

Optimization of Shear Walls with the Combination of Genetic Algorithm and Artificial Neural Networks

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Abstract

Objectives: In this study, the cost of a reinforced concrete structures containing medium ductile shear walls, which were similar in plan and height, has been optimized by the combination of Genetic Algorithm and Artificial Neural Networks. **Methods:** The selected structure was a 13-storey building with four types of shear walls, which was supposed to be built in Tehran. The costs estimated for this research included the cost of concrete and reinforcement used in the walls. By changing the measure of shear walls, some steel rods, and cement altered. **Results:** Accordingly, the ranges of shear walls were recognized as the independent variables and the concrete and steel rod results were dependent variables. Beams, columns and the width of the shear walls were the same on all types. The prices of concrete and support of shear walls have been used for back propagation neural network training. Before optimization by neural network in the section of neural network training, the Genetic Algorithm steel bar function is defined. The steel bar function included the costs of concrete and steel bars used in shear walls. **Conclusion:** Afterwards, the best combination of four types of shear walls was selected using Genetic Algorithm. Finally, the optimum shear wall area to the plan area of regular concrete buildings with medium ductile shear walls is presented.

Keywords: Genetic Algorithms, Neural Networks, Optimization, Shear Walls

1. Introduction

According youthful population of Iran and the resulting increase in demand for housing, construction sector today is of particular importance. Land prices have increased significantly due to increased housing demand; the price of materials has increased the same for this reason. The fact that there are limited lands for construction and habitation of people should be also considered. Every day, the significant increase in the prices because of inflation can be seen and it affects the prime cost of construction. The dimensions of buildings had been designed using technical capabilities and experiences of engineers during the past projects. Currently, optimization methods are performed by solving complex mathematical equations, integrations and differential equations. The variables in these methods are considered continuously which a

big deficiency in the optimization. Genetic Algorithm is an artificial intelligence method first proposed¹. The first civil engineering problem was solved using Genetic Algorithm². This approach considers three bands to solve the truss problems. Different configurations of truss were designed using developed expert system and then a similar configuration was optimized using Genetic Algorithm. In the studies³, a Genetic Algorithm was formed out for time and labor costs. In an article, Genetic Algorithm was used to identify the vibrations of damaged areas⁴. Other scholars have also used Genetic Algorithms for optimization⁵⁻⁷. In⁸, the bearing capacity of a biaxial reinforced concrete column was examined by Genetic Algorithm⁸. Researchers also have used Genetic Algorithm to optimize shear walls and other optimization problems in civil engineering⁹⁻¹². Other researchers have also studied the issues such as optimizing industrial

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roofing, optimizing building frames, optimizing concrete reinforcement and other optimization problems using artificial intelligence in civil engineering¹³⁻¹⁶. Due to the disadvantages of old algorithms, the use of artificial intelligence is implied nowadays. Finding all the cost levels (all possible values of functions) to determine the minimum cost is in the heart of all optimization algorithms. Because of the weakness of the traditional optimization algorithms, efficient and powerful algorithms such as natural optimizers are emerged. These methods are based on an intelligent search in a great but limited space. These algorithms, unlike the old ones, do not need to calculate the derivatives and hence there is no limit for discontinuous cost functions and discrete variables.

2. Modeling

In this research, a 13-storey building, which is uniform in plan and height Figure 1 has been modeled with Etabs 9.7^{17,18}. The length and width of the building has not changed in modeling and only the length of shear walls ranges from 3 to 6 m. The thicknesses of shear walls are constant and equal to 35 cm. All building components such as beams and columns are the same in all models and have not changed. The walls are divided into three categories as specified in Figure 1.

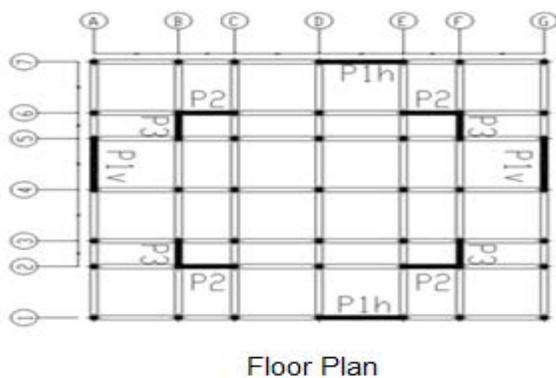


Figure 1. Case study plan.

