Metaheuristically optimized nano-MgO additive in freeze-thaw resistant concrete: a charged system search-based approach

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Abstract

With progressive advances in the synthesis, characterization, and commercialization of nanoparticles and nanomaterials, these modern engineered materials are becoming an ingredient of innovative structural materials for various applications in civil and construction engineering. In this research, MgO nanoparticles were systematically added to normal concrete samples in order to investigate the effect of these nanomaterials on the durability of the samples under freeze and thaw conditions. The compressive and tensile strengths as well as the permeability of concrete samples containing nanoparticles were measured and compared with the corresponding values of control samples without nanoparticles. The curing time of the concrete samples, the amount of nanoparticles, and the water-cement ratios \((w/c)\) were the variables of the experiments. Moreover, data clustering and the Charged System Search (CSS) algorithm were utilized as the numerical analysis and optimization methods. The regression analysis before clustering and after clustering proved the process of clustering is a prerequisite of regression analysis. Furthermore, the CSS optimization method showed that the optimum amount of nano MgO is 1% of the weight of cement, which can increase the compressive strength of concrete by 9.12% more than plain samples over 34 days.

1. Introduction

In cold regions, hydraulic structures are generally under repetitive freeze and thaw conditions. It is known that an increased number of microcracks, mass loss, and decline in the mechanical properties of concrete are the results of rapid temperature changes during freezing and thaw cycles [1]. For promoting the life span of concrete, decreasing the permeability of concrete seems to be a reasonable approach. According to a wide range of previous studies [2–10] which investigated the influence of nano-sized crystals and pores by adding nanometer scaled materials like nano-SiO\(_2\), nano-Fe\(_3\)O\(_4\), nano-ZnO\(_2\), and nano-Al\(_2\)O\(_3\), nanopowders can fill the pores and reduce the permeability of concrete. As a result, the durability and mechanical properties of concrete could be improved effectively in this fashion. The nano-filler effect enables nano-powders to decrease the permeability of concrete, especially through creating the interfacial transition zone (ITZ) with homogeneous texture and less porosity [11]. In a previous study, nano-kaolinite clay (NKC) was added to concrete and the resistance of samples was tested under the freeze and thaw condition. They substituted cement with different percentages of NKC and put the samples in a freeze-thaw cabinet and measured the mechanical and physical properties of samples regularly. The research demonstrated that samples containing 5% of NKC showed maximum compressive strength and high resistance to chloride diffusion [12]. In another research, nano-silica was added to Portland Cement Concrete (PCC). They observed that nano-silica improved the compressive strength and paste density of the samples subjected to the freeze-thaw action, while reducing external damage to them [13]. Because of the importance and difficulty of the procedure of concrete deterioration by repeated freeze and thaw cycles, numerous theories have been proposed by researchers for recognizing the freeze-thaw action and its role in the...
destruction of concrete. Four theories for describing frost action have been proposed: Power’s hydraulic pressure theory in 1945 [14], Power and Helmuth’s osmotic pressure theory [15], Larson and Cady’s theory [16], and the desorption theory by Litvan [17]. In 1998, the pore solution of concrete was studied by changes in electrical conductivity under the freeze and thaw action [18]. Topcu and Shengel (2004) [19] conducted a study on the properties of concrete made from aggregates of waste concrete (WCA). They put the samples under the freeze-thaw condition and concluded that the durability and workability of the concrete with WCA decreased in reverse proportion to their endurance under the freeze and thaw cycles. Hazaree et al [20] carried out a series of laboratory experiments on the roller-compacted concrete (RCC); they investigated the effect of different amounts of cement content and the air entrained on the concrete durability under the freeze-thaw condition. It was discovered that air entrainment influences the strength of concrete and its resistivity against the freeze-thaw condition. In 2016, the workability and durability of self-compacting concrete (SCC) under the coupling effect of salt freeze-thaw and flexural load were studied in experimental research. Tian et al [21] showed that salt freeze-thaw had a small effect on surface erosion.

Knowing that the effect of nano-MgO on the mechanical properties of concrete in freeze-thaw condition has not been evaluated or limited to the investigation of a few parameters like modulus of elasticity and mass loss, this paper aims to study the compressive strength, tensile strength, and permeability of concrete containing nano MgO in freeze-thaw condition. Choosing an appropriate data mining approach is necessary for many experimental research studies. The purpose of such analyses is to establish a connection between input and output data, or to predict/optimize certain variables. In the current study, there were three types of data: (i) the compressive strength, (ii) the tensile strength, and (iii) the permeability data. The Self Organizing Map (SOM) was used for the clustering of each type of data independently. The results showed that performing clustering with SOM had an effective role by making the data smoother and was efficient in preparing the data for optimization. Furthermore, the Charged System Search (CSS) optimization algorithm [22] was utilized to find the optimum amount of nano-MgO in concrete.

