Optimization of structural elements in highly seismic areas using neural networks

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Abstract. The aim of this research is to use Artificial Neural Networks (ANN) to dimension structural elements in regular 6-storey buildings. The necessary data for the training of the algorithm was elaborated manually with the help of the ETABS software, these were 30 buildings of reinforced concrete with a system of structural walls. The configuration and training of the neural network was carried out in the MATLAB software. The validation was carried out in an additional analyzed building in which the concrete savings were calculated, and the requirements of the current regulations were verified. Finally, the dimensioning obtained with the neural network generated a reduction of more than 10% in the total volume of concrete used in a 6-level building and establishes that the algorithm used provides effective results for an optimal design.

1. Introduction

Nowadays the importance of pre-dimensioning the structural elements and not generating cost overruns is increasing. Because construction costs depend on the amount of materials (concrete, steel and formwork), i.e. the direct costs of the project, and these in turn are related to the dimensions of the sections of the structural elements. However, in order to carry out an adequate pre-dimensioning that does not generate a cost overrun of 28% of the total estimated cost [1], it is necessary to carry out an iterative process based on the designer's criteria.

In the calculation of the optimal dimensions of columns, beams and shear walls there are previous investigations in which methodologies such as artificial intelligence, quadratic sequential programming [2], among others, are used. In AI some of the most common optimization techniques are particle swarm optimization (PSO), simulated annealing (SA) and artificial neural networks.

In the context of artificial intelligence, the particle swarm optimization (PSO) technique was proposed in 2013 for the calculation of beam sections to reduce construction costs [3]. Another method is the artificial neural network, which was used to optimize structural elements (beams and columns) in buildings [4]. In these investigations, the optimization of the sections provided a saving of 6.7% and 8.4% when compared with a conventional design method [3] and with the application of the Simulated Annealing (SA) technique (explaining the process of the technique) in two building models, they achieved a saving of 33.8% and 34.1% for each one of the models [5]. However, the optimization of sections was done individually (beams or columns) [2], [3], [5]-[9][10] or in the case of a building only columns and beams.

In this research, a methodology capable of optimizing the dimensions in columns, beams and reinforced concrete shear walls is proposed, based on preliminary design data of proposed multi-family
buildings. This will reduce the cost overrun of the materials that are used when the structural elements are over-dimensioned, and in turn will reduce the time to obtain the dimensions. For this purpose, a neural network algorithm will be developed to reduce by 10% the cost overrun when estimating the optimal dimensions of the structural elements (columns, beams and shear walls).

2. Methodology

To optimize the dimensions of the structural elements, neural networks were used, so buildings were modeled with a system of structural and regular 6-story walls. The preliminary dimensions of the buildings were selected as input data and the measurements of beams, columns and shear walls as output variables. Then, the training was carried out with the information collected and the validation of the neural network configured through the modeling of a new building. Finally, it was calculated the concrete difference that is obtained when dimensioning a building with neural networks and in a conventional way [11], from this, the concrete saving was calculated.

2.1. Information gathering and classification of structures

Regular structures were modeled and analyzed in the ETABS software with a minimum floor area of 100 m² and a maximum of 1300 m², with a story height of 3.0 m. The structural analysis was carried out using the National Building Regulation (RNE) in its chapters E 020, E030 and E060, for this purpose 30 types of structures in plant were proposed based on the indicated parameters. Then it was defined the possible dimensions that the buildings will have in plant: width (A) and length (L) and it was verified that the area that occupies is within the established limits.

The scheme of one of the cases is shown in Figure 1, the number of columns in each axis (X and Y) were variable and at their own discretion. The location of the shear walls in both directions was strategic at the discretion of the researcher. In addition, each model has at least one elevator, located in the center of the building and in some cases at the ends, depending on the floor area. Figure 2 shows the isometric view.

For the modeling, the loads used were dead and live loads; for the seismic analysis, the static and modal spectral analysis was used with the following seismic parameters in a high seismicity zone:

- Maximum horizontal acceleration (Z) = 0.45g
- Importance Factor (U) = 1
- Soil factor (S) = 1
- Reduction Coefficient (R) = 6

Then we proceeded with the reduction of the length of the cut walls because this is more important in the lateral displacements, with that length the structural analysis was made to verify the drifts, this process was iterative and we obtained a final length of shear wall in the X and Y direction with drifts less or equal to 0.007 according to the NTP E. 0.30 (Peruvian Technical Standard). This process was carried out for all 30 models and Figure 3 shows the comparison of drifts between the initial model which consists of the building pre-dimensioned in a conventional way and the optimized structure with the dimensions of reduced structural elements of case 19.