3. Signs and Symptoms

The symptoms and signs used in this study include:

Ag: Cross-section of the wall.

As: Cross-section of the steel bars.

Ccc: The cost of 1 m³ of concrete.

Ccs: The cost of 1 kg of steel bar.

F(x): Target function.

Fctd: Tensile strength of concrete.

n: Total number of samples.

Vcc: total price of concrete in shear wall

Vu: Ultimate shear force under the load factor.

Vr: Ultimate shear strength of the section.

V_c: ultimate shear strength provided by the concrete

V_s: Ultimate shear strength provided by the shear reinforcement.

Wst: Total costs of the shear reinforcement.

δ: Relative displacement of the storey.

Fyd: Yield strength of steel bars.

Fcd: Compressive strength of concrete.

h_i: Height of the ith floor.

ρ_{n,h}: The horizontal steel ratio of the cross section.

4. Genetic Algorithm

Genetic Algorithm is an optimization method inspired by living nature that can be classified as a numerical method of direct and random search. This algorithm is based on iteration; its basic principles are adopted from genetics. It has been invented by emulating some of processes observed in natural evolution. It effectively uses the old knowledge existed in a population to find new and improved solutions. Moreover, genetics is the science of inheritance and transfer of biological pages from generation to generation Figure 2. The main factor of biological pages transfer in organisms is chromosomes and genes and their function is in such a way that the stronger chromosomes and genes will remain at the end and poorer genes poor and chromosomes will be destroyed. In other words, the result of interplay between genes and chromosomes is survival of the fittest and superior creatures. Genetic Algorithm operates with bit strings that each show the whole set of variables. However, most methods treat special variables independently. Genetic Algorithms perform random selection to help search; so it does not require derived information. These algorithms select the most appropriate strings among random organized data. In each generation, a new group of strings is created using the best parts of the previous sequences and the new random part in order to obtain an appropriate result. Although these algorithms are random, they are not included in the simple random

algorithms. They effectively discover the past information in the exploration, space to step toward the best solution by a new research point with better results. Genetic Algorithms consider numerous points of the search space in each repetition. Therefore the chance of convergence to a local maximum is decreased. In most conventional research techniques (gradient system), the governing decision rule passes from one point to another. These schemes can have some dangerous peaks in the search spaces; since they might converge to a local peak. Figure 2 presents some local best points and a global one. Therefore, Genetic Algorithms produce a complete population of strings (points) and then it examines each point individually and eventually forms a fresh population with improved points by combining their contents. Regardless of doing a search, simultaneous consideration of several points in Genetic Algorithms matches them with parallel machines; because of the evolution of each point is an independent process. Therefore, Genetic Algorithm only needs information about the quality of solutions generated by each set of variables. However, some optimization methods need information or even need a comprehensive understanding of the structure and variables. As Genetic Algorithms do not need such specific information about the problem, it is more flexible than most search methods.

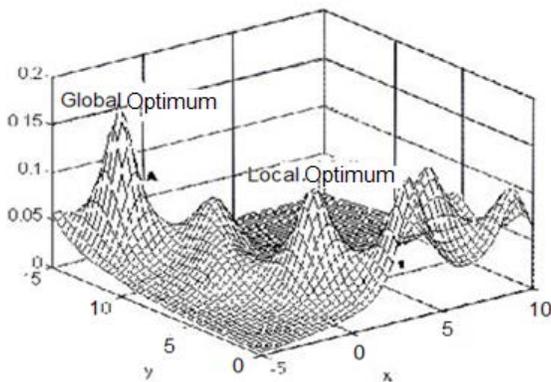


Figure 2. The local and global optimum points.

5. Neural Networks

Neural networks, with the remarkable ability to derive meanings from complicated or imprecise data are used to extract patterns and identify the methods that are very complex and difficult to be known by humans and other

computer techniques. A trained neural network can be used as an expert in the field of analyzing the information that it has taken into account. This expert can be used to estimate new custom items and answer “what gets” questions. In this study, the data are linked with neural networks and then optimized by Genetic Algorithms.