2. Materials and preparations

For the simulation of the environment in cold areas, a freeze-thaw cabinet was used in the experiments. Figure 1(a) shows the concrete samples in the freeze-thaw chamber. The samples were under freeze-thaw cycles according to ASTM C666 [23]. In all the samples, Portland cement type II was used, where fine and coarse aggregates were extracted from local aggregate deposits. The maximum size of coarse aggregate was 19 mm and the fineness modulus (FM) for sand was 3.2. Grading curves for fine and coarse aggregate were considered according to the ASTM C33 standard [24] as shown in figures 1(b) and (c). Also, the mixture proportions of concrete were defined based on the standard ACI-211 [25]. The size of nano-MgO particles was less than 40 nm, and their density and purity were 3.58 g m$^{-3}$ and 99%, respectively. Details of the nanopowder analysis are shown in table 1.

In this study, 98 cubic concrete specimens (10 × 10 × 10 cm) and 78 cylindrical concrete specimens (10 × 20 cm) were prepared with different percentages of nano-MgO particles, which were supposed to be 0, 0.5%, 1%, and 1.5% of the cement weight. The concrete mixture was designed by using ACI 211-89. The primary water to binder ratio was considered to be 0.62 and the application of superplasticizer made it possible to decrease the water to binder ratio while retaining the workability of the mixture (slump = 75–100 mm). By using 0.5% and 1% superplasticizer, it was possible to reduce the water to binder ratio to 0.49 and 0.44, respectively, while the slump amount was constant (75–100 mm). It is noteworthy that the use of superplasticizer in higher amounts could have harmful effects on the mechanical properties of concrete. The water-cement ratios (w/c) were 0.44, 0.49, and 0.62. The samples were under the curing process for periods of 7, 28, and 56 days. The curing procedures were carried out in water tanks with temperatures 23 ± 2 °C in the laboratory condition. The properties of samples have been summarized in table 2.

The nanomaterial was used in the solution form, prepared using an ultrasonic stirring instrument (processor) with different amounts of nano-MgO dissolved in water for 5 min. This solution was added to the mixture and stirred for 3 min. The ultrasonic processor has different tips, and is capable of producing a wide range of acoustic power densities. We used tip H7 (with a diameter of 7 mm) that can produce a wavelength of 175 μm and a power density of 300 W cm$^{-2}$.

3. Methods

In this research, Artificial Neural Network (ANN) was utilized for regression analyses. Moreover, to achieve efficient results from these analyses, clustering was exploited as a pre-analysis task. Finally, the CSS analysis was performed to optimize the result data set.
Figure 1. (a) Concrete samples in the freeze-thaw chamber. (b & c) Grading curves of coarse (b) and fine (c) aggregates.

Table 1. Chemical properties of MgO nanopowder.

| Magnesium oxide (MgO) nanopowder certificate of analysis | MgO | Na (ppm) | K (ppm) | Ca (ppm) |
|--------------------------------------------------------|-----|----------|---------|----------|
| >99%                                                   | <750 ppm | <218 ppm | <760 ppm |

Table 2. Summary of the properties of experimental samples.

| Type of samples | w/c | Nano-MgO (%) | Curing period (days) |
|-----------------|-----|---------------|----------------------|
| Cubic samples (10 × 10 × 10) | 0.44, 0.49, 0.62 | 0, 0.5, 1, 1.5 | 7, 28, 56 |
| Cylindrical samples (10 × 20) | | | |
3.1. Artificial neural network (ANN)

Artificial Neural Network (ANN) is one of the predictive tools for which no specific equation is needed [26]. ANN is capable of being trained through the observation of input and output data sets. It can find potential relations between them or perform generalizations in order to generate a result when there is no output for a special input. To have an effective neural network, it is important to have a sufficient data set for accurate training and testing. ANN has become popular and widely used in civil engineering problems; for example, ANN has been applied for the approximation of the compressive strength of concrete [27], studying the interface between rock and concrete in arch dams, and predicting piezometric levels in the rock-concrete joints [28]. In another research, [29] ANN was implemented to reduce the corrosion of concrete in sewage systems by the usage of glass beads. Researchers employed (ANN) to estimate the loss of mass and volume in specimens. Lee et al. [30] proposed a theoretical model based on ANN and used a fiber–reinforced polymer (FRP) rather than stirrups for bearing shear force in flexural members by applying ANN for the estimation of shear strength in the members. They proposed some mathematical formulas for predicting the shear strength, with the obtained equations outperforming other existing formulas.

