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THE USE OF ARTIFICIAL NEURAL NETWORKS AND METAHEURISTIC ALGORITHMS TO OPTIMIZE THE COMPRESSIVE STRENGTH OF CONCRETE

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ABSTRACT

Cement, water, fine aggregates, and coarse aggregates are combined to produce concrete, which is the most common substance after water and has a distinctly compressive strength, the most important quality indicator. Hardened concrete's compressive strength is one of its most important properties. The compressive strength of concrete allows us to determine a wide range of concrete properties based on this characteristic, including tensile strength, shear strength, specific weight, durability, erosion resistance, sulfate resistance, and others. Increasing concrete's compressive strength solely by modifying aggregate characteristics and without affecting water and cement content is a challenge in the direction of concrete production. Artificial neural networks (ANNs) can be used to reduce laboratory work and predict concrete's compressive strength. Metaheuristic algorithms can be applied to ANN in an efficient and targeted manner, since they are intelligent systems capable of solving a wide range of problems. This study proposes new samples using the Taguchi method and tests them in the laboratory. Following the training of an ANN with the obtained results, the highest compressive strength is calculated using the EVPS and SA-EVPS algorithms.

Keywords: Compressive Strength of Concrete; Artificial Neural Networks; Taguchi's Method; Optimization.

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1. INTRODUCTION

As one of the most widely used engineering materials in the world, concrete is the most commonly used substance after water. Concrete has a distinctly compressive strength, which

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is the most important indicator of its quality. Concrete is obtained by combining cement, water, fine aggregates, and coarse aggregates. In addition to these cases, concrete additives have also received considerable attention in recent years. The compressive strength of concrete is one of the most important properties of hardened concrete as a building material. As a result of the compressive strength of concrete, many different properties of concrete can be determined from it and are related to this characteristic, including tensile strength, shear strength, specific weight, durability, erosion resistance, sulfate resistance, and other concrete properties. It is a challenge in the direction of concrete production to increase the compressive strength of concrete solely by modifying the characteristics of the aggregate used and without altering the amount of water and cement used. The construction of concrete has been the subject of numerous research studies, some of which are briefly discussed below:

Using the methodology of Life Cycle Assessment, Habert et al. [1] evaluated the environmental impact of geopolymer concrete production. In their research, they found that the production of geopolymer concrete has a lower impact on global warming than the production of standard Ordinary Portland Cement (OPC) concrete, but a higher impact on other environmental categories than global warming. It was also noted that industrial waste could be used to produce geopolymer concrete, as well as that the use of activated clays and blast furnace slag as a mix-design technology could reduce the need for binder.

A review by Imbabi *et al*. [2] in 2012 examined the current state-of-the-art in cement production and presented some emerging green alternatives, such as energy-efficient, low carbon production methods, geopolymers, carbon negative cements and novel concrete designs. The application of ultrafine nano materials in concrete has been explored by Norhasri *et al*. [3] In the study, the application of ultrafine nano materials partially replace cement on a weight basis, thereby reducing the cement content and preventing the formation of microporosity. Using reactive powder concrete (RPC) as a matrix and the construction of accessible pores, Li *et al*. [4] developed a high strength pervious concrete pavement to overcome the challenges of low strength, high likelihood of clogging, and inconvenient maintenance. Pervious concrete of high strength has the potential to be used in a wide variety of applications. Based on the concrete 3D printing technology, Asprone *et al*. [5] presented a novel approach to the fabrication of reinforced concrete members. The approach enabled the fabrication of free-form structurally optimized reinforced concrete elements, thus reducing concrete consumption and fabricating lighter structures.

According to Sajedi and Shafieinia [6], axial compression testing was conducted on reinforced concrete columns constructed from high-strength concrete and enclosed by glass fiber-reinforced plastic casing and carbon fiber-reinforced polymer. Six cylindrical HSC-reinforced concrete columns were prepared, and two groups were formed: one with a single CFRP layer and one with two CFRP layers. If a fire occurs within a structure adjacent to a concrete slab, the heat can increase internal stresses and reduce its thickness, posing a threat to the structural integrity of that segment. Accordingly, Afkhami *et al*. [7] studied the behavior of concrete slabs exposed to fire using finite element (FE) software along with subroutines. Sabbaghian and Kheyroddin [8] investigated HPFRCC's splitting tensile strength, compressive strength, and bulk density.108 cylinders and cube specimens were tested at 7 and 28 days following the formulation of 18 HPFRCC mix proportions with 1% steel fibers (30 mm length) and a mathematical exponential function between STS and CS

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was proposed, along with three distinct fractions of steel fibers in volume. To predict the resistance of UHPC to chloride ion penetration at ages up to 28 days under a variety of curing regimes, Khaksefidi *et al*. [9] developed a simple and non-destructive surface electrical resistivity (ER) method. ER, CS and density increased with age, but chloride environments posed greater damage than sulphate environments.

