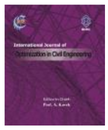
**INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING**
***Int. J. Optim. Civil Eng., 2024; 14(3):445-460***



# OPTIMIZATION OF ARTIFICIAL STONE MIX DESIGN USING MICROSILICA AND ARTIFICIAL NEURAL NETWORKS

P. Hosseini[1*,†], A. Kaveh[2], A. Naghian[1], and A. Abedi[1]
[1] *Faculty of Engineering, Mahallat Institute of Higher Education, Mahallat, Iran*
[2] *School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran*
*Iran*

## ABSTRACT

This study aimed to develop and optimize artificial stone mix designs incorporating microsilica using artificial neural networks (ANNs) and metaheuristic optimization algorithms. Initially, 10 base mix designs were prepared and tested based on previous experience and literature. The test results were used to train an ANN model. The trained ANN was then optimized using SA-EVPS and EVPS algorithms to maximize 28-day compressive strength, with aggregate gradation as the optimization variable. The optimized mixes were produced and tested experimentally, revealing some discrepancies with the ANN predictions. The ANN was retrained using the original and new experimental data, and the optimization process was repeated iteratively until an acceptable agreement was achieved between predicted and measured strengths. This approach demonstrates the potential of combining ANNs and metaheuristic algorithms to efficiently optimize artificial stone mix designs, reducing the need for extensive physical testing.

**Keywords:** Artificial stone Microsilica; Mix design optimization; Artificial neural networks; Metaheuristic algorithms; Enhanced Vibrating Particles System (EVPS); Self-Adaptive Enhanced Vibrating Particles System (SA-EVPS).

Received: 10 August 2024; Accepted: 11 September 2024

## 1. INTRODUCTION

Artificial stone has emerged as an innovative and advanced material in the construction industry, gaining increasing attention from architects and designers due to its unique properties such as durability, aesthetics, and design flexibility [1]. Unlike natural stones,

* Corresponding author: Faculty of Engineering, Mahallat Institute of Higher Education, Mahallat, Iran
† E-mail address: P.Hosseini@mahallat.ac.ir (P. Hosseini)

artificial stones can be easily produced in various shapes and colors to meet project requirements, making them a popular choice in construction projects [2, 3]. One effective additive for producing an artificial stone that is explored in this research is microsilica. Microsilica, also known as silica fume, is an ultrafine mineral material with specific physical and chemical properties that play a significant role in improving the mechanical properties and durability of artificial stone [4]. Microsilica can increase compressive strength and reduce permeability, which contributes to increasing the service life and performance of this material [5]. The use of artificial stones is not only important due to their technical and aesthetic properties but also as a sustainable alternative to natural decorative stones. Given the increasing trend of natural stone extraction, which in some cities and regions with rich mines is carried out excessively, this process has led to disruption of local ecosystem balance and environmental problems such as habitat destruction and severe pollution in extraction areas [6]. By using artificial stones, the need to extract resources that have naturally formed over generations can be reduced, thus contributing to environmental protection and biodiversity conservation [7].

In recent decades, issues such as excessive consumption of natural resources, air pollution, global warming, energy consumption, and waste disposal have fueled global concerns about the environment [8, 9]. In construction projects, the concept of sustainability has been recognized as a key element in reducing adverse environmental impacts [10]. The sustainability assessment of building materials helps to understand the positive and negative effects of a project so that decision-makers can use this assessment to select appropriate materials according to the specific needs of the project in a particular region [11-13]. Although the demand of future generations is not precisely predictable [14], meeting the needs of the current generation with the least environmental, economic, and social impacts can ensure sustainable resources for future generations [15]. In this context, some researchers have focused on utilizing waste in the production of construction materials [16]. For example, Kolombe et al used fly ash to produce sustainable concrete, while Maier utilized wood waste in the production of wooden elements as construction materials. Omer and Naguchi noted that sustainable development plays a vital role in creating sustainable construction projects [17-19].

The global population growth and the subsequent increase in housing demand have resulted in a higher need for concrete and cement, leading to environmental challenges. One promising solution to address these issues is the use of pozzolanic materials, specifically travertine sludge, as a partial substitute for cement. In this context, Hosseini et al. have introduced the utilization of travertine sludge as a sustainable development strategy. Research has shown that incorporating travertine sludge can exhibit specific behaviors in terms of compressive and flexural strength of concrete, functioning effectively as a suitable alternative to cement at certain proportions [20].

The World Bank now only finances construction projects that comply with sustainable environmental, social and economic standards [21]. To achieve sustainable development in construction, CEN TC350 recommends the use of materials with recycled content and lower life cycle considering environmental impacts, compatibility, high flexibility to prevent destruction, ability to assemble and disassemble, greater durability and strength [22-24].