ANN, as one of the efficient methods, consists of several processors which are named units or neurons [31]. Each neuron can communicate with other neurons by channels, which are called connections. Every connection has a weight that refers to the data of what type of connection transfers it. Mathematical and logical operations are applied to the transferred data in the units. The efficiency of ANN is proved for finding a relation between input and output data to make a prediction when there is not an answer for special input data. To have an effective neural network, it is important to have enough data set for accurate training and testing; also, it is very important to have a well-designed network with a suitable architecture. There are some factors with high significance that affect the efficiency of a network such as the number of neurons and hidden layers, and the sort of operational functions. Different types of ANN have been developed and utilized such as Hopfield, Cohonen, and backpropagation network [32]. Back Propagation (BP) has been applied in several civil engineering problems [33–36]. BP is built by different components such as the input layer, one or more hidden layers, and the output layer. The input layer is made up of components that define the agents that have probable effects on the outputs of the network but do not involve in the computational procedure. In the process of learning in the BP method, it is supposed that errors produced from output neurons spread back to the hidden layers and input neurons. These error signals help the network to correct the coefficients and weights of the model by utilization of a rule whose name is generalized delta learning. It works by the gradient reduction of the error method. The number of neurons in the hidden layer mainly affects the convergence speed. The other factors are the value of the learning rate and the number of the training data set. A trial and error method could be used for finding a suitable network structure.

There are some parameters that verify the performance of the model which can be expressed in terms of predicted value, $R_{ij}$, and observed value, $R_{nj}$, as follows [37]:

1. Pearson’s coefficient $R^2$ defined as

$$R^2 = \frac{\sum_{j=1}^{k}(R_{ij} - \bar{R})^2}{\sum_{j=1}^{k}(R_{nj} - \bar{R})^2} \quad (1)$$

where $\bar{R}$ is the mean value of the observed data and $k$ is the number of variables.

2. The mean squared error (MSE) defined as

$$MSE = \frac{\sum_{i=1}^{n}(R_{mi} - R_{ai})^2}{n} \quad (2)$$

where $n$ is the sample size.

3. The root mean square error (RMSE)

$$RMSE = \sqrt{MSE} \quad (3)$$

4. The mean absolute error (MAE)

$$MAE = \frac{\sum_{i=1}^{n}|R_{mi} - R_{ai}|}{n} \quad (4)$$

5. The mean absolute percentage error (MAPE)

$$MAPE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| \frac{R_{mi} - R_{ai}}{R_{mi}} \right| \quad (5)$$
3.2. Clustering
One of the most widely-used unsupervised neural network models is the self-organizing maps (SOM) which have two main advantages: (1) it can reduce the dimension of input data, as the network has the potential to convert a multi-dimensional input space to a lower dimension discrete map; (2) there is no assumption about input data, because SOM is an unsupervised learning method. Figure 2 shows the mapping process of the input dataset from a high dimension to a two-dimensional space.

In this research, the input data includes \( \frac{w}{c} \) ratio, nano-MgO percentage, curing period of samples, compressive and tensile strength. In table 3, the parameters of SOM models are shown.

In the past two decades, SOM has been used in a variety of engineering fields for a diverse range of purposes. For instance, the prediction of groundwater level was made using a SOM-aided stepwise cluster inference model [38]. Furthermore, a hybrid SOM and K-means clustering method was used for the planning and management of water distribution systems [39]. In another research work, the SOM clustering method was used for the noise removal of corrosion monitoring of steel reinforcement in concrete [40].

‘Cluster analysis’ or ‘clustering’ classifies a set of data in different groups. The data or objects in each group have the same or similar values. In other words, the purpose of all clustering analyses is to use the distance or similarity matrices to classify the objects or data in groups [41]. In figures 3(A) and (B), a set of compressive test data and tensile strength data respectively having two attributes were classified based on their distance from each other. Clusters can be thought of as groups with relatively small distances among their members, the dense areas of data space, or areas with special statistical distributions. As a result, clustering can be considered to be a multi-objective optimization problem.

There are different algorithms for different clustering models; some of the clustering models are as follows: Connectivity model [42], Centroid models [43], Distribution models [44], Density models [45], and Neural models [46]. Ease of use and high calculation speed make neural models efficient in comparison with other models. One of the subsets of the neural models is SOM that is a kind of ANN that uses a special method of learning called the unsupervised method. The use of this method enables us to make a lower dimension (commonly two-dimensional) representation of the discrete space of the input data set. Similar to other ANN models, SOMs work in two ways, namely training and mapping. Training exploits input data to create the map, whereas mapping classifies a new input vector automatically. The map space of SOM is a visible part of it, consisted of units which are called nodes or neurons. The map space is characterized as a two-dimensional restricted area, usually represented as a hexagonal or rectangular grid. Between the nodes, there are weight vectors with the same dimension as the input vector. While nodes are placed in a fixed position, the training procedure consists of weight vectors moving toward the input data without ruining the SOM structure, giving the SOM the ability to reduce the dimension of input data space.