In order to reduce laboratory work and predict concrete's compressive strength, artificial neural networks (ANNs) can be used. ANNs are intelligent systems that can solve problems in a wide range of applications, including optimization, prediction, modeling, clustering, pattern recognition, simulation, and many others. These are some of the research studies in which ANNs have been used as a powerful tool. Göthals *et al*. [10] investigated the development and application of artificial neural networks for the prediction of macroinvertebrate communities. It revealed that the applied model training and validation methodologies can often be improved, and moreover crucial steps in the modelling process are often inadequately documented. Sinha and Wang [11] developed Artificial Neural Network (ANN) prediction models for permeability, maximum dry density, and optimal moisture content of soils using the results of classification, compaction, and permeability tests. According to Palavar *et al*. [12] the effect of aging parameters on the wear behavior of PM Inconel 706 (IN 706) superalloy was experimentally investigated and an ANN model was developed to predict weight loss after wear tests. In both prediction and classification, neural networks have been widely used. Therefore, Laguna and Marti [13] compared a training procedure that achieves a high degree of accuracy within a short timeframe with several variants of a commercial training program. In terms of improving energy efficiency in building energy management systems, building energy prediction is a promising research area. One of the best approaches is to use artificial neural networks. A review of twelve ANN architectures for building energy prediction is provided by Lu and Lu [14], along with a discussion of three challenges and open issues. Shariati *et al*. [15] aimed to predict the compressive strength of concrete incorporating furnace slag and fly ash as partial replacements for cement in their study, which used a hybrid artificial neural network and genetic algorithm. The results of the study indicated that the ANN-GA model was superior to the ANN-BP model in terms of predicting compressive strength. Furthermore, artificial neural networks are also widely used in civil engineering in addition to what was briefly mentioned [16-20].

For ANN to be utilized efficiently and in a targeted manner, metaheuristic algorithms can be applied. Recent research has indicated a substantial interest in metaheuristic algorithms from a wide range of fields, particularly engineering. Metaheuristic algorithms are practical optimization methods in addition to their ability to obtain near-optimal solutions to any problem. They can be applied to a variety of problems and provide more efficient solutions [21]. A few of these methods are as follows:

Charged System Search (CSS) and Hybrid Charged System Search (HCSS) [22, 23], Grey Wolf Optimizer (GWO) [24], Teaching–Learning-Based Optimization (TLBO) [25], Differential Evolution algorithm (DE) [26], A Sine Cosine algorithm (ASC) [27], Enhanced Vibrating Particles System (EVPS) and SA-EVPS [28-30], Simplified Dolphin Echolocation optimization (SDE) [31], Modified Dolphin Monitoring (MDM) [32], Colliding Bodies Optimization (CBO) [33].

In this study, five basic designs were obtained by changing the amount of aggregates

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used with different sizes while maintaining the amounts of water, cement, and additives constant. New samples were then proposed using the Taguchi method and were tested in the laboratory. Following the training of an Artificial Neural Network (ANN) with the obtained results, the EVPS and SA-*EVPS* algorithms were used to determine the highest compressive strength. The obtained results were then tested in the laboratory and their experimental compressive strength was compared with the ANN results.

This paper is organized as follows: Section one contains an introduction. In the second section, EVPS and SA-EVPS algorithms are briefly explained. The third and fourth sections provide an overview of ANNs and Taguchi methods, respectively. In the fifth section, a numerical problem is presented, and in the last section, a conclusion is presented.

2. A BRIEF EXPLANATION OF THE EVPS AND SA-EVPS ALGORITHMS

The EVPS algorithm, which is an improved version of the VPS algorithm, is widely used in optimizing structural engineering problems [34-38]. While the EVPS algorithm uses eight variables that are experimentally determined, these parameters are considered specific values by default and are responsible for controlling search accuracy, exploration and exploit phases, convergence speed, as well as overall algorithm behavior. Thus, in the SA-EVPS algorithm, all of these parameters have a significant impact and all eight parameters mentioned above are also optimized before the main optimization is performed. In the SA-EVPS algorithm, all eight parameters are first optimized using the EVPS algorithm, and then the main optimization is performed [30, 38]. The flowchart of the SA-EVPS algorithm is presented in Figure 1 in order to provide greater clarity.