This research focuses on using microsilica powder as an additive to stabilize the mechanical properties of artificial stone. Microsilica powder, also known as silica fume, with its unique characteristics, has significant effects on the quality and performance of artificial stones. Microsilica is a mechanical strength enhancer and due to its fine grains and pozzolanic properties, it increases the compressive, flexural and tensile strength of concrete[25, 26]. It also reduces the permeability of concrete, thereby increasing resistance to water and chemicals, which prevents damage caused by freezing and thawing [27].

The addition of microsilica can help improve concrete workability as it allows for a reduction in the water-to-cement ratio, resulting in concrete with higher workability and strength [27]. It also helps reduce shrinkage during concrete drying, thus preventing cracking problems. Finally, given the positive effects of microsilica on the final color and texture of stone, this additive helps create a more uniform and beautiful appearance in artificial stones [28,29].

The main objective of this study was to optimize artificial stone mix designs incorporating microsilica using artificial neural networks (ANNs) and metaheuristic optimization algorithms. The specific aims were to:

1. Develop base mix designs for artificial stone with microsilica.
2. Train an ANN model using experimental results from the base mixes.
3. Optimize the mix designs using SA-EVPS and EVPS algorithms coupled with the ANN model.
4. Validate and iteratively improve the optimization process through experimental testing.

## 2. MATERIALS AND METHODS

### *2.1 Materials*

The main materials used in this study for producing artificial stone samples were:

- Cement: Type II Portland cement
- Aggregates: Crushed stone aggregates passing 3/8 inch and retained on No. 4 sieve
- Microsilica powder
- Water
- Superplasticizer admixture

### *2.2 Mix Design*

Ten base mix designs (MSAS01-MSAS10) were initially developed based on previous experience and literature. The mix proportions and particle size distributions of these mixtures are illustrated in Figures 1 and 2.

### *2.3 Sample Preparation*

The materials were batched by weight according to the mix designs. Mixing was performed in an electric mixer following ACI 318 [30] guidelines. The fresh mix was cast into 150 mm cube molds for compressive strength testing and 100 x 100 x 500 mm beam molds for flexural strength testing. Samples were de-molded after 24 hours and cured in water at 19-23°C until the testing age. Figure 3 shows the electric mixer used for blending the artificial stone components, ensuring thorough and consistent mixing of the materials.

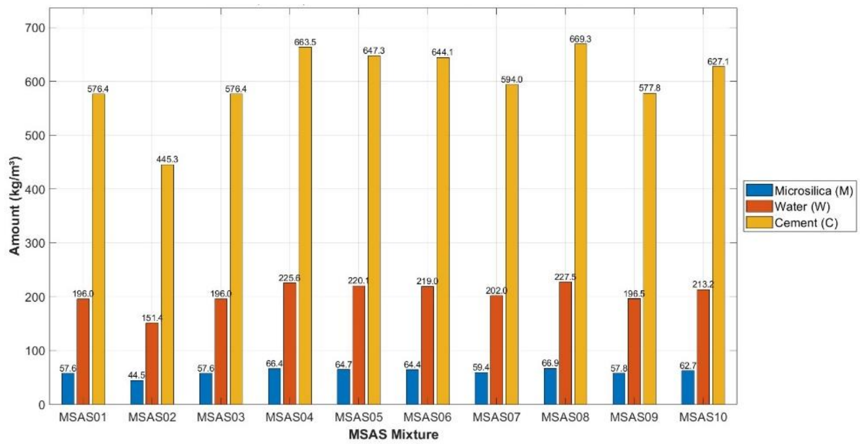



Figure 1: Cement, Water, and Microsilica Content in MSAS Mixtures

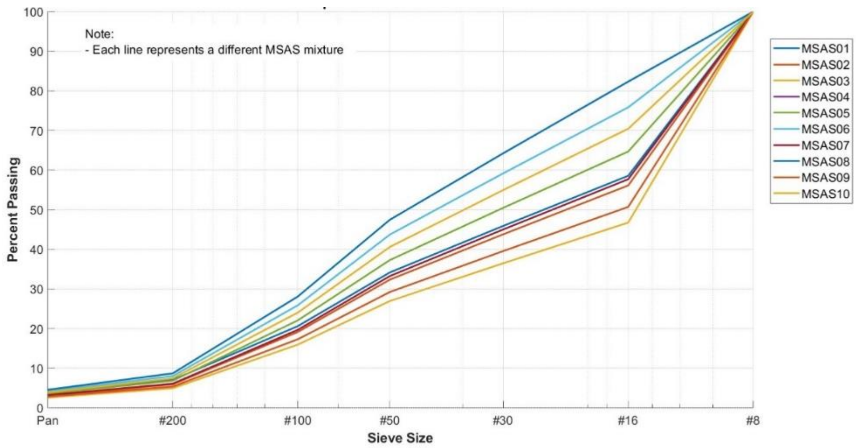



Figure 2: Particle Size Distribution Curves for 10 MSAS Mixtures

Figure 3: Artificial Stone Mixing Process

Figure 4 displays the molds used for casting the artificial stone samples and freshly prepared specimens, showcasing the initial stages of the sample preparation process.