Figure 1 Plan view type 19 (25x30m)  
Figure 2 Isometric view of plant type 19
Figure. 3 Drift comparison between the initial and optimized models

It is observed that, as the length of the shear walls in both directions and in some cases the cross-sectional area of the columns was reduced, the drifts of each level gradually increased until reaching the limit of 0.007 provided by RNE E.060. After performing the indicated procedure, the dimensions shown in Table 1 were obtained.

| Element                      | Dimension | Measure (m) |
|------------------------------|-----------|-------------|
| Perimeter column             | Width     | 0.40        |
|                              | Depth     | 0.40        |
| Central column               | Width     | 0.45        |
|                              | Depth     | 0.45        |
| Beam in X direction          | Width     | 0.30        |
|                              | Depth     | 0.55        |
| Beam in Y direction          | Width     | 0.30        |
|                              | Depth     | 0.60        |
| Shear walls in X direction   | Thickness | 0.20        |
|                              | Length    | 18.00       |
| Shear walls in Y direction   | Thickness | 0.25        |
|                              | Length    | 22.00       |

These dimensions were obtained after an iterative process and are those necessary to obtain a maximum drift of 0.0068 very close to the limit of 0.007, however, to be used as training data will be changed from units and columns are entered as area, then shows the data finally used in this case for training.

- Perimeter column area = 1600 cm²
- Center column area = 2025 cm²
- Length of shear wall in X direction = 1800 cm
- Thickness of shear wall in length X = 20 cm
- Length of shear wall in Y direction = 2200 cm
- Thickness of shear wall in Y direction = 25 cm
- Width of beam in X direction = 30 cm
- Depth of beam in X direction = 55 cm
- Width of beam in Y direction = 30 cm
- Depth of beam in Y direction = 60 cm
We changed from units to centimeters to obtain results with greater precision, since we work with larger numbers and in the case of columns we decided to train with the cross-sectional area because most cases use square section columns.

2.2. Architecture of the artificial neural network

For the elaboration of the neural network, input data was established, defined by the preliminary data we have of the building's architecture, and the dimensions of the structural elements will be identified as output variables as shown in Figure. 4.

Where variables A, B, C and D are the input data of the ANN width, length, maximum span in the X direction and maximum span in the Y direction; and variables 1 to 10 represent the output data representing the area of the columns located at the corners and perimeters, the area of the columns located in the internal part of the building, the accumulated length and width of the cutting walls used (X direction and Y direction), the base and height of the most critical beam in the X and Y direction.

![Figure. 4 Architecture of the artificial neural network](image)

The elaboration of the neural network was carried out in the MATLAB software with the help of the “nntool”. The number of neurons in the hidden layer of the neural network will be defined according to the convergence and training needs that arise in each model. A total of 10 tests were performed with different layers and numbers of neurons in each one; and the network 10 was selected for presenting greater homogeneity and correlation with respect to the other networks as shown in Table 2.

**Table 2. Correlation coefficient of test networks**

| Net | [Input - Number of neurons - Output] | R - Training | R - Test | R - Validation | R - total |
|-----|-------------------------------------|-------------|----------|----------------|----------|
| 1   | [4 10 10]                           | 0.984       | 0.953    | 0.910          | 0.967    |
| 2   | [4 15 10]                           | 0.902       | 0.909    | 0.971          | 0.917    |
| 3   | [4 20 10]                           | 0.956       | 0.925    | 0.980          | 0.956    |
| 4   | [4 10 10]                           | 0.718       | 0.784    | 0.882          | 0.754    |
| 5   | [4 10 15 10]                        | 0.928       | 0.912    | 0.970          | 0.934    |
| 6   | [4 15 15 10]                        | 0.759       | 0.831    | 0.810          | 0.760    |
| 7   | [4 20 25 10]                        | 0.994       | 0.983    | 0.971          | 0.989    |
| 8   | [4 20 20 10]                        | 0.792       | 0.817    | 0.756          | 0.788    |
| 9   | [4 25 20 10]                        | 0.983       | 0.998    | 0.941          | 0.975    |
| 10  | [4 25 25 10]                        | 0.982       | 0.980    | 0.983          | 0.982    |
The database for the training of the artificial neural network was compiled by designing 30 types of buildings with the same number of floors but with column separations in both variable axes, which were structured, analyzed and designed. When the initially proposed sections had a resistance well above the requested ones, the cross sections were reduced and redesigned, until obtaining the necessary sections to satisfy the requests. The final sections obtained were used for training and validation of the neural network.

2.3. Methodology validation
In this stage the algorithm was executed with the preliminary data of a building called input variables, this building was different from those used in the training, from these data the dimensions of the structural elements were calculated. The results obtained from the analysis are shown in the following chapter.

Additionally, the neural network was executed with one of the data used in the training to validate that the results it provides are approximate, the output dimensions and the variation that was obtained in comparison to the calculated data is shown in Table 3.

| Output variable                                      | Output ETABS | Neural network output | Variation% |
|------------------------------------------------------|--------------|-----------------------|------------|
| Perimeter column area (cm²)                          | 900          | 880.17                | 2.2%       |
| Center column area (cm²)                             | 1225         | 1161.96               | 5.1%       |
| Shear wall length in X direction (minor) (cm)         | 2200         | 2173.75               | 1.2%       |
| Shear wall thickness in X direction (minor) (cm)      | 20           | 23.77                 | 18.9%      |
| Length of shear walls in Y direction (major) (cm)     | 1900         | 1770.34               | 6.8%       |
| Shear wall thickness in Y direction (major) (cm)       | 20           | 20.28                 | 1.4%       |
| Beam width in X direction (minor) X (cm)              | 25           | 27.02                 | 8.1%       |
| Beam depth in X direction (minor) (cm)                | 40           | 45.16                 | 12.9%      |
| Beam width in Y direction (major) (cm)                | 25           | 29.95                 | 19.8%      |
| Beam depth in Y direction (major) (cm)                | 50           | 46.74                 | 6.5%       |