6. Procedural Restrictions

Regulations used in this research include part 9 of national building code of Iran (concrete building code) and also part 6 of the same code (loads on buildings)¹⁸⁻²⁰. The Iranian concrete building code presents the following relationships for shear:

$$V_{cc} = v_{cbw} d = 0.20c \sqrt{f_c b w d} \tag{1}$$

$$V_s = V_u - V_c = \phi_s A_v f_y \frac{d}{s} \tag{2}$$

$$\rho_h > 0.0025 \tag{3}$$

$$V_r \leq 5v_{chd} = 50c \sqrt{f_c b w d} \tag{4}$$

$$\rho_n > 0.0015 \tag{5}$$

Moreover, according to the loads on buildings code, the following relations are used to control the lateral displacement:

$$\delta_m = 0.7R \times \delta_w \tag{6}$$

$$\delta_m \leq 0.02 \times h \tag{7}$$

$$\delta < 0.005 \tag{8}$$

The building frame alone should preserve its stability under 25% of earthquake forces too. Cracking coefficients are 0.35 for beams and 0.7 for columns and un-cracked shear walls. For cracked shear walls, this factor is 0.35. The material profile follows:

| | | |
|----------------------------------|------------------------------|---------|
| Concrete | $f_c = 280 \frac{kg}{cm^2}$ | |
| Rebar | $f_y = 4200 \frac{kg}{cm^2}$ | |
| Number of floors | | 13 |
| Total height of the building | | 40.20 m |
| Importance coefficient | | 1 |
| Coefficient of building behavior | 8 | |
| Base Acceleration | | 0.35 |

The system used in this study was medium reinforced concrete frame and medium concrete shear walls.

7. Using the Samples Designed for Neural Network Data

To obtain the data required by neural networks to link the samples, 83 samples of shear walls with different lengths were used. Artificial Neural Networks consist of a set of neurons (processing units) as well as the link between them with adjustable weight (depending on the conditions of the problem). Neural network consists of an input layer, one or more hidden layer and one output layer. Because the Genetic Algorithm is not capable of linking the data, the samples are linked by neural networks and then optimized by Genetic Algorithms. The samples are designed for shear by software ETABS 9.7 for the three wall types. The results can be seen in Table 1 to Table 3. The structure of Artificial Neural Networks

can be seen in Figure 3. The networks used in this study are back propagation type which is made of two input layers, 5 hidden layers, and 1 output layer. The costs of concrete and steel bars have been used as input neurons and the optimized price as the output neuron. The neural network used has been trained under supervision. Figure 4 to Figure 6 shows the performance of neural networks for the walls 1, 2 and 3. The neural network is able to solve nonlinear problems. Figure 6 shows the square of neural networks errors. As shown in Figure 4 to Figure 6, the neural networks are very accurate and have been well trained. It is clear that the amounts of reinforcement and concrete are changed by the length of wall; it means the length of each wall is considered as the independent variable and its steel bars and concrete are the dependent variables.