![Figure 2. Mapping process of a high dimensional input vector to two-dimensional nodes.](image)

| Models | \( X_1 \) | \( X_2 \) | \( X_3 \) | \( X_4 \) |
|--------|----------|----------|----------|----------|
| SOM (1) | \( \frac{w}{c} \) ratio | Nano-MgO \% | Curing period (day) | Compressive strength (MPa) |
| SOM (2) | \( \frac{w}{c} \) ratio | Nano-MgO \% | Curing period (day) | Tensile strength (MPa) |
After training, the SOM map can produce vectors from the input space to the nodes with the smallest distance. The mathematical principle of SOM algorithms can be described as follows: \( \mathbf{x} \) is an input data vector and \( \mathbf{x} \in \mathbb{R}^n \) can be compared with all the \( m_i \) in any model vector, the smallest Euclidean distance is described as \( \| \mathbf{x} - m_i \| \) and it is usually made to define the best matching node, denoted by subscript \( c \).

Figure 3. Illustrations related to the SOM analysis for (A) a compressive strength data set, and (B) a tensile strength data set. For each data set the following figures are depicted: (a) SOM sample hits; (b) SOM neighbor distances; (c) SOM weight planes.
\[
\|x - m_c\| = \min_i \{\|x - m_i\|\}
\]

or
\[
c = \arg\min_i \{\|x - m_i\|\}
\]

where \(\arg\min\) stands for the argument of minimum, which determines input data when the minimum value of output is given. During learning, those nodes, which are topographically adjacent according to a certain distance limit, activate each other to learn from the same input. A learning process calculates \(m_i\) by the following equation where the first value of \(m_i(0)\) is chosen randomly

\[
m_i(t + 1) = m_i(t) + h_{i\alpha}(t)[x(t) - m_i(t)]
\]

where \(t\) is an integer representing the discrete-time coordinate, and \(h_{i\alpha}(t)\) is vicinity kernel, which is a function defined over the net points. Generally, \(h_{i\alpha}(t)\) is described by

\[
h_{i\alpha}(t) = h(\|r_c - r_i\|, t)
\]

where \(r_c \in \mathbb{R}^2\) and \(r_i \in \mathbb{R}^2\) are the radius vectors of nodes \(c\) and \(i\), respectively, in the array. Another vicinity kernel is defined by a widely-used Gaussian function expressed as

\[
h_{i\alpha} = \alpha(t) \exp\left(-\frac{\|r_c - r_i\|^2}{2\sigma^2(t)}\right)
\]

where \(\alpha(t)\) is another scalar-valued learning rate, and \(\sigma(t)\) describes the width of the kernel.

### 3.3. The CSS algorithm

In this research, in order to find the optimum amount of nano-MgO in concrete, we utilized the Charged System Search (CSS) optimization algorithm [22]. This method was inspired by some concepts of physics and mechanics, namely Coulomb’s law of electrostatics and the Newtonian laws of mechanics [47]. The CSS algorithm is a powerful metaheuristic method with no need to gradient information which are often difficult or time-consuming to provide. Furthermore, the influence of the initial solutions on the final optimum points is neglectable in this method. Therefore, the CSS algorithm was considered to be a suitable approach for this research work.

There are several agents in the CSS algorithm which are called charged particles (CPs). In fact, every probable solution that includes some decision variables is assumed to be a CP [48]. Each CP can be supposed as a charged sphere that applies an electric force to other CPs. This electric force can be estimated by Coulomb’s and Gauss’s laws. The new location of CPs is determined by the motion laws in physics. One CP may influence other CPs depending on their fitness values and separation distances. CSS has several utilities in optimization problems; especially, it can be used in non-smooth or non-convex domains [49]. Furthermore, the gradient information and continuity of the search space are not necessary for this approach. The advantage of the CSS approach has been proved through using standard benchmark functions and some well-studied engineering design problems [50]. In some other studies, CSS was utilized for the optimization of frame structures [51] and 3D reinforced concrete structures [52] and the performance-based seismic design of steel frames [53]. The algorithm is briefly described as the following [54].