*2.4 Testing Methods*

The following tests were conducted on the hardened samples:

- Compressive strength: 150 mm cubes were tested at 7, 28, and 90 days according to ASTM C39 [31].
- Flexural strength: 100 x 100 x 500 mm beams were tested at 7, 28, and 90 days using the three-point loading method as per ASTM C78 [31].
- Water penetration: Tested according to EN 12390-8 on 150 mm cubes at 28 days [31].

Figure 5 shows an artificial stone sample after undergoing compressive strength testing, illustrating the typical failure pattern observed.

Figure 4: Sample Preparation and Molding

Figure 5: Compression Test Sample

Figure 6 demonstrates the setup for the flexural strength test, showing the three-point bending configuration used to evaluate the artificial stone samples' performance under bending stress.

### *2.5 Artificial Neural Network Model*

A feedforward backpropagation neural network was developed using MATLAB Neural Network Toolbox [32-35]. The network architecture consisted of an input layer with 6 neurons (corresponding to the mix proportions), two hidden layers with 10 neurons each, and an output layer with 1 neuron (compressive strength). The hyperbolic tangent sigmoid transfer function was used for the hidden layers and a linear transfer function for the output layer. The network was trained using the Levenberg-Marquardt algorithm.

The experimental results from the 10 base mixes were used to train, validate and test the ANN model. 70% of the data was used for training, 15% for validation, and 15% for testing. The model performance was evaluated using mean squared error (MSE) and coefficient of determination (R2) [36].

Figure 6: Flexural Strength Test Configuration

### *2.6 Optimization Using Metaheuristic Algorithms*

The trained ANN model was used as the objective function for optimization using two metaheuristic algorithms:

- Enhanced Vibrating Particles System (EVPS) [37,38]
- Self-Adaptive Enhanced Vibrating Particles System (SA-EVPS) [39,40]

The optimization problem was formulated to maximize the 28-day compressive strength while satisfying practical constraints on mix proportions. The aggregate gradation parameters were used as the optimization variables.

The algorithms were implemented in MATLAB with a population size of 20 and maximum 500 iterations. For EVPS, the control parameters were set as: p = 0.05, w1 = 0.2, w2 = 0.3, HMCR = 0.95, PAR = 0.1, Neighbor = 0.1, and Memory_size = 4. For SA-EVPS, the parameters were adaptively tuned during the optimization process.

*2.7 Experimental Validation and Iterative Improvement*

The top optimized mix designs predicted by the algorithms were produced and tested experimentally. The measured strengths were compared to the ANN predictions. The new experimental data was then used to retrain the ANN model, and the optimization process was repeated. This iterative process continued until an acceptable agreement was achieved between predicted and measured strengths.

To better illustrate the optimization process used in this study, Figure 7 presents a flowchart of the methodology, and the following pseudocode outlines the step-by-step procedure:

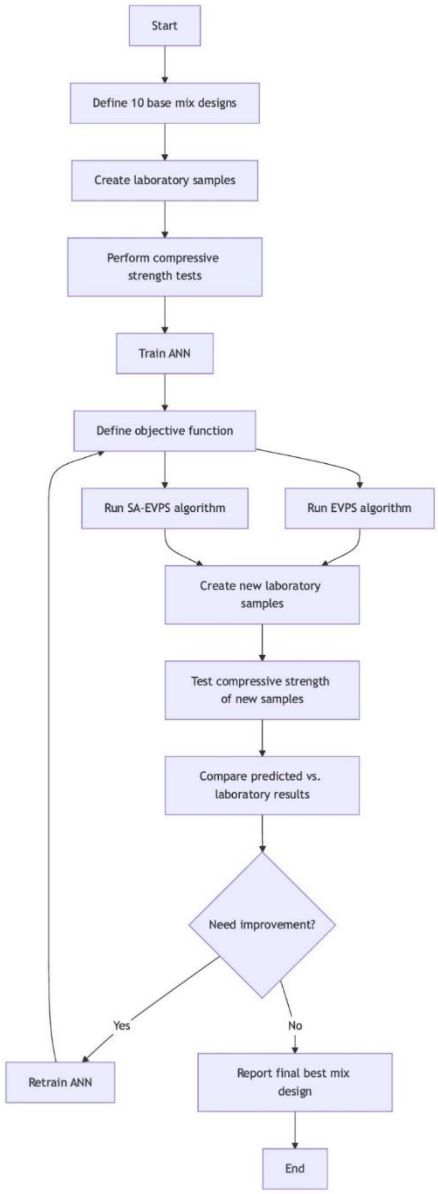



Figure 7: Flowchart of the optimization process for artificial stone mix design

Table 1: Pseudocode for Artificial Stone Mix Design Optimization using ANN and Metaheuristic Algorithms