Table 1. Data obtained from shear wall 1

| Wall type | Sample number | Length of the wall (m) | The cost of concrete (IRR) | The cost of rebar (IRR) | Total (IRR) |
|-----------|---------------|------------------------|----------------------------|-------------------------|-------------|
| P1 | 1 | 3.00 | 3,744,000 | 677,040 | 4,421,040 |
| P1 | 2 | 3.1 | 3,868,800 | 700,560 | 4,569,360 |
| P1 | 3 | 3.2 | 3,993,600 | 722,400 | 4,716,000 |
| P1 | 4 | 3.3 | 4,118,400 | 726,600 | 4,845,000 |
| P1 | 5 | 3.4 | 4,243,200 | 767,340 | 5,010,540 |
| P1 | 6 | 3.5 | 4,368,000 | 789,600 | 5,157,600 |
| P1 | 7 | 3.6 | 4,492,800 | 812,280 | 5,305,080 |
| P1 | 8 | 3.7 | 4,617,600 | 834,960 | 5,452,560 |
| P1 | 9 | 3.8 | 4,742,400 | 857,640 | 5,600,040 |
| P1 | 10 | 3.9 | 4,867,200 | 879,900 | 5,747,100 |
| P1 | 11 | 4 | 4,992,000 | 903,000 | 5,895,000 |
| P1 | 12 | 4.1 | 5,116,800 | 924,000 | 6,040,800 |
| P1 | 13 | 4.2 | 5,241,600 | 947,940 | 6,189,540 |
| P1 | 14 | 4.3 | 5,366,400 | 970,200 | 6,336,600 |
| P1 | 15 | 4.4 | 5,491,200 | 992,880 | 6,484,080 |
| P1 | 16 | 4.5 | 5,616,000 | 1,003,800 | 6,619,800 |
| P1 | 17 | 4.6 | 5,740,800 | 1,037,400 | 6,778,200 |
| P1 | 18 | 4.7 | 5,865,600 | 1,060,500 | 6,926,100 |
| P1 | 19 | 4.8 | 5,990,400 | 1,083,600 | 7,074,000 |
| P1 | 20 | 4.9 | 6,115,200 | 1,105,860 | 7,221,060 |
| P1 | 21 | 5 | 6,240,000 | 1,128,540 | 7,368,540 |
| P1 | 22 | 5.1 | 6,364,800 | 1,150,800 | 7,515,600 |
| P1 | 23 | 5.2 | 6,489,600 | 1,173,480 | 7,663,080 |
| P1 | 24 | 5.3 | 6,614,400 | 1,196,160 | 7,810,560 |
| P1 | 25 | 5.4 | 6,739,200 | 1,218,000 | 7,957,200 |
| P1 | 26 | 5.5 | 6,864,000 | 1,241,100 | 8,105,100 |
| P1 | 27 | 5.6 | 6,988,800 | 1,264,200 | 8,253,000 |
| P1 | 28 | 5.7 | 7,113,600 | 1,286,460 | 8,400,060 |
| P1 | 29 | 5.8 | 7,238,400 | 1,309,140 | 8,547,540 |
| P1 | 30 | 5.9 | 7,363,200 | 1,331,400 | 8,694,600 |
| P1 | 31 | 6 | 7,488,000 | 1,354,080 | 8,842,080 |

Table 2. Data obtained from shear wall 1

| Wall type | Sample number | Length of the wall (m) | The cost of concrete (IRR) | The cost of rebar (IRR) | Total (IRR) |
|-----------|---------------|------------------------|----------------------------|-------------------------|-------------|
| P2 | 1 | 4 | 2,496,000 | 451,290 | 2,947,290 |
| P2 | 2 | 4.1 | 2,558,400 | 462,630 | 3,021,030 |
| P2 | 3 | 4.2 | 2,620,800 | 473,970 | 3,094,770 |
| P2 | 4 | 4.3 | 2,683,200 | 485,310 | 3,168,510 |
| P2 | 5 | 4.4 | 2,745,600 | 496,440 | 3,242,040 |
| P2 | 6 | 4.5 | 2,808,000 | 507,780 | 3,242,040 |
| P2 | 7 | 4.6 | 2,870,400 | 519,120 | 3,242,040 |
| P2 | 8 | 4.7 | 2,932,800 | 530,250 | 3,242,040 |
| P2 | 9 | 4.8 | 2,995,200 | 541,716 | 3,242,040 |
| P2 | 10 | 4.9 | 3,057,600 | 552,930 | 3,242,040 |
| P2 | 11 | 5 | 3,120,000 | 552,930 | 3,242,040 |
| P2 | 12 | 5.1 | 3,182,400 | 552,930 | 3,242,040 |
| P2 | 13 | 5.2 | 3,244,800 | 552,930 | 3,242,040 |
| P2 | 14 | 5.3 | 3,307,200 | 552,930 | 3,242,040 |
| P2 | 15 | 5.4 | 3,369,600 | 552,930 | 3,242,040 |
| P2 | 16 | 5.5 | 3,432,000 | 552,930 | 3,242,040 |
| P2 | 17 | 5.6 | 3,494,400 | 552,930 | 3,242,040 |
| P2 | 18 | 5.7 | 3,556,800 | 552,930 | 3,242,040 |
| P2 | 19 | 5.8 | 3,619,200 | 552,930 | 3,242,040 |
| P2 | 20 | 5.9 | 3,681,600 | 552,930 | 3,242,040 |
| P2 | 21 | 6 | 3,744,000 | 552,930 | 3,242,040 |
| P2 | 1 | 4 | 2,496,000 | 451,290 | 2,947,290 |
| P2 | 2 | 4.1 | 2,558,400 | 462,630 | 3,021,030 |
| P2 | 3 | 4.2 | 2,620,800 | 473,970 | 3,094,770 |
| P2 | 4 | 4.3 | 2,683,200 | 485,310 | 3,168,510 |
| P2 | 5 | 4.4 | 2,745,600 | 496,440 | 3,242,040 |
| P2 | 6 | 4.5 | 2,808,000 | 507,780 | 3,242,040 |
| P2 | 7 | 4.6 | 2,870,400 | 519,120 | 3,242,040 |
| P2 | 8 | 4.7 | 2,932,800 | 530,250 | 3,242,040 |
| P2 | 9 | 4.8 | 2,995,200 | 541,716 | 3,242,040 |
| P2 | 10 | 4.9 | 3,057,600 | 552,930 | 3,242,040 |

