulation of ANN

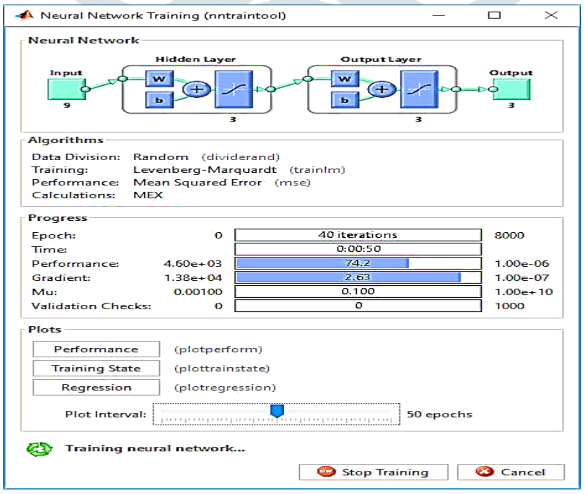


Figure 5 Training of ANN

Based on input / output values that are fed into ANN needs to be trained for mapping out input – output relations whether they are linear or non-linear. Training is a process in which ANN tries to fit all the input and output values by multiplying weight to input parameter and comparing it with output value provided in output dataset. "Epoch" can be defined as number of iterations in ANN i.e. 1000 epoch means it will be iterated for 1000 times to get lesser error. If error is more than 3%, then epoch value was changed to greater than 1000 and training was repeated.

After completion of training phase, it was important to simulate the ANN with a sample data for higher accuracy. In simulation input data which was in the range of ANN training data was fed into ANN and simulated. Also it was checked for input parameters values outside the input range of training data.

2.6 Tool Validation

Validation of the artificial neural network is important. Using simulated ANN new input values which must be in the range of dataset are provided from calculations done in above sections and comparing output values with actual values of maximum deflection, ductility ratio and rotation gives % of error or tolerance. Initial validation showed about 0.5% tolerance for all parameters. For more validation ANSYS model can also be prepared and results can be compared with the output values of ANN model. Another validation was done after completion of the training of ANN.

2.7 Error Checking

Table 2 Results Comparisions

Original Ductility Ratio μ	Original Deflection (mm)	Original Rotation (degree)	ANN O/P Ductility Ratio μ	ANN O/P Deflection (mm)	ANN O/P Rotation (degree)
2.4807	25.8743	0.8017	2.455893	24.9686995	0.793683
2.7630	28.8182	0.8929	2.73537	27.809563	0.883971
2.5650	24.4697	0.7582	2.53935	23.6132605	0.750618
2.9191	426.3891	3.8435	2.889909	411.4654815	3.805065
2.8949	422.9619	3.5351	2.865951	408.1582335	3.499749
2.9995	431.9504	3.3650	2.969505	416.832136	3.33135
1.4848	89.9761	1.5393	1.469952	86.8269365	1.523907
2.6554	55.5420	1.7205	2.628846	53.59803	1.703295
2.2196	21.1751	0.6561	2.197404	20.4339715	0.649539
2.0555	61.2397	1.4935	2.034945	59.0963105	1.478565
1.3910	59.0087	1.1867	1.37709	56.9433955	1.174833
2.6713	105.3813	1.8027	2.644587	101.6929545	1.784673
1.4328	55.4745	1.3530	1.418472	53.5328925	1.33947
2.8935	65.0418	1.3080	2.864565	62.765337	1.29492

After successful completion of ANN training and simulation, it is important to validate the tool for errors whether it is providing acceptable results or not. Validation of values was based on Special report by ASCE illustration and a real project with design outputs. Comparison between different output parameters were also done. Error margin in output values between tool output and real project design output should be less than 3%. Thus, the accuracy of the tool should be 3%.

[redacted] RESULTS AND CONCLUSION

Salient observations noted from the applications of the neural networks during this work were:

1. Neural networks are powerful as these can process information more rapidly than traditional computer systems. They are also able to process the information when the input data is either incomplete or noisy. The true power and advantage of neural networks lies in their ability to represent, both linear and non-linear relationships.
2. It is also observed that neural network reduce the computational time required for the implementation by a significant amount as compared to the existing conventional methods.
3. Although providing great results, input values provided that are outside the range of trained ANN doesn't provide correct results. So, it is important to consider wider input parameter ranges.
4. Error tolerance can be changed with changing the values of algorithms, and training parameters such as epoch, validation checks and error_tolerance. Although it should be noted that training time is also important.
5. In this project error percentage of output data were about 1%, 0.35% and 1.5% thus providing great results of ductility ratio, end support rotation and maximum deflection respectively.

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