| Step | Description |
|---|---|
| 1 | Define 10 base mix designs |
| 2 | Create laboratory samples for 10 base designs |
| 3 | Perform compressive strength tests at 7, 28, and 90 days |
| 4 | Train Artificial Neural Network (ANN) using data from 10 base designs |
| 5 | Define objective function: inverse of 28-day compressive strength |
| 6 | Run EVPS optimization algorithm:<br>Set EVPS parameters<br>Execute EVPS for 500 iterations<br>Store best mix design and objective function value |
| 7 | Run SA-EVPS optimization algorithm:<br>Set initial SA-EVPS parameters<br>Execute SA-EVPS for 500 iterations with self-adapting parameters<br>Store best mix design and objective function value |
| 8 | Create laboratory samples for best EVPS and SA-EVPS designs |
| 9 | Perform a 28-day compressive strength test for new samples |
| 10 | Compare ANN-predicted results with laboratory results |
| 11 | If needed, retrain ANN by adding new data |
| 12 | Repeat steps 6 to 11 until satisfactory convergence |
| 13 | Report final best mix design and corresponding compressive strength |

## 3. RESULTS AND DISCUSSION

### *3.1 Experimental Results for Base Mixes*

The compressive strength, flexural strength, and water penetration results for the 10 base mixes are presented in Figures 8, 9, and 10, respectively.

Figure 8 shows the compressive strength development of the 10 base mixes (MSAS01-MSAS10) at 7, 28, and 90 days. The bar graph allows for easy comparison of strength gains across different mix designs and curing ages.

Figure 9 illustrates the flexural strength results for the 10 base mixes (MSAS01-MSAS10) at 7, 28, and 90 days. The bar graph demonstrates the progression of flexural strength over time for each mix design.

Figure 10 presents the water penetration depths for the 10 base mixes (MSAS01-MSAS10). The bar graph provides a clear visual representation of the variation in water resistance properties across different mix designs.