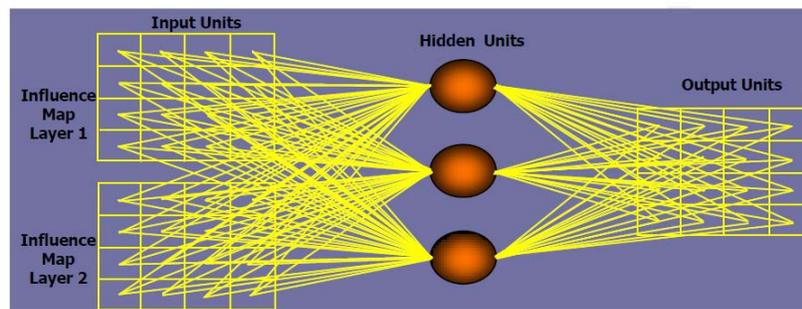


Figure 3. The general structure of Artificial Neural Networks.

Table 3. Data obtained from shear wall 3

| Wall type | Sample number | Length of the wall (m) | The cost of concrete (IRR) | The cost of rebar (IRR) | Total (IRR) |
|-----------|---------------|------------------------|----------------------------|-------------------------|-------------|
| P3 | 1 | 3.00 | 2,232,000 | 485,940 | 2,717,940 |
| P3 | 2 | 3.1 | 2,306,400 | 502,138 | 2,808,538 |
| P3 | 3 | 3.2 | 2,457,600 | 518,336 | 2,975,936 |
| P3 | 4 | 3.3 | 2,613,600 | 534,534 | 3,148,134 |
| P3 | 5 | 3.4 | 2,774,400 | 550,732 | 3,325,132 |
| P3 | 6 | 3.5 | 2,774,400 | 566,930 | 3,506,930 |
| P3 | 7 | 3.6 | 3,196,800 | 583,128 | 3,506,930 |
| P3 | 8 | 3.7 | 3,285,600 | 599,326 | 3,884,926 |
| P3 | 9 | 3.8 | 3,465,600 | 615,524 | 4,081,124 |
| P3 | 10 | 3.9 | 3,650,400 | 631,722 | 4,282,122 |
| P3 | 11 | 4 | 3,840,000 | 647,920 | 4,487,920 |
| P3 | 12 | 4.1 | 4,034,400 | 664,118 | 4,698,518 |
| P3 | 13 | 4.2 | 4,233,600 | 680,316 | 4,913,916 |
| P3 | 14 | 4.3 | 4,437,600 | 696,514 | 5,134,114 |
| P3 | 15 | 4.4 | 4,646,400 | 712,712 | 5,359,112 |
| P3 | 16 | 4.5 | 4,860,000 | 728,910 | 5,588,910 |
| P3 | 17 | 4.6 | 5,078,400 | 745,108 | 5,823,508 |
| P3 | 18 | 4.7 | 5,301,600 | 761,306 | 6,062,906 |
| P3 | 19 | 4.8 | 5,529,600 | 777,504 | 6,307,104 |
| P3 | 20 | 4.9 | 5,762,400 | 793,702 | 6,556,102 |
| P3 | 21 | 5 | 6,000,000 | 809,900 | 6,809,900 |
| P3 | 22 | 5.1 | 6,242,400 | 826,098 | 7,068,498 |
| P3 | 23 | 5.2 | 6,489,600 | 842,296 | 7,331,896 |
| P3 | 24 | 5.3 | 6,741,600 | 858,494 | 7,600,094 |
| P3 | 25 | 5.4 | 6,998,400 | 874,692 | 7,873,092 |
| P3 | 26 | 5.5 | 7,260,000 | 890,890 | 8,150,890 |
| P3 | 27 | 5.6 | 7,526,400 | 907,088 | 8,433,488 |
| P3 | 28 | 5.7 | 7,797,600 | 923,286 | 8,720,886 |
| P3 | 29 | 5.8 | 8,073,600 | 939,484 | 9,013,084 |
| P3 | 30 | 5.9 | 8,354,400 | 955,682 | 9,310,082 |
| P3 | 31 | 6 | 8,640,000 | 971,880 | 9,611,880 |