3. AN OVERVIEW OF ARTIFICIAL NEURAL NETWORKS (ANNS)

Biological neural networks are the basis of artificial neural networks, which can learn patterns and predict results in high dimensional spaces of problems. Artificial neural networks are intelligence tools inspired by biological neural networks. In a noisy and complex dataset, they can map a set of inputs to a set of outputs [39]. In recent years, artificial neural networks, which were inspired by the biological nervous system, have evolved from being a theoretical concept to becoming a widely used technology applied to a variety of problems. They can provide appropriate solutions to problems that cannot be solved conventionally. An artificial neural network (ANN) is an intelligence tool that has been used extensively in various applications such as function approximation, classification, time series prediction, etc. In fact, an ANN can model almost any complex relationship between inputs and outputs. A large part of the performance of neural networks is determined by the training process, which determines the weights and biases of the network. This can result in a good estimation of the actual output of the problem based on the weights and biases of the network [40].

It is seen in Figure 2 that within each neuron, a weighted sum of inputs is calculated, and this value, along with a bias value, is transformed by an activation function. This value is then transferred to the nearby neurons. During training, the weights and biases of the

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network are adjusted in such a way that the minimal error between target values (actual values) and output values (network values) is achieved.

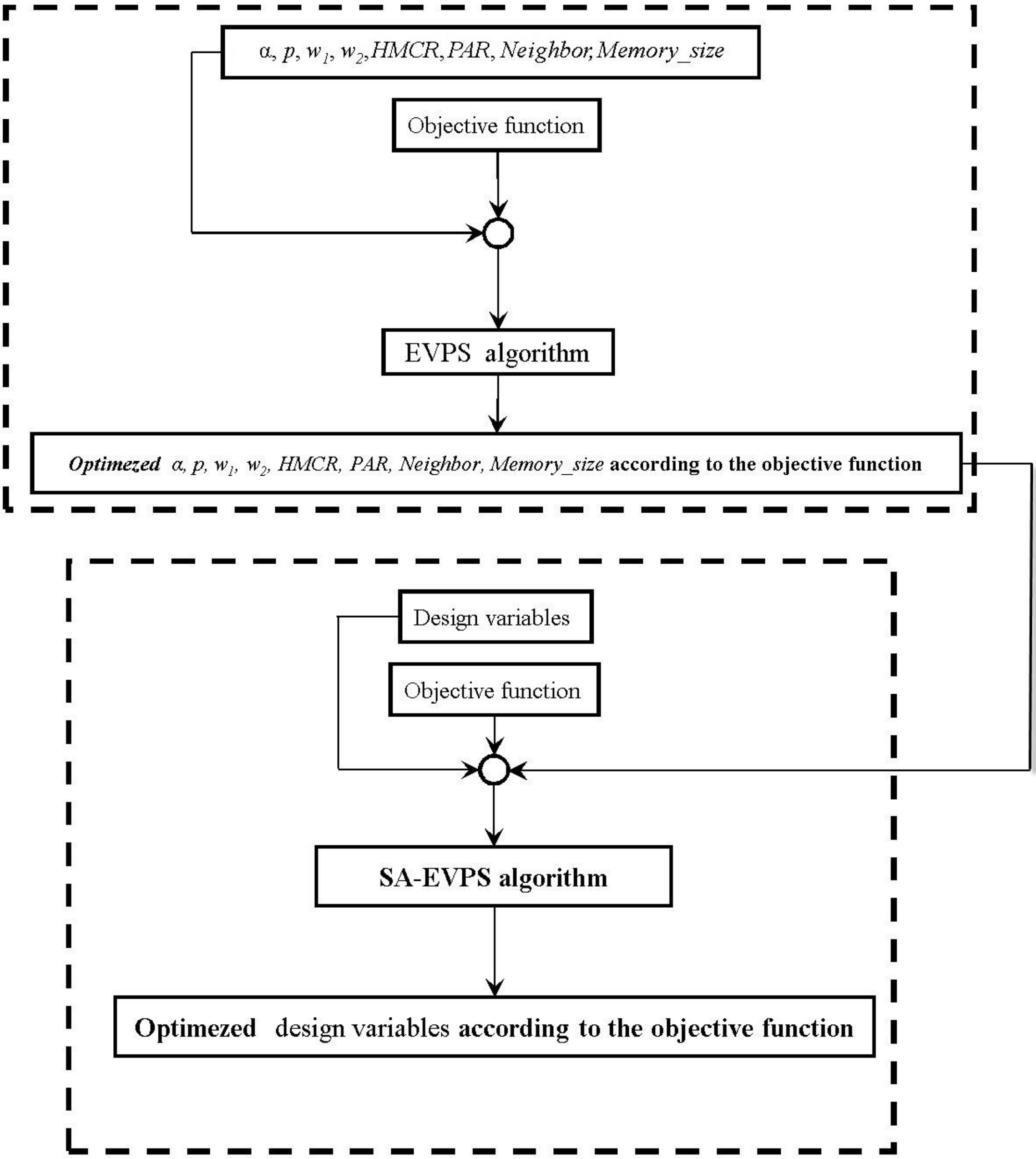

Figure 1. Schematic illustration of the SA-EVPS algorithm [38]