#### 3.3.1. Initialization

The initial locations of particles are determined randomly by the following equation

\[
x^0_{ij} = x_{i,\text{min}} + r \, \text{and} \,(x_{i,\text{max}} - x_{i,\text{min}}), \quad i = 1, 2, ..., n
\]

where \(x^0_{ij}\) is the initial value of the \(i\)th variable for the \(j\)th particle; \(x_{i,\text{min}}\) and \(x_{i,\text{max}}\) are the minimum and maximum values of the \(i\)th variable, respectively; and \(\text{rand}\) is a random number in the interval [0, 1].

#### 3.3.2. Quantity of particle’s charge

The amount of particle’s charge \(q_i\) is calculated by the following equation

\[
q_i = \frac{\text{fit}(i) - \text{fit}_{\text{worst}}}{\text{fit}_{\text{best}} - \text{fit}_{\text{worst}}}, \quad i = 1, 2, ..., n
\]

where \(\text{fit}(i)\) is the value of the objective function of particle \(i\), \(\text{fit}_{\text{best}}\) and \(\text{fit}_{\text{worst}}\) are the best and worst values for the objective function, respectively, and \(n\) is the number of all charged particles.

#### 3.3.3. Electrical forces applied to particles

Every CP in this method is supposed to be a sphere with a radius of \(R\) and with a uniform distribution of electrical charge, where \(R\) can be calculated as follows
\[ R = 0.1 \times \max \{ (x_{i, \text{max}} - x_{i, \text{min}} | i = 1, 2, \ldots, n) \}. \]  

Moreover, the distance between two particles can be defined as

\[ r_{ij} = \frac{\| X_j - X_i \|}{(X_i + X_j)/2 - B_{\text{best}}} + \varepsilon \]  

where \( X_i \) and \( X_j \) are respectively the locations of the \( i \)th and \( j \)th particles, \( X_{\text{best}} \) is the position of the best particle, and \( \varepsilon \) is a small positive number. The probability that a CP is attracted by another CP can be expressed as

\[ P_{ij} = \begin{cases} 
1 & \frac{\text{fit}(i) - \text{fit(\text{best})}}{\text{fit}(j) - \text{fit}(i)} \text{rand} \quad \text{fit}(j) \, \text{fit}(i) \\
0 & \text{else}
\end{cases} \]  

Given the above relationships, the resultant force \( F_j \) that was applied to the \( j \)th particle can be calculated using the following equation

\[ F_j = q \sum_{i, i \neq j} \left( \frac{q_{ij} r_{ij}}{R} \right) p_{ij} (X_i - X_j) \right) \begin{cases} 
\text{rand} \, \text{rand} \, \text{rand} \\
\text{else}
\end{cases} \]  

\[ F_j = q \sum_{i, i \neq j} \left( \frac{q_{ij} r_{ij}}{R} \right) p_{ij} (X_i - X_j) \right) \begin{cases} 
\text{rand} \, \text{rand} \, \text{rand} \\
\text{else}
\end{cases} \]  

\[ X_{i, \text{new}} = \text{rand}_1 k_a \frac{F_j}{m_j} \Delta t^2 + \text{rand}_2 k_v \Delta t + \text{rand}_3 \]  

\[ X_{i, \text{new}} = \frac{X_{i, \text{new}} - X_{i, \text{old}}}{\Delta t} \]  

where \( k_a \) is the acceleration coefficient; \( k_v \) is the velocity coefficient; \( \text{rand}_1 \) and \( \text{rand}_2 \) are random numbers in the interval \([0, 1] \); \( m_j \) represents the mass of the \( j \)th particle; \( \Delta t \) is the time step; and \( k_a \) and \( k_v \) are the control coefficients of the velocity and applied resultant force, respectively, expressed as follows

\[ k_a = 0.5 (1 + \text{iter} / \text{iter}_{\text{max}}) \]  

\[ k_v = 0.5 (1 - \text{iter} / \text{iter}_{\text{max}}) \]  

where \( \text{iter} \) is the current iteration and \( \text{iter}_{\text{max}} \) is the number of all iterations. In figure 4, the flowchart of the CSS algorithm is presented.

### 4. Numerical results and analyses

In this study, some cubic and cylindrical samples with different amounts of nano-MgO powder were prepared and subjected to freeze and thaw cycles. There were three samples for each series of cubic samples and two samples for each series of cylindrical samples. Different mechanical properties such as compressive strength, tensile strength, and permeability were measured according to ASTM C39 \[54\], ASTM C496/C496M-17 \[55\], and DIN 1048 \[56\], respectively.