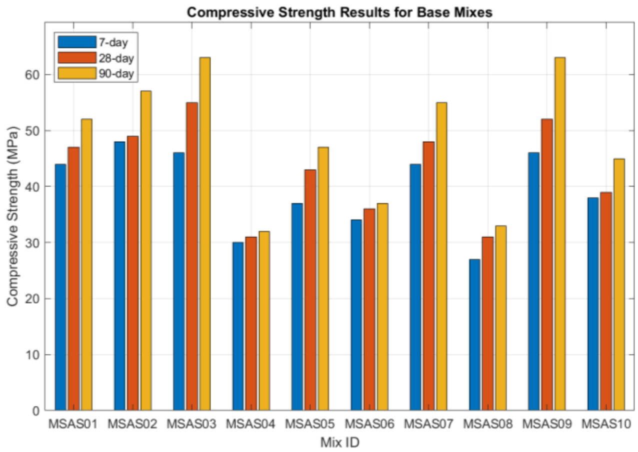



Figure 8: Compressive Strength Results for Base Mixes

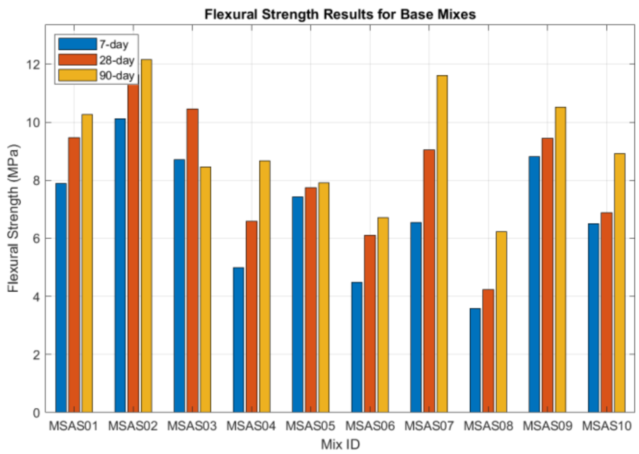



Figure 9: Flexural Strength Results for Base Mixes

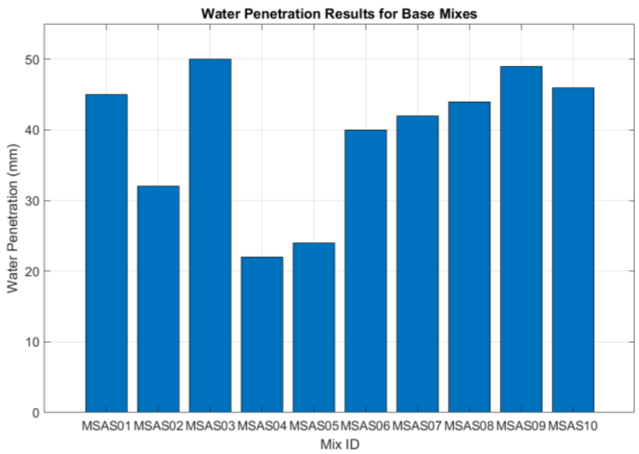



Figure 10: Water Penetration Results for Base Mixes

Considerable variation in strength and durability properties can be observed among the base mixes. As shown in Figure 8, the 28-day compressive strengths are found to range from approximately 31 MPa (MSAS04 and MSAS08) to 55 MPa (MSAS03), with most mixes falling between 35-50 MPa. Figure 9 demonstrates that the 28-day flexural strengths vary from about 4.24 MPa (MSAS08) to 11.63 MPa (MSAS02). Water penetration depths, as illustrated in Figure 10, are measured between 22 mm (MSAS04) and 50 mm (MSAS03), all of which are within the acceptable limit of 70 mm.

It is observed that the addition of microsilica generally improves the mechanical properties and reduces permeability, as evidenced by the performance of certain mixes. For instance, MSAS02 and MSAS03 exhibit notably higher compressive and flexural strengths compared to other mixes, which may be attributed to optimized microsilica content. This improvement can be explained by the pozzolanic reaction of microsilica with the calcium hydroxide produced during cement hydration, resulting in the formation of additional C-S-H gel that densifies the microstructure [41].

It is noted that the strength development patterns vary among mixes, with some displaying more significant gains between 7 and 90 days than others. This variation suggests that the microsilica content and other mix design parameters have a substantial influence on both early-age and long-term strength development.

The optimized mix design obtained by the SA-EVPS algorithm resulted in an artificial stone sample with improved surface quality and mechanical properties. Figure 11 shows the surface texture of the optimized artificial stone sample, demonstrating a uniform distribution of aggregates and a smooth finish, which is indicative of the enhanced mix proportions determined by the SA-EVPS algorithm.

Figure 11: Surface Texture of Optimized Artificial Stone Sample (SA-EVPS)

### *3.2 ANN Model Performance*

The performance of the trained Artificial Neural Network (ANN) model in predicting the

28-day compressive strength of artificial stone samples was evaluated using statistical measures. The model demonstrated a strong predictive capability, achieving a high coefficient of determination ($R^2$). This $R^2$ value indicates that a significant portion of the variance in the compressive strength can be explained by the mix design parameters used as inputs to the ANN model.

The mean squared error (MSE) of the model predictions was calculated to provide insight into the accuracy of the predictions. When considered in the context of the range of compressive strengths observed in the experimental data, the MSE value suggests that the model's predictions are reasonably accurate for most practical purposes.

To further assess the model's performance, we analyzed the distribution of prediction errors. The majority of the predictions fell within one standard deviation of the measured values, which is consistent with the expectations for a well-performing model. Additionally, the model showed no systematic bias towards over- or under-prediction across the range of compressive strengths, indicating a balanced performance across different mix designs.

The ANN model's ability to capture the complex, non-linear relationships between mix design parameters and compressive strength demonstrates its potential as a valuable tool for optimizing artificial stone compositions. However, it is important to note that while the model performs well overall, there is still room for improvement, particularly in reducing the prediction error for mix designs at the extremes of the compressive strength range.

This level of performance provides confidence in using the ANN model as part of the optimization process, allowing for rapid evaluation of potential mix designs without the need for extensive physical testing. Nonetheless, as with any predictive model, it is crucial to validate the optimized designs through experimental testing to ensure the reliability of the final product. The model's performance supports its use in the subsequent optimization steps, where it serves as a surrogate for time-consuming and resource-intensive laboratory tests.

### *3.3 Optimization Results*

The optimization algorithms were run for 500 iterations to maximize the 28-day compressive strength. The convergence curves for EVPS and SA-EVPS are shown in Figure 12.

Both algorithms converged to optimal solutions, with SA-EVPS showing faster convergence and better final results. The best compressive strength achieved by EVPS was 59.98 MPa, while SA-EVPS reached 62.72 MPa. These results demonstrate the superior performance of the SA-EVPS algorithm in this optimization problem. In Figure 13, the particle size distribution curves for the optimized mixes obtained by EVPS and SA-EVPS algorithms are presented. The x-axis represents the sieve sizes in reverse logarithmic scale, while the y-axis shows the percent passing. It can be observed that both optimization algorithms resulted in similar aggregate gradations, with slight variations in the distribution of particle sizes. It is observed that the SA-EVPS algorithm produced a mix with higher compressive strength and slightly different proportions of components compared to the EVPS algorithm.