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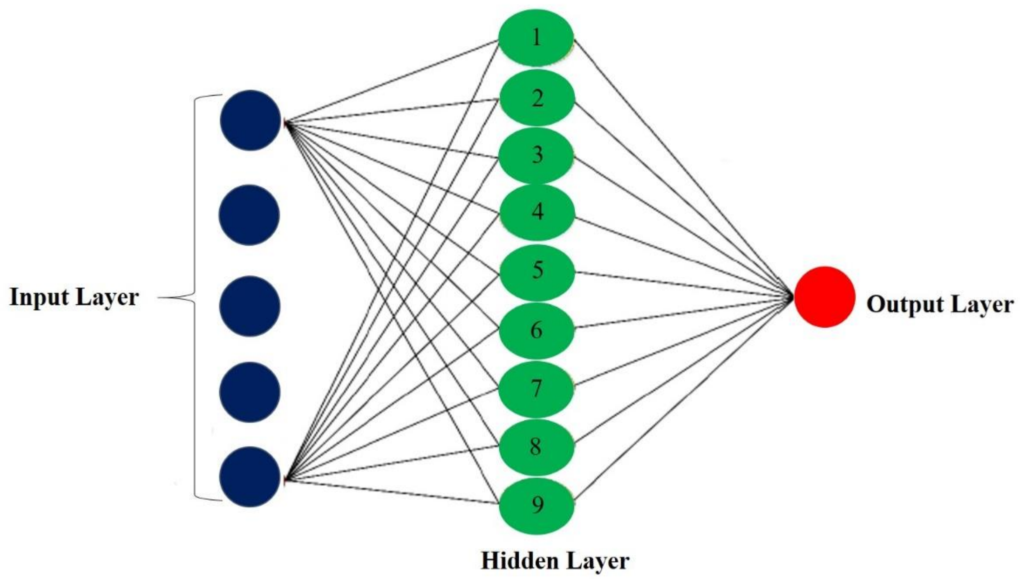

Figure 2. A schematic of an ANN structure showing an input, an output, and a hidden layer

4. BRIEF OVERVIEW OF TAGUCHI'S METHOD

The Taguchi method is a statistical technique that improves product quality, and has been applied to engineering, biotechnology, marketing, and advertising in recent years [41]. There are three basic and simple concepts that comprise Taguchi's philosophy. Concepts such as these include:

- During the production process, quality should be designed, not checked.
- The best way to achieve quality is to minimize the deviation from the specified value.
- A product must be designed to be safe against uncontrollable environmental conditions.

In the Taguchi method, two groups of factors are considered in the design of experiments. First, there are the controllable factors that have certain levels in the design and are under control; In the Taguchi method, it is described as a signal. Another category is disturbance factors, which affect the reaction of a process but cannot be controlled; they are called noise in the Taguchi method. Taguchi experiments are designed in a way so that disturbance factors are minimized [42].

In addition, this method has the advantage of determining how each factor contributes to the test results. As a result of the ANOVA table for the test data, the decision maker has the capability of ranking the factors in order of their importance. As a result of this ranking, the decision maker may be persuaded to combine two or more controllable factors in order to reduce the costs associated with the experimental design. The ANOVA study determines the relative effects of factors in different sections [43].