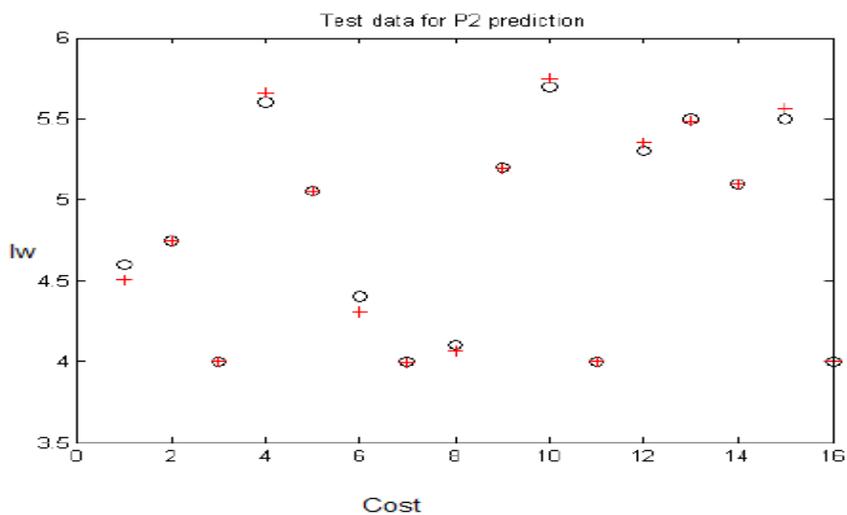


Figure 4. The neural network performance for Wall 2.

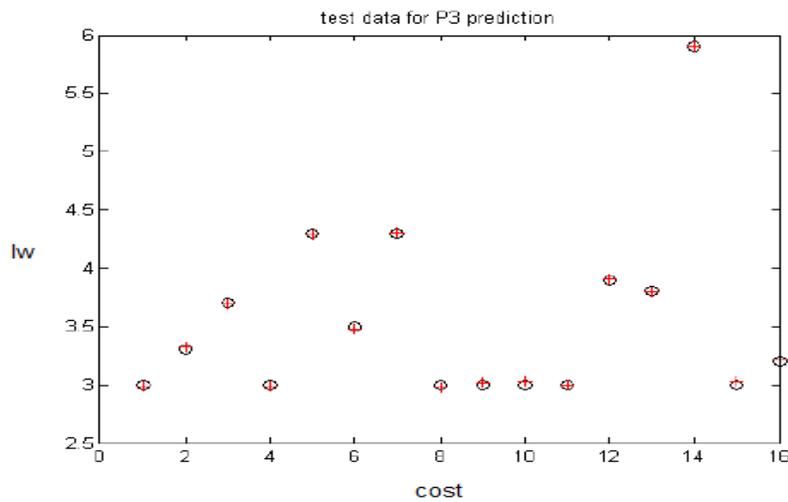


Figure 5. The neural network performance for Wall 3.