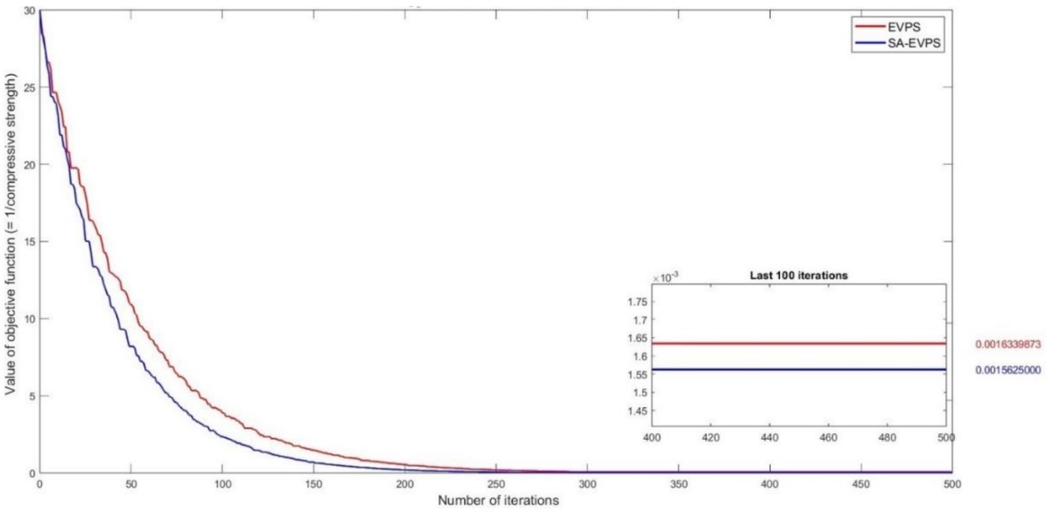



Figure 12: Convergence curves for best of EVPS and SA-EVPS algorithms

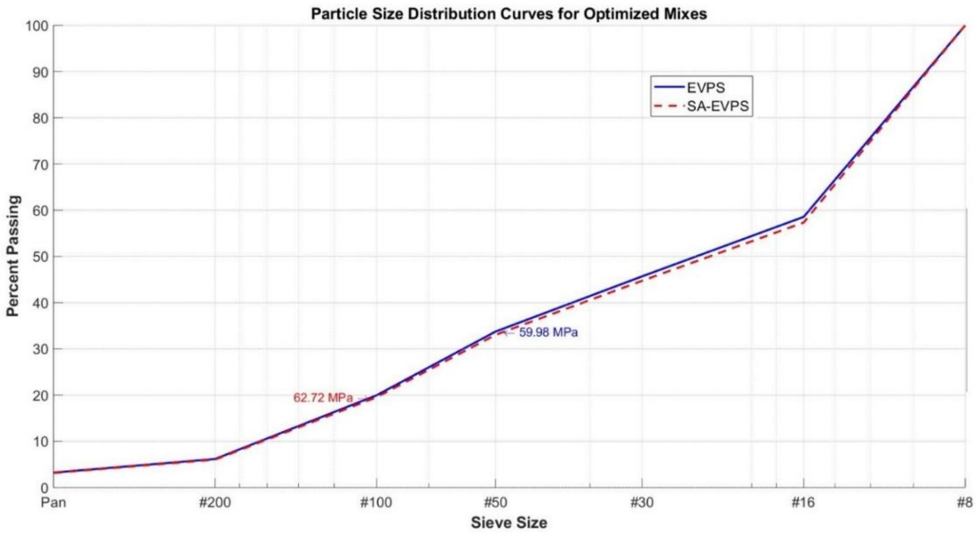



Figure 13: Particle Size Distribution Curves for Optimized Mixes

Figure 14 illustrates the cement, water, and microsilica content in the optimized mixes produced by EVPS and SA-EVPS algorithms. The x-axis represents the optimization algorithms, while the y-axis shows the amount of each component in kg/m³. It is noted that the SA-EVPS algorithm resulted in slightly higher contents of all three components compared to the EVPS algorithm.