5. NUMERICAL EXAMPLE

In this article, first, the compressive strength of five basic designs was determined by changing the amount of aggregates of different sizes while keeping the amount of water, cement, and additives constant. According to the aggregate size, the aggregates were classified into six sizes, so the six factors influencing the compressive strength of the samples are the same as the six values of the six types of aggregate granulation size. Thus, the design variables and the effectors are the same six components. From five basic designs, 81 proposed designs were selected using Taguchi method, and all 81 samples were made in the laboratory and their compressive strength was determined. As a matter of fact, without the Taguchi method, it would be necessary to obtain a large number of samples with combinations of 5 basic designs in order to analyze the sensitivity of the effect of the six influencing factors mentioned, a process that would be practically impossible to determine in the laboratory for their compressive strength. In accordance with Taguchi method results, an artificial neural network was trained (with input data from the six variables mentioned above) and the results of the ANN were compared to the experimental data obtained in the lab, Figure 3.

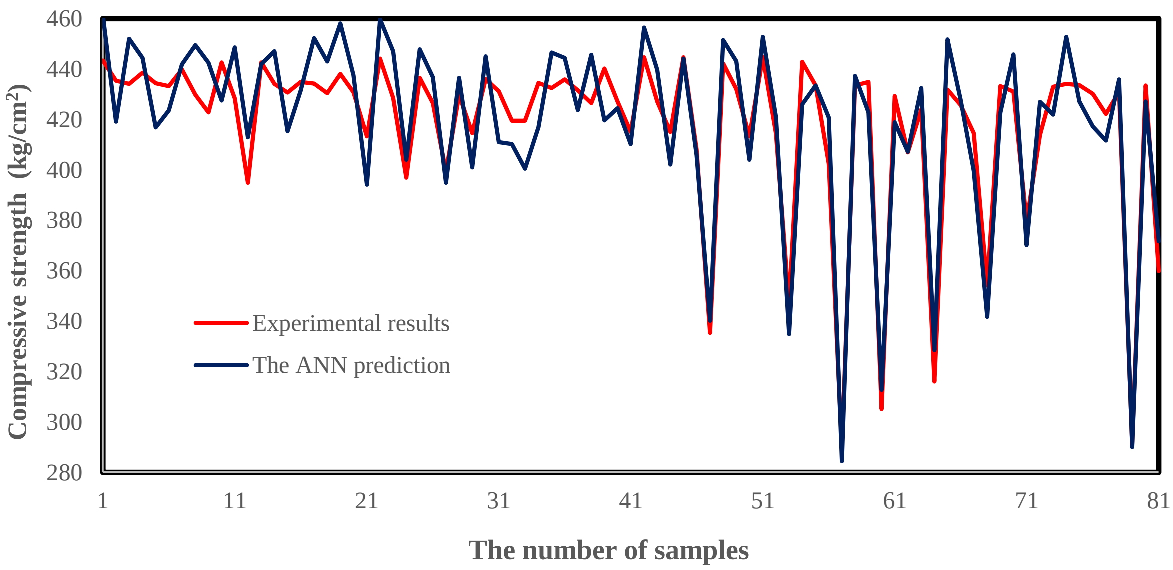

Figure 3. Comparison of laboratory compressive strength (at 28 days) results with those obtained from a trained ANN for proposed Taguchi method designs

With the knowledge of the compressive strength of the samples, proposed by the Taguchi method and the training of the artificial neural network, the optimal design has been determined by using the EVPS and SA-EVPS metaheuristic algorithms from the ANN as the objective function. The optimization process consists of 30 independent runs with a population size of 20. In the EVPS algorithm, p, w_1, w_2, *HMCR*, *PAR*, *Neighbor* and *Memory_size* are respectively 0.05, 0.2, 0.3, 0.3, 0.95, 0.1, 0.1, and 4. The SA-EVPS algorithm parameters that are self-adaptive are shown in Table 1. Figure 4 illustrates the

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convergence curves for EVPS and SA-EVPS. As shown in Figure 4, the objective function is equal to the inverse of the compressive strength derived from the ANN.