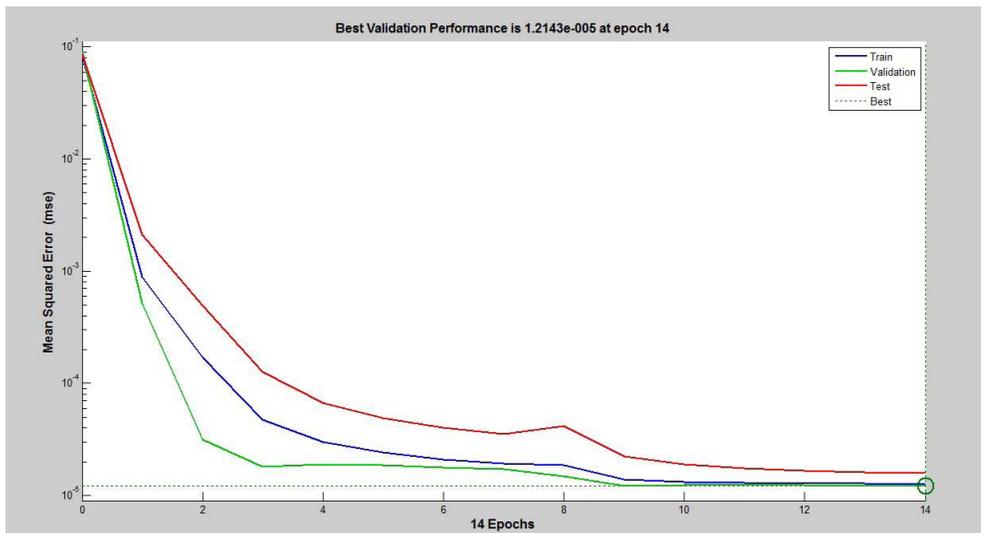


Figure 6. Neural network error.

8. Optimization with Combining Genetic Algorithms and Neural Networks

In this research, combining neural networks and Genetic Algorithms gave very accurate and close to reality answers. In fact, neural networks are used to obtain the best way for optimization and linking data. The neural network parameters are then optimized by Genetic Algorithms. In fact, according to the Figure 4 and Figure 5, the relations between the walls 1 and 2 are obtained by a neural network and then the relationship between these two walls and the wall 3 is obtained. Finally, these parameters are optimized

by Genetic Algorithms. To combine Genetic Algorithm and neural networks, the training part of neural networks is separated from MATLAB toolbox and defined the target function of Genetic Algorithm²¹. Genetic Algorithm optimized the problem by replacing chromosomes with neurons. In metal buildings reducing the weight of building means optimizing the cost of construction. But in concrete buildings, reducing the weight of building does not necessarily lead to the optimization of construction cost. For this reason, Genetic Algorithm target function (9) is defined.

$$f_x = C_{cc} V_{cc} + C_{cs} W_{st} \tag{9}$$

After performing Genetic Algorithm, optimization has been done in accordance with Table 4.

Table 4. Optimized values of Genetic Algorithm

| Label | P1h | P1v | P2 | P3 |
|----------------------|-------|-------|------|-------|
| Initial Length (m) | 6 | 6 | 4 | 3 |
| Optimized Length (m) | 3.071 | 5.757 | 2.68 | 2.095 |

9. Conclusions

According to the results obtained from this study, some ratios are proposed to obtain the optimum lengths of shear walls. In regular concrete buildings, assuming appropriate distribution of shear walls in the plan, the required area of shear walls are between 0.0870 to 0.105 of the surface area of the plan. In other words, the minimum area ratio of shear walls is 0.087 to satisfy the concrete building code requirements. As the total costs of steel bars and concrete must be minimized in concrete buildings to optimize the structure costs, the target function introduced in this article can be used for solving similar optimization problems. Also, in concrete structures optimization problems, the combination of back propagation neural networks and Genetic Algorithms are strongly recommended to be used.