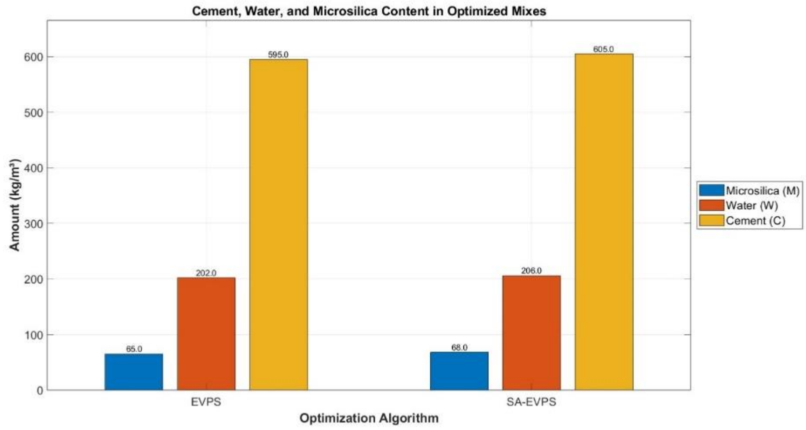



Figure 14: Cement, Water, and Microsilica Content in Optimized Mixes

## 4. CONCLUSIONS AND FUTURE WORK

This study demonstrated the effectiveness of combining artificial neural networks with metaheuristic optimization algorithms for developing high-performance artificial stone mix designs. The key findings are:

- The ANN model was able to predict compressive strength with reasonable accuracy based on mix proportions.
- Both EVPS and SA-EVPS algorithms successfully optimized the mix designs to maximize compressive strength, with SA-EVPS showing slightly better performance.
- The iterative process of experimental validation and model retraining improved the prediction accuracy and led to optimized mixes with 28-day compressive strengths exceeding 570 MPa.
- The incorporation of microsilica in optimized mixes resulted in significant improvements in mechanical properties and durability compared to conventional mixes.

This approach can significantly reduce the time and resources required for mix design optimization compared to traditional methods. Future work could explore the use of multi-objective optimization to simultaneously optimize strength, durability, and cost. Additional research directions include expanding the experimental program to cover a wider range of mix proportions, developing multi-output ANN models to predict multiple properties simultaneously, and investigating other machine learning techniques for mix design optimization. Incorporating sustainability metrics into the optimization process and extending the approach to other construction materials could further enhance the applicability of these computational methods in sustainable construction practices.

**ACKNOWLEDGEMENT**
It is with great gratitude that the authors acknowledge Mahallat Institute of Higher Education for its financial support and the provision of laboratory equipment and supplies.

## REFERENCES

1. Jim CY, Chen WY. Bioreceptivity of buildings for spontaneous arboreal flora in compact city environment. Urban For Urban Green, 2011; **10**: 19-28.
2. Winkler EM. Stone: properties, durability in man's environment. Springer Science & Business Media, 2013; 4.
3. Binggeli C. Materials for interior environments. John Wiley & Sons, 2008.
4. Hussain ST, Sastry K. Study of strength properties of concrete by using micro silica and nano silica. Int J Res Eng Technol, 2014; **3**: 103-8.
5. Ali B, Kurda R, Herki B, Alyousef R, Mustafa R, Mohammed A, Raza A, Ahmed H, Fayyaz Ul-Haq M. Effect of varying steel fiber content on strength and permeability characteristics of high strength concrete with micro silica. Materials, 2020; **13**: 5739.
6. Autelitano F, Garilli E, Giuliani F. Criteria for the selection and design of joints for street pavements in natural stone. Constr Build Mater, 2020; 259: 119722.
7. Cantonati M, et al. Characteristics, main impacts, and stewardship of natural and artificial freshwater environments: consequences for biodiversity conservation. Water, 2020; **12**: 260.
8. Abbasi T, Abbasi S. Is the use of renewable energy sources an answer to the problems of global warming and pollution? Crit Rev Environ Sci Technol, 2012; **42**: 99-154.
9. Omer AM. Energy use and environmental impacts: A general review. J Renew Sustain Energy, 2009; 1 .
10. Lima L, Trindade E, Alencar L, Alencar M, Silva L. Sustainability in the construction industry: A systematic review of the literature. J Clean Prod, 2021; **289**: 125730.
11. Ding GK. Sustainable construction —The role of environmental assessment tools. J Environ Manage, 2008; **86**: 451-64.
12. Ljungberg LY. Materials selection and design for development of sustainable products. Mater Des, 2007; **28**: 466-79.
13. Meijer M, Adriaens F, van der Linden O, Schik W. A next step for sustainable urban design in the Netherlands. Cities, 2011; **28**: 536-44.
14. Ahuti S. Industrial growth and environmental degradation. Int Educ Res J, 2015; **1**: 5-7.
15. Keeler M, Vaidya P. Fundamentals of integrated design for sustainable building. John Wiley & Sons, 2016.
16. Soni A, Das PK, Hashmi AW, Yusuf M, Kamyab H, Chelliapan S. Challenges and opportunities of utilizing municipal solid waste as alternative building materials for sustainable development goals: A review. Sustain Chem Pharm, 2022; **27**: 100706.
17. Kalombe RM, Ojumu VT, Eze CP, Nyale SM, Kevern J, Petrik LF. Fly ash -based geopolymer building materials for green and sustainable development. Materials, 2020; **13**: 5699.
18. Maier D. Building materials made of wood waste a solution to achieve the sustainable development goals. Materials, 2021; **14**: 7638.