Table 1. SA-EVPS algorithm parameters that are self-adaptive (optimized)

No.	Parameter	Value
1	α	0.065411
2	p	0.35474
3	w_1	0.732654
4	w_2	0.21554
5	HMCR	0.0845451
6	PAR	0.83211
7	Neighbor	0.85484
8	Memory_size	1

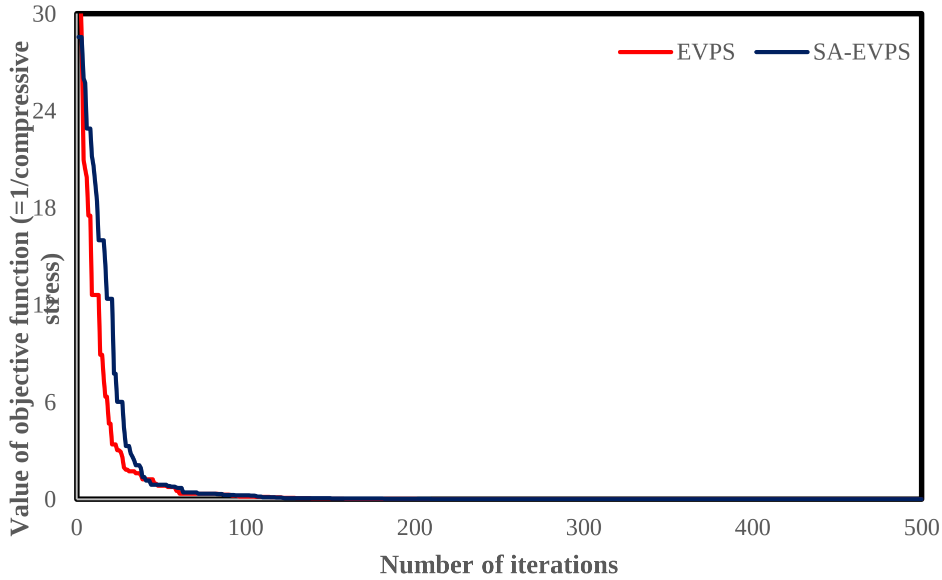

Figure 4. The EVPS and SA-EVPS convergence curves

In order to clarify the results, the aggregates were divided into two categories: gravel and sand, so that according to the ASTMD 422-63, the boundary between gravel and sand sieve size is 4.75 mm. So, the retained amount on the sieve is 4.75 mm in the range of gravel, and the passed amount is considered sand. According to Table 2, the five basic designs with the best compressive strength were derived from the Taguchi method, along with the optimal solution derived from the EVPS and SA-EVPS algorithms. In table 2, the laboratory results are compared with the ANN results for compressive strength for five basic designs, the best of Taguchi method, and the best EVPS algorithm and SA-EVPS algorithm design. Based on this table, the best answer can be attributed to the SA-EVPS algorithm.

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Table 2: Comparison of the five basic design, laboratory results, and results from EVPS and SA-EVPS algorithms for compressive strength

	Type of design	Quantity of material(kg/m^3)					Compressive Strength at 28 days (kg/cm^2) (15cm×15cm cube sample)	
		Gravel	Sand	Cement	Water	additive	The ANN Prediction	Experimental Results
1	Basic design 1	433	1411	397	159	5.4	414	420
2	Basic design 2	323	1520	397	159	5.4	422	431
3	Basic design 3	215	1593	397	159	5.4	448	428
4	Basic design 4	494	1322	397	159	5.4	423	405
5	Basic design 5	529	1258	397	159	5.4	420	433
6	Taguchi's best design	588	1198	397	159	5.4	452	444
7	EVPS's best design	503	1304	397	159	5.4	490	481
8	SA-EVPS's best design	412	1372	397	159	5.4	491.5	487

Comparing the laboratory results and the trained artificial neural network, it can be concluded that the ANN has performed with acceptable and appropriate accuracy. In addition, the SA-EVPS algorithm provided the best answer, although the EVPS algorithm also performed well in this example. Compared to the five basic designs, Taguchi's method produced better results, but it was weaker than the EVPS and SA-EVPS algorithms.

5. CONCLUSOINS

Five basic designs were selected in this study which had good compressive strength compared to the amount of water and cement used. In this study, six design variables, the amount of aggregate with different sizes, have been taken into account. Based on the results obtained from the Taguchi method and five basic designs, an artificial neural network was trained based on the results obtained from the Taguchi method and the five basic designs. Upon comparing the laboratory results with the results obtained from the ANN, it was found that the used ANN produced appropriate and acceptable results. The trained artificial neural network and the EVPS and SA-EVPS metaheuristic algorithms were then used to define an optimization problem in order to determine a design with the highest compressive strength, and the results of the optimization were also analyzed in the laboratory, which demonstrated that the results met the target in a satisfactory manner. For further research, it is recommended that the process used in this article be used.

