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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 proposed[1]. The first civil engineering problem was solved using Genetic Algorithm[2]. 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 studies[3], a Genetic Algorithm was formed out for time and labor costs. In an article, Genetic Algorithm was used to identify the vibrations of damaged areas[4]. Other scholars have also used Genetic Algorithms for optimization[5–7]. In[8], the bearing capacity of a biaxial reinforced concrete column was examined by Genetic Algorithm[8]. Researchers also have used Genetic Algorithm to optimize shear walls and other optimization problems in civil engineering[9–12]. 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 engineering[13–16]. 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.

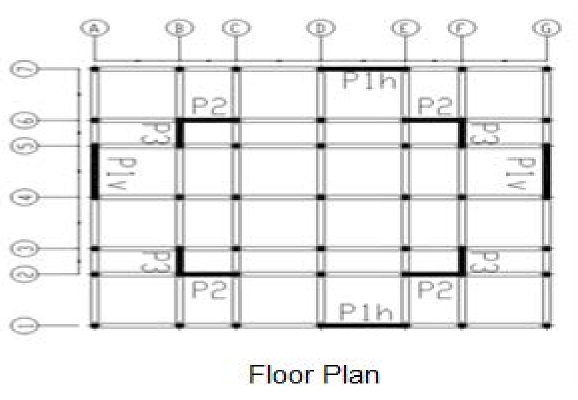

Figure 1. Case study plan.

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 m^3 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.
hi: Height of the i^{th} floor.
ρn,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.

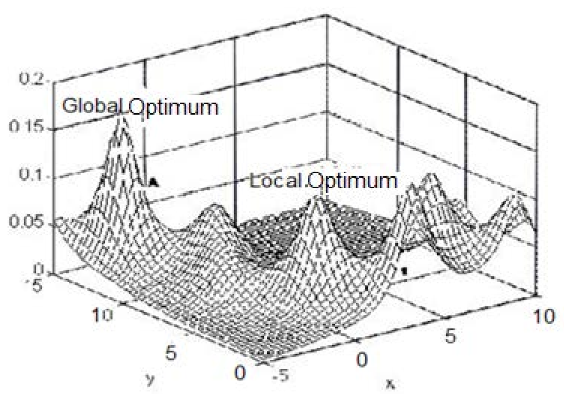

Figure 2. The local and global optimum points.

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:

$$V cc = vcbw\ d = 0.2\phi c\sqrt{fc}bwd \quad (1)$$

$$Vs = Vu - Vc = \phi sAvfy\frac{d}{s2} \quad (2)$$

$$\rho h > 0.0025 \quad (3)$$

$$Vr \le 5vchd = 5\phi c\sqrt{fc}bw\ d \quad (4)$$

$$\rho n > 0.0015 \quad (5)$$

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

$$\delta_m = 0.7R \times \delta_w \quad (6)$$

$$\delta_m \le 0.02 \times h \quad (7)$$

$$\delta < 0.005 \quad (8)$$

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

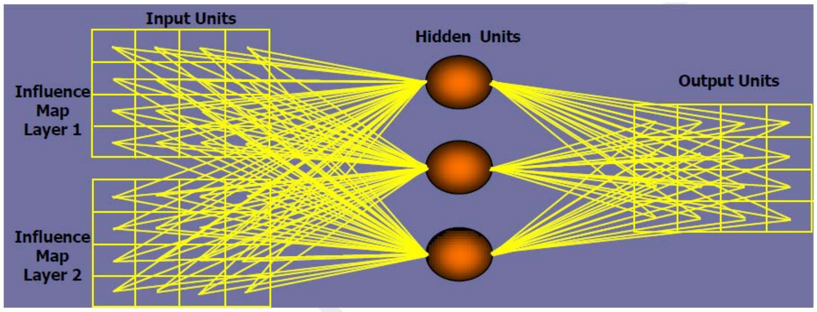

Figure 3. The general structure of Artificial Neural Networks.