Neural Net Clustering was exploited to group the data by similarity; it trained the network and promoted its performance by creating different diagrams. 98 data for compressive strength and 78 data for tensile strength and permeability from experiments were independently used for the purpose of clustering. The clustering tool of the software MATLAB was utilized for the classification of the data set. After loading the data set, the size of the two-dimensional map was defined. For example, if the size was 5, it meant there were \( 5^2 = 25 \) groups and all the data set was classified into these 25 groups according to their similarities. In this research, samples were made in 36 groups (samples in each group had the same value for \( w/c \), curing period, and nanopowder percentage); thus, the size of the two-dimensional map was considered to be 6, with the related results shown in figure 3. In particular, figure 3(A)(a) illustrates the status of clustering neurons for the compressive strength data, where the number in the center of each hexagon shows the number of training data associated with that cluster. Figure 3(B)(a) displays the same type of information for the tensile strength data. In figures 3(A)(b) and (B)(b), the hexagons with blue color depict neurons and the red lines indicate neighboring neurons. The color of lines between neurons represents distances, with darker colors showing larger and lighter ones representing smaller distances. Figures 3(A)(c) and (B)(c) show a weight plane for each element of the input vector. They are visual symbols of the weights that connect each input to each neuron (darker colors indicate larger weights).
According to the above description, the process of clustering is a prerequisite for regression analysis. For estimating the relationships among different variables, regression analysis is a useful method that can predict the behavior of variables. Regression analysis includes different statistical processes, enabling us to understand how
dependent variables change when independent variables are changed. In this analysis, 70% of data was considered for training, 15% for validation, and 15% for testing. Figure 5 shows the R-squared value for the regression analysis of compressive strength (before clustering) for training, validation, and testing data set. After clustering the data, another regression analysis was performed.

As shown in figure 6, the R-squared value for training, validation, and testing the data set after the clustering of data were 0.95, 0.87, and 0.93, respectively, which showed an acceptable improvement in fitness between the target and output data in comparison with R-squared values before clustering.

The same procedure was performed for the tensile strength data. As can be seen from figure 7, there was a good adaptation between the target and output data in comparison with figure 8, which refers to the tensile strength data before clustering.

The error histograms for compressive strength before clustering and after clustering are illustrated in figures 9 and 10, respectively.
By comparing the two diagrams, it can be concluded that the error domain was decreased and also the width of error bins (columns) became smaller after clustering. The same result was true for less severity in figures 11 and 12, which illustrated the error histogram for the tensile strength data set before and after clustering. As can be seen from figure 12, the error domain was decreased in comparison with figure 11, confirming that clustering improved the results.

5. Experimental results and discussion

5.1. Compressive strength tests

In order to evaluate the effect of nano-MgO on the compressive strength of normal concrete, cubic samples with different percentages of this nanomaterial were created and after curing for 7, 28, and 56 days, they were put in a freeze-thaw chamber for 300 cycles according to ASTM C666 and tested according to standard ASTM C39. Compressive test results are shown in table 4. As shown in this table, depending on the w/c ratio and curing duration, the effect of nano-MgO on the compressive strength of concrete samples was variable. For example, the maximum effect of nano-MgO on samples with the w/c ratio of 0.44 and 0.62 for the curing period of 56 days can be reached by using 1% and 0.5% of this nanopowder, respectively. It can increase the compressive strength by approximately 9.12% and 2.7% for the 56-day cured samples with the w/c ratio of 0.44 and 0.62, respectively, in comparison with the control samples. For w/c = 0.49 and a curing period of 56 days, the
maximum strength enhancement occurred when the nanopowder amount is 1.5%, with an increased compressive strength up to 17.1%. These improvements in compressive strength could be associated with the contribution of nanopowder addition to the formation of chains of micro-structures.

5.2. Tensile strength tests

For the investigation of tensile strength, a splitting tensile strength test (also known as the Brazilian test) was conducted according to ASTM C496 [55] on cylindrical 10 × 20 concrete samples which were subjected to 300 cycles of freeze-thaw. Figure 13(A) shows a cylindrical sample during the splitting test. These samples contained different percentages of nano-MgO. The properties and the mean value of tensile strength are shown in table 5.
which summarizes the results of the splitting test on 78 concrete samples. The curing durations were 7, 28, and 56 days. As shown in table 5, the maximum tensile strength was gained for samples with $w/c = 0.44$, 1% nano-MgO, and cured for 56 days. Importantly, adding 1% of nano-MgO could increase tensile strength by around 10.6% in comparison with the control samples. Also, the positive effect of nano-MgO on other samples with 7 and 28 days of curing can be seen in this table. On the other hand, for $w/c = 0.49$, the maximum value was gained for the 56-day cured samples with 1.5% of nano-MgO. It enhanced tensile strength to 4.2 MPa which means 3.3% more than that of the control samples. For samples with the $w/c$ of 0.62, adding 0.5% and 1% of nano-MgO made a 3% improvement in tensile strength in comparison with the control samples.