10. References

- Goldberg DE. Genetic Algorithms in search, optimization and machine learning. 13th ed. Addison-Wesley; 1989 Jan.
- Rajeev S, Krishnamoorthy CS. Discrete optimization of structures using Genetic Algorithm. *Journal of Structural Engineering*. 1992 May; 118(5):1233–50.
- Feng C, Liu L, Burns SC. Using Genetic Algorithm to solve construction time-cost trade off problems. *Journal of Computing in Civil Engineering*. 1997 Jul; 11(3):184–9.
- Friswell MI, Penny JT, Garvey SD. A combined genetic and Eigen sensitivity algorithm for the location of damage in structures. *Computers and Structures*. 1999 Nov; 69(5):547–56.
- Specifications for structures to be built in the disaster areas. 1997. Available from: <https://www.yumpu.com/en/document/view/23906558/specification-for-structures-to-be-built-in-disaster-areas>
- Stanley KO, Miikkulainen R. Evolving neural networks through augmenting topologies. *Evolutionary Computation*. 2002; 10(2):99–127.
- Castilho VC, El Debs MK, Nicoletti MC. Using a modified Genetic Algorithm to minimize the production costs for slabs of precast pre-stressed concrete joists. *Engineering Applications of Artificial Intelligence*. 2007 Jun; 20(4):519–30.
- Rafiq MY, Southcombe C. Genetic Algorithm in optimal design and detailing of reinforced concrete biaxial columns supported by a declarative approach for capacity checking. *Computers and Structures*. 1998 Nov; 69(4):443–57.
- Saka MP. Optimum design of grillage systems using Genetic Algorithm. *Computer-Aided Civil and Infrastructure Engineering*. 1998 Jul; 13(4):297–302.
- Sahab MG, Ashour AE, Toropov VV. Cost optimization of reinforced concrete flat slab buildings. *Engineering Structures*. 2005 Feb; 27(3):313–22.
- Saini B, Sehgal VK, Gambhir ML. Least-cost design of singly and doubly reinforced concrete rebar using Genetic Algorithm optimized Artificial Neural Network based on Levenberg-Marquardt and Quasi-Newton back propagation learning techniques. *Structural and Multidisciplinary Optimization*. 2007 Sep; 34(3):243–60.
- Ramasamy JV, Rajasekaran S. Artificial Neural Network and Genetic Algorithm for the design optimization of industrial roofs - A comparison. *Computers and Structures*. 1996; 58(4):747–55.
- Pezeshk S, Camp CV, Chen D. Design of nonlinear framed structures using genetic optimization. *Journal of Structural Engineering*. 2000 Mar; 126(3):382–8.
- Keyhani A, Shafiee A. Effectiveness of Seismic retrofit for existing concrete buildings using nonlinear static analysis. *Indian Journal of Science and Technology*. 2016 Jan; 9(2):1–8.
- Gen M, Cheng R. Genetic Algorithms and engineering design. New York: John Wiley and Sons, Inc; 1997 Jan.
- Montana J, Davis L. Training feed forward neural networks using Genetic Algorithms. 11th International Joint Conferences on Artificial Intelligence. 1989; 1:762–7.
- Paykani A, Akbarzadeh A, Shervanitabar MT. Experimental investigation of the effect of exhaust gas recirculation on performance and emissions characteristics of a diesel engine fueled with biodiesel. *International Journal of Engineering and Technology*. 2011 Jun; 3(3):239–43.
- Shapiro AF. The merging of neural networks, fuzzy logic and Genetic Algorithms. *Insurance: Mathematics and Economics*. 2002 Aug; 31(1):115–31.
- MATLAB. 2016. Available from: <https://en.wikipedia.org/wiki/MATLAB>
- Mashadi B, Mahmoudi-Kaleybar M, Ahmadizadeh P, Oveis A. A path-following driver/vehicle model with optimized lateral dynamic controller. *Latin American Journal of Solids and Structures*. 2014 Aug; 11(4):613–30.
- Esfahani SN, Andani MT, Moghaddam NS, Mirzaeifar R, Elahinia M. Independent tuning of stiffness and toughness of additively manufactured titanium-polymer composites: Simulation, fabrication and experimental studies. *Journal of Materials Processing Technology*. 2016 Dec; 238:22–9.