REFERENCES

1. Habert G, J.B d’Espinose de Lacaillerie, and Roussel N. An environmental evaluation of geopolymer based concrete production: reviewing current research trends. *Journal of Cleaner Production* 2011; **19**(11): 1229-38
2. Imbabi M.S, Carrigan C, and McKenna S. Trends and developments in green cement and concrete technology. *International Journal of Sustainable Built Environment* 2012;

[DOI: 10.22068/ijoce.2023.13.3.558]

1(2): 194-216

3. Norhasri M.S.M,. Hamidah M.S, and. Fadzil A.M. Applications of using nano material in concrete: A review. *Construction and Building Materials* 2017; **133**: 91-7
4. Li J, Li J, Zhang Y, Liu G, Peng X. Preparation and performance evaluation of an innovative pervious concrete pavement. *Construction and Building Materials* 2017; **138**: 479-85
5. Asprone D, Auricchio F, Menna C, Mercuri V. 3D printing of reinforced concrete elements: Technology and design approach. *Construction and Building Materials* 2018; **165**: 218-31
6. Sajedi F, and Shafieinia M. Evaluation and comparison of GFRP casing and CFRP sheets application on the behavior of circular reinforced concrete column made of high-strength concrete. Asian Journal of Civil Engineering 2019; 20(8): 1153-61
7. Afkhami V, Dehghani E, and Arezoumandi M. Effect of exposure to fire on a concrete slab with calcareous aggregate. *Asian Journal of Civil Engineering* 2021; **22**(6): 1075-84
8. Sabbaghian M, and Kheyroddin A. The Relationship between Compressive Strength and Splitting Tensile Strength of high-Performance Fiber-Reinforced Cementitious Composites. *Journal of Rehabilitation in Civil Engineering* 2023; **11**(4): 1-21
9. Khaksefidi S, Ghalehnovi M, De Brito J, Rahdar H A. Effect of Chloride and Sulphate Environments on the Compressive Strength, Density and Electrical Resistivity of Ultra-High Performance Concrete (UHPC). *Journal of Rehabilitation in Civil Engineering*; 2022. **10**(3): 158-86.
10. Goethals, PLM, Goethals PL, Dedecker AP, Gabriels W, Lek S,De Pauw N. Applications of artificial neural networks predicting macroinvertebrates in freshwaters. *Aquatic Ecology* 2007; **41**(3): 491-508
11. Sinha, S.K, and M.C. Wang. Artificial Neural Network Prediction Models for Soil Compaction and Permeability. *Geotechnical and Geological Engineering* 2008; **26**(1): 47-64
12. Palavar O, D. Özyürek, and A. Kalyon. Artificial neural network prediction of aging effects on the wear behavior of IN706 superalloy. *Materials & Design* 2015; **82**: 164-72
13. Laguna M, and R. Martí. Neural network prediction in a system for optimizing simulations. *IIE Transactions* 2002; **34**(3): 273-82
14. Lu, C., S. Li, and Z. Lu, *Building energy prediction using artificial neural networks: A literature survey*. Energy and Buildings, 2022. **262**: p. 111718.
15. Shariati M, Mafipour MS, Mehrabi P, Ahmadi M, Wakil K, Trung NT, Toghroli A. Prediction of concrete strength in presence of furnace slag and fly ash using Hybrid ANN-GA (Artificial Neural Network-Genetic Algorithm). *Smart Structures and Systems, An International Journal* 2020; **25**(2): 183-95
16. Kaveh A, Khalegi HA. Prediction of strength for concrete specimens using artificial neural network. *Asian Journal of Civil Engineering* 2000; **2**(2): 1-13.
17. Kaveh A, Servati H. Design of double layer grids using back-propagation neural networks. *Computers and Structures* 2001; **79**: 1561-68
18. Kaveh A, Gholipour Y, Rahami H. Optimal design of transmission towers using genetic algorithm and neural networks. *International Journal of Space Structures*, 2008; **23**(1): 1-19
19. Kaveh A, Bakhshpoori T, Hamze-Ziabari SM. GMDH-based prediction of shear

strength of FRP-RC beams with and without stirrups, *Comput. Concr.* 2018; **22(2)**: 197-207.