### 5.3. Permeability tests

The permeability of the cylindrical samples was measured according to the DIN 1048 [56] standard. The bottom of cylindrical samples was placed under the water pressure of 5 bar for 72 h, then a splitting test was performed and the amount of water penetration was measured. Figure 13(B) shows the measurement of permeability for a cylindrical sample after performing the splitting test, with the results summarized in table 6. According to this table, the least value of permeability occurred in the 56-day cured samples with 1% of nano-MgO and the $w/c$ ratio of 0.44 which decreased the mean permeability to 1.3 cm, while the corresponding mean value in control samples was 3.6 cm. On the other hand, for $w/c = 0.49$ and 0.62, the least permeability occurred by the usage of 1.5% nanopowder and the 56-day cured samples. The reason why the nano-MgO decreased permeability of samples is that there were plenty of nano-sized holes in the texture of concrete. Some of these holes were
connected, so that water could pass through them; they could be blocked by the usage of nano-MgO, and as a result, it reduced the permeability of the concrete.

5.4. CSS analyses

Although using nano-MgO leads to the enhancement of the mechanical properties of concrete, the excessive amount of this nanopowder has destructive effects. This behavior is related to the expanding trait of nano-MgO. By the completion of the hydration process, an increment in volume will happen because the hydrated MgO needs more space. Lower amounts of nano-MgO have a positive role in improving the mechanical properties of concrete such as permeability. The reason is that increased volume of hydrated nano-MgO fills the pores of the

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**Figure 13.** (A) A cylindrical sample under the splitting test (adapted from [57]). (B) Measurement of permeability after the splitting test. (C) Convergence value versus the number of iterations for (a) compressive strength, (b) tensile strength, and (c) permeability.
concrete and as a result porosity and permeability will decrease. This improving process will continue, up to a specific amount of nano-MgO which is the most efficient amount. Excessive amounts of nano-MgO lead to high inner stresses and extension of cracks will be inevitable. In order to find the optimum amount of nano-MgO, which improves compressive and tensile strength, as well as permeability, and leads to the highest durability and the best mechanical properties, CSS was used as the optimization method. The algorithm of CSS was prepared in MATLAB and the results of the neural network model were used as the cost functions in the CSS model. This process was performed for three data sets of experimental results, i.e. the data associated with compressive strength, tensile strength, and permeability.

5.4.1. CSS for compressive strength

Figure 13(C(a)) shows the convergence of compressive strength versus the number of iterations. It can be seen that, after 18 iterations, the results converged to 630 kg cm\(^{-2}\) (61.78 MPa). The CSS analysis showed that the convergence occurred in samples with \(w/c = 0.44\), curing duration of 34 days, and nano-MgO amount of 1%. This means that an amount of nano-MgO less than 1% and a curing period of fewer than 34 days did not lead to acceptable results for compressive strength.

5.4.2. CSS for tensile strength

Experimental results of tensile strength were analyzed using the CSS method. The results have been shown in figure 13(C(b)). The convergence value of tensile strength was 47.12 kg cm\(^{-2}\) (4.62 MPA) and this happened after 18 iterations. Optimizing by CSS method showed that the best results were gained by the usage of 1% nano-MgO for a \(w/c\) ratio of 0.44 and a curing period of 34 days.

5.4.3. CSS for permeability

In theory, the addition of nano-MgO to the mixture of concrete should reduce the permeability value; analysis of the experiment results with the CSS method proved the expectation. As shown in figure 13(C(c)), the results showed convergence after 15 iterations. The convergence value of permeability was 1.1 cm. CSS analysis showed that this permeability value was gained by the usage of 1% nano-MgO in samples with a \(w/c\) ratio of 0.44 and a curing period of 34 days.

By putting together the results of the three CSS analyses, it can be concluded that the best results were obtained in concrete samples with a \(w/c\) ratio of 0.44 and a nano-MgO addition of 1% after 34 days of curing. It is noteworthy that, in this research, the search space is continuous; for example, the domain of the curing period

| % Nano-MgO | \(w/c = 0.44\) | \(w/c = 0.49\) | \(w/c = 0.62\) |
|------------|---------------|---------------|---------------|
|            | 7 28 56       | 7 28 56       | 7 28 56       |
| 0 %        | 4 16 43.4     | 3.88 3.9 4.07 | 2.4 2.78 2.95 |
| Standard Deviation | 0.8 0.59 0.02 | 0.67 1 0.11 | 0.21 0.33 0.28 |
| 0.5%       | 4.2 4.44 4.54 | 3.7 3.75 3.9 | 2.5 2.8 3     |
| Standard Deviation | 0.77 0.37 0.32 | 0.28 0.09 0.31 | 0.09 1.2 0.18 |
| 1 %        | 4.36 4.5 4.8  | 3.8 4.05 4.1 | 2.2 2.9 3.04  |
| Standard Deviation | 0.37 0.31 0.1  | 0.19 0.06 0.04 | 0.24 0.66 0.24 |
| 1.5 %      | 4.2 4 4.43    | 4.07 4.18 4.2 | 2.3 2.51 2.7  |
| Standard Deviation | 0.13 0.33 0.28 | 0.02 0 0.14  | 0.27 0.21 0.38 |