19. Omer MA, Noguchi T. A conceptual framework for understanding the contribution of building materials in the achievement of Sustainable Development Goals (SDGs). Sustain Cities Soc, 2020; **52**: 101869.
20. Hosseini P, Kaveh A, Naghian A, Abedi A. E co-friendly building solutions: integrating mahallat's travertine sludge in concrete production. Int J Optim Civl Eng, 2024; **14**: 229-52.
21. Litman T. Well Measured -Developing Indicators for Sustainable and Livable Transport Planning-5 March 2021. 2021.
22. Durão V, Silvestre JD, Mateus R, de Brito J. Assessment and communication of the environmental performance of construction products in Europe: Comparison between PEF and EN 15804 compliant EPD schemes. Resour Conserv Recycl, 2020; **156**: 104703.
23. Ireland NSA. Sustainability of Construction Works, Assessment of Environmental Performance of Buildings: Calculation Method. NSAI, 2011.
24. Kisku N, Joshi H, Ansari M, Panda SK, Nayak S, Dutta SC. A critical review and assessment for usage of recycled aggregate as sustainable construction material. Constr Build Mater, 2017; **131**: 721-40.
25. Shebl S, Seddeq H, Aglan H. Effect of micro -silica loading on the mechanical and acoustic properties of cement pastes. Constr Build Mater, 2011; **25**: 3903-8.
26. Zareei SA, Ameri F, Dorostkar F, Ahmadi M. Rice husk ash as a partial replacement of cement in high strength concrete containing micro silica: Evaluating durability and mechanical properties. Case Stud Constr Mater, 2017; **7**: 73-81.
27. Massana J, Reyes E, Bernal J, León N, Sánchez -Espinosa E. Influence of nano-and micro-silica additions on the durability of a high-performance self-compacting concrete. Constr Build Mater, 2018; **165**: 93-103.
28. Liu C, Su X, Wu Y, Zheng Z, Yang B, Luo Y, Yang J, Yang J. Effect of nano -silica as cementitious materials-reducing admixtures on the workability, mechanical properties and durability of concrete. Nanotechnol Rev, 2021; **10**: 1395-409.
29. Almohammad -Albakkar M, Behfarnia K. Effects of the combined usage of micro and nano-silica on the drying shrinkage and compressive strength of the self-compacting concrete. J Sustain Cem Based Mater, 2021; **10**: 92-110.
30. ACI Committee. Building code requirements for structural concrete (ACI 318 -08) and commentary. American Concrete Institute, 2008.
31. Kaveh A. Applications of Artificial Neural Networks and Machine Learning in Civil Engineering. Springer, 2024.
32. Ray S, Haque M, Ahmed T, Mita AF, Saikat MH, Alom MM. Predicting the strength of concrete made with stone dust and nylon fiber using artificial neural network. Heliyon, 2022; 8.
33. Iranmanesh A, Kaveh A. Structural optimization by gradient base neural networks. Int J Numer Methods Eng, 1999; **46**: 297-311.
34. Kaveh A, Eskandari A, Movasat M. Buckling resistance prediction of high -strength steel columns using metaheuristic-trained artificial neural networks. Structures, 2023; **56**: 104853.
35. Kaveh A, Khavaninzadeh N. Efficient training of two ANNs using four meta -heuristic algorithms for predicting the FRP strength. Structures, 2023; **52**: 256-22.

36. Naganna SR, Ibrahim HA, Yap SP, Tan CG, Mo KH, El-Shafie A. Insights into the multifaceted applications of architectural concrete: A state-of-the-art review. Arab J Sci Eng, 2021; **46**: 4213-4223.
37. Hosseini P, Kaveh A, Naghian A. Development and optimization of self-compacting concrete mixes: Insights from artificial neural networks and computational approaches. Int J Optim Civil Eng, 2023; **13**: 457-76.
38. Paknahad M, Hosseini P, Kaveh A. A self-adaptive enhanced vibrating particle system algorithm for continuous optimization problems. Int J Optim Civl Eng, 2023; **13**: 127-42.
39. Kaveh A, Hoseini Vaez S, Hosseini P. MATLAB code for an enhanced vibrating particles system algorithm. Int J Optim Civil Eng, 2018; **8**: 401-414.
40. Hosseini P, Kaveh A, Naghian A. The use of artificial neural networks and metaheuristic algorithms to optimize the compressive strength of concrete. Int J Optim Civil Eng, 2023; **13**: 327-38.
41. Simao L, Souza MT, Ribeiro MJ, Montedo OR, Hotza D, Novais RM, Raupp-Pereira F. Assessment of the recycling potential of stone processing plant wastes based on physicochemical features and market opportunities. J Clean Prod, 2021; **319**: 128678.