20. Kaveh A, Khavaninzadeh N**.** Efficient training of two ANNs using four meta-heuristic algorithms for predicting the FRP strength. *Structures* 2023; **52**: 256-72
21. Kaveh A. Improved cycle bases for the flexibility analysis of structures. *Computer Methods in Applied Mechanics and Engineering* 1976; **9**(3): 267-72.
22. Kaveh A, and Talatahari S. Hybrid charged system search and particle swarm optimization for engineering design problems. *Engineering Computations* 2011; **28**(4): 423-40
23. Kaveh A and Zolghadr A. Topology optimization of trusses considering static and dynamic constraints using the CSS. *Applied Soft Computing* 2013; **13**(5): 2727-34
24. Mirjalili S, S.M Mirjalili, and A. Lewis. Grey wolf optimizer. *Advances in engineering software* 2014; **69**: 46-61
25. Rao R.V, V.J. Savsani, and D. Vakharia. Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. *Computer-Aided Design* 2011; **43**(3): 303-15
26. Qin A.K, V.L. Huang and P.N. Suganthan. Differential evolution algorithm with strategy adaptation for global numerical optimization. *IEEE transactions on Evolutionary Computation* 2008; **13**(2): 398-417
27. Mirjalili S. SCA: a sine cosine algorithm for solving optimization problems. *Knowledge-based systems* 2016; **96**: 120-33
28. Kaveh A, Hoseini Vaez S and Hosseini P. MATLAB code for an enhanced vibrating particles system algorithm. *Int J Optim Civl Eng* 2018; **8**(3): 401-14
29. Kaveh A, Hoseini Vaez S and Hosseini P. Enhanced vibrating particles system algorithm for damage identification of truss structures. *Scientia Iranica* 2019; **26**(1): 246-56
30. Paknahad M, Hosseini P and Hakim S.J.S. SA-EVPS algorithm for discrete size optimization of the 582-bar spatial truss structurE. *Int J Optim Civl Eng* 2023; **13**(2): 207-17
31. Kaveh A, Vaez S.R.H, and Hosseini P. Simplified dolphin echolocation algorithm for optimum design of frame. *Smart Struct Syst* 2018; **21**(3): 321-33
32. Kaveh A, Vaez S.H, and Hosseini P. Modified dolphin monitoring operator for weight optimization of frame structures. *Periodica Polytechnica Civil Engineering* 2017; **61**(4): 770-9
33. Kaveh A and Mahdavi V.R. Colliding bodies optimization: a novel meta-heuristic method. *Computers & Structures* 2014; **139**: 18-27
34. Haji Mazdarani M, Hoseini Vaez SR, Hosseini P, Fathali MA. Reliability-based layout optimization of concentrically braced in 3D steel frames. *Structures* 2023; 47: 1094-112
35. Hosseini P, Hatami N, Hoseini Vaez, S.R. Reliability-Based Optimum Design of Dome Truss Structures through Enhanced Vibration Particle System. *Journal of Rehabilitation in Civil Engineering* 2023; **11**(3): 47-67
36. Hosseini P, Hoseini Vaez SR, Fathali MA, Mehanpour H. Reliability assessment of transmission line towers using metaheuristic algorithms. *Int J Optim Civl Eng* 2020; **10**(3): 531-51.
37. Kaveh, Hoseini Vaez SR, Hosseini P, Bakhtiari M. Optimal Design of Steel Curved Roof Frames by Enhanced Vibrating Particles System Algorithm. *Periodica*

[DOI: 10.22068/ijoce.2023.13.3.558]

Polytechnica Civil Engineering 2019; **63**(4): 947-960

38. Paknahad M, P Hosseini and Kaveh A. A self-adaptive enhanced vibrating particle system algorithm for continuous optimization problems. *Int J Optim Civl Eng* 2023; **13**(1): 127-42
39. Yegnanarayana B. Artificial neural networks. *PHI Learning Pvt. Ltd* 2009.
40. Zou J, Y Han, S-S. Overview of artificial neural networks. *Artificial neural networks methods and applications* 2009: 14-22
41. Chen WH, Uribe MC, Kwon EE, Lin KYA, Park YK, Ding L, Saw LHA. Comprehensive review of thermoelectric generation optimization by statistical approach: Taguchi method, analysis of variance (ANOVA), and response surface methodology (RSM). *Renewable and Sustainable Energy Reviews* 2022; **169**: 112917.
42. Lv B, J Cai. Simulation and analysis of geometric parameters based on Taguchi method in Y-Y microfluidic device for circulating tumor cell separation by alternating current dielectrophoresis. *Journal of Chromatography A* 2023; **1693**: 463894.
43. Hong C.W. Using the Taguchi method for effective market segmentation. *Expert Systems with Applications* 2012; **39**(5): 5451-9.

[DOI: 10.22068/ijoce.2023.13.3.558]