The maximum percentage variation obtained is 19.8% while the minimum was 1.2%, however, the maximum value was obtained in the dimension of beam base width, in which it was obtained a length of 29.95 cm by the execution of the neural network compared to 25 cm calculated, the difference was 4.95 cm being this difference acceptable in engineering.

2.4. Calculation of concrete savings
The final stage of the research consisted in comparing the volume of concrete needed in a building dimensioned with neural networks and conventionally. From this information, the difference of concrete between both structures was calculated to finally indicate the savings obtained, the results obtained are shown in the following chapter.

3. Resulted
3.1. Neural network testing
The validation of the algorithm was done by running the neural network with a new building and its input data are shown below:
- Building width of 20 m
- Building length of 21 m
- Beam span in the direction of the building width of 4.50 m
- Span of beams in direction of building length of 5.00 m

With the input data the selected neural network was executed, with this the optimal dimensions that each structural element should have were obtained, these are shown in Table 4.
With the dimensions provided by the neural network for the beams, columns and shear walls, the modeling and structural analysis of the building was performed, the cross section chosen for the column was square, the dimensions of the beam were rounded to a multiple of 5cm and the length of the shear walls were strategically distributed in both directions. From this, the elastic drifts were obtained and multiplied by 0.75R to obtain the inelastic drifts as indicated by RNE E.060. These results are shown in Table 5.

### Table 5. Test 2 neural network story drifts

| Story | Case       | Elastic drift | Inelastic drift |
|-------|------------|---------------|-----------------|
| 6     | Earthquake-X | 0.0011        | 0.0051          |
| 5     | Earthquake-X | 0.0012        | 0.0052          |
| 4     | Earthquake-X | 0.0011        | 0.0051          |
| 3     | Earthquake-X | 0.0010        | 0.0046          |
| 2     | Earthquake-X | 0.0008        | 0.0035          |
| 1     | Earthquake-X | 0.0003        | 0.0016          |
| 6     | Earthquake-Y | 0.0015        | 0.0067          |
| 5     | Earthquake-Y | 0.0016        | 0.0071          |
| 4     | Earthquake-Y | 0.0016        | 0.0071          |
| 3     | Earthquake-Y | 0.0015        | 0.0065          |
| 2     | Earthquake-Y | 0.0011        | 0.0050          |
| 1     | Earthquake-Y | 0.0005        | 0.0023          |

The maximum drift obtained was 0.0071, this value exceeds the maximum of 0.007 established by NTE 0.30 for reinforced concrete buildings. However, the difference it exceeds is minimal and can be reduced by increasing its length by 5% or at the discretion of the designer.

#### 3.2. Concrete saving calculation

The volume of concrete used in the building dimensioned with the use of neural networks and in a conventional way was obtained from the load measurements necessary for the seismic analysis, these volumes calculated for the neural network and the conventional method are shown in Table 6.

### Table 6. Concrete volume comparison

| Method       | Volume of concrete (m³) | Total volume (m³) |
|--------------|-------------------------|-------------------|
|              | Column | Beam | Shear wall |                  |
| Neural networks | 28.0    | 162.9 | 153.4      | 344.4            |
| Conventional  | 21.8    | 129.1 | 232.2      | 383.1            |
It was observed that in the case of the building, a difference of 38.7 m$^3$ of total concrete was obtained in favor of the building dimensioned with the use of neural networks. However, the volume of columns and beams is lower in the building analyzed conventionally, while the volume to be used in cut walls is considerably higher. This difference of concrete to be used in the first case represents a saving of 10.11% compared to the conventional method.

4. Conclusions

With the use of neural networks, a saving of 10.11% of used concrete was obtained in comparison to the same structure dimensioned in a conventional way. However, a greater volume of concrete was obtained in columns and beams due to the fact that there is a greater number of these structural elements, while in shear walls a notable difference was obtained by using a shorter length of shear walls in both directions.

The maximum drift obtained in the building dimensioned with neural networks is 0.0071, this value exceeds by 0.0001 the maximum allowed. However, this parameter can be reduced by increasing the length of the cut-off walls in a minimum or by placing them in a different shape, which concludes that neural networks can be used to obtain dimensions of structural elements that provide us with an optimal drift and consequently use a smaller amount of concrete for their construction.

The neural network elaborated in this research can be used in buildings that have a regular plan geometry and that the relation between the major and minor side does not exceed in 1.5, with approximate seismic parameters, a structural system of structural walls and of 6 levels with a mezzanine height of 3.00 m approximately. Since for the training stage, data with similar characteristics to those mentioned was used.

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