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

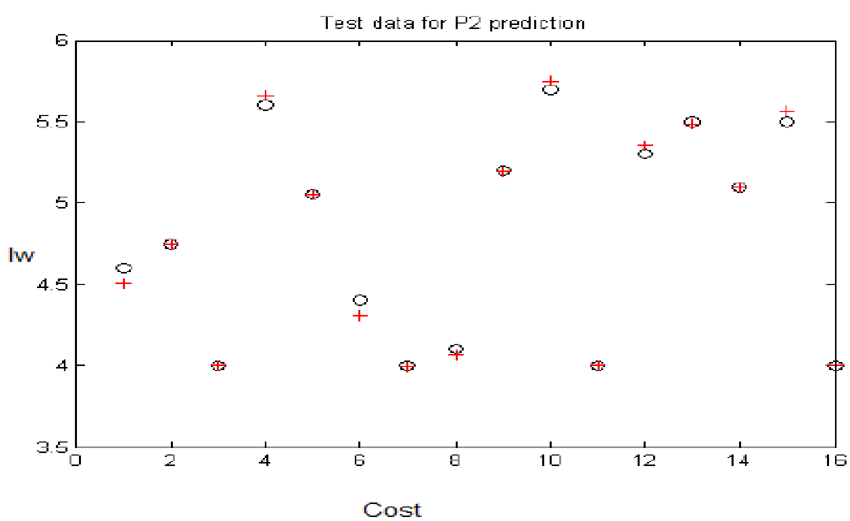

Figure 4. The neural network performance for Wall 2.

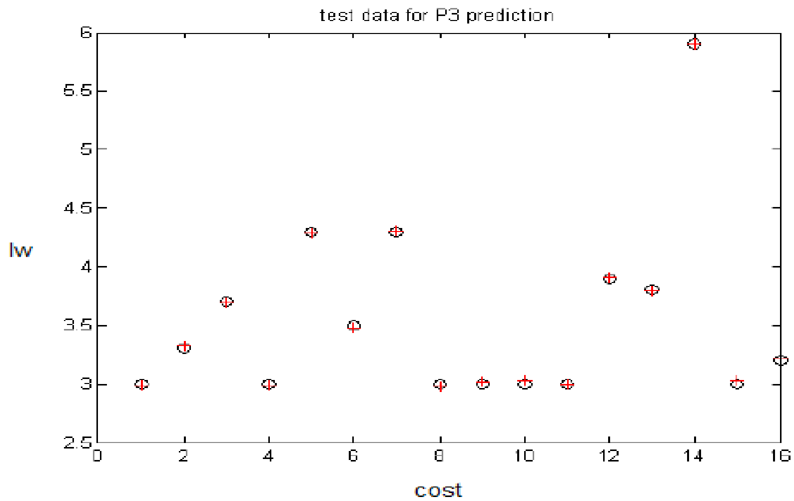

Figure 5. The neural network performance for Wall 3.

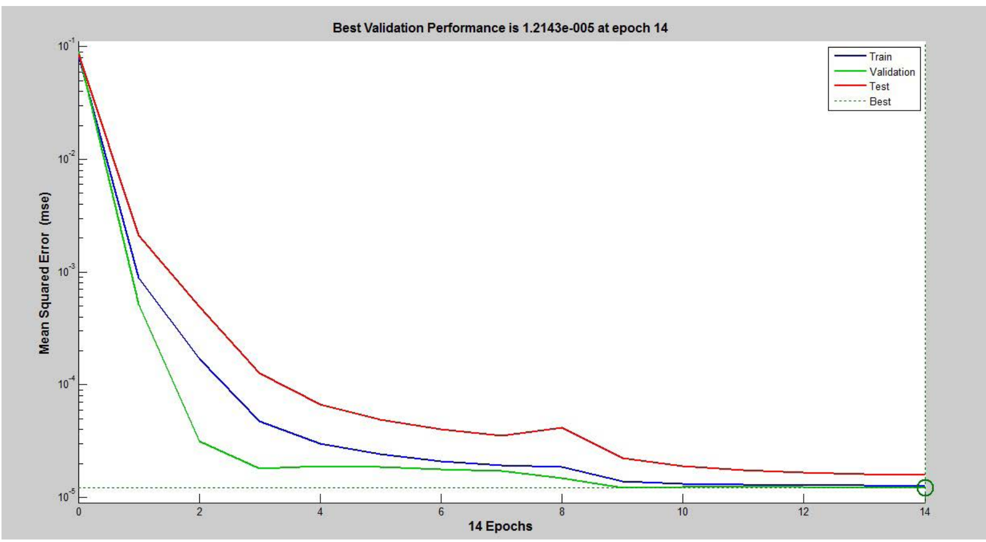

Figure 6. Neural network error.

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 Algorithm[21]. 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.

$$f_x = C_{cc}V_{cc} + C_{cs}W_{st} \quad (9)$$

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.

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