**Table 5.** Mean value of tensile strength [MPa] and standard deviation.

| % Nano-MgO | \(w/c = 0.44\) | \(w/c = 0.49\) | \(w/c = 0.62\) |
|------------|---------------|---------------|---------------|
|            | 7 28 56       | 7 28 56       | 7 28 56       |
| 0 %        | 4.4 3.8 3.6   | 7.5 6.9 5.4   | 10.1 10 8     |
| Standard Deviation | 0.75 0.35 0.4 | 1 0.42 1.2 | 0.35 0.28 0.14 |
| 0.5%       | 3.9 3.5 3     | 7.2 4.3 4.1   | 8.4 7 5.9     |
| Standard Deviation | 0.28 0.42 0.14 | 0.21 0.56 0.07 | 0.28 0.14 0.42 |
| 1%         | 3 1.5 1.3     | 6.1 4.7 3.6   | 8.6 6.6 6.4   |
| Standard Deviation | 0.2 0.14 0.7 | 0.21 0 0.05  | 0.14 0.42 1.2 |
| 1.5%       | 3.4 3.4 3     | 5.6 2.5 2.5   | 7.2 7.1 5.1   |
| Standard Deviation | 1.9 0.95 1.44 | 0.35 0.21 0.2 | 0.14 0.7 0.28 |

**Table 6.** Mean value of permeability [cm] and standard deviation.
is suggested to be 0–56 days, so the result of optimization analysis for the curing days could be any number in this domain.

5.5. Validation of the CSS analysis

To investigate the accuracy of the results from the CSS analysis, some additional experimental concrete samples were created with the same properties as the main samples, for which CSS proposed optimal values for w/c, amount of the nanopowder, and the curing period. For this purpose, three groups of samples were made. Group 1 consisted of 5 cubic 10 × 10 × 10 samples for testing the compression strength, group 2 contained 5 cylindrical 10 × 20 samples for measuring the tensile strength, and group 3 included 5 cylindrical 10 × 20 samples for the investigation of permeability. The samples were exposed to 300 cycles of freeze-thaw according to ASTM C666 (2015). The properties of samples and the obtained results have been summarized in tables 7–9 for the compressive strength test, tensile strength test, and permeability, respectively. As shown in table 7, the mean value of the compressive strength results was 61.6 MPa, while the highest and lowest differences between the compressive strength data and the predicted value of the CSS analysis were 0.5 and 0.098 MPa, respectively, with RMSE = 3.04. In table 8, the tensile strength data for the validation of the CSS analysis are shown. The mean value of the tensile strength data was 4.58 MPa, while the predicted value by the CSS analysis was 4.62 MPa, and the difference between the resulted mean value and the predicted value was 0.34, with

| Table 7. Results of compressive strength tests for the validation of CSS analysis. |
|---|
| w/c = 0.44 Nano MgO = 1% Curing period = 34 days |
| Name of sample | Compressive strength [MPa] |
| Comp1 | 61.49 |
| Comp2 | 61.63 |
| Comp3 | 62 |
| Comp4 | 61.3 |
| Comp5 | 61.68 |
| Mean value = 61.63 RMSE = 3.04. |

| Table 8. Results of tensile strength tests for the validation of CSS analysis. |
|---|
| w/c = 0.44 Nano MgO = 1% Curing period = 34 days |
| Name of sample | Tensile strength [MPa] |
| Tens1 | 4.44 |
| Tens2 | 4.28 |
| Tens3 | 4.73 |
| Tens4 | 4.6 |
| Tens5 | 4.86 |
| Mean value = 4.58 RMSE = 2.12. |

| Table 9. Results of permeability tests for the validation of CSS analysis. |
|---|
| w/c = 0.44 Nano MgO = 1% Curing period = 30 days |
| Name of sample | Permeability [cm] |
| Perm1 | 1.3 |
| Perm2 | 1.8 |
| Perm3 | 1.3 |
| Perm4 | 1 |
| Perm5 | 1.3 |
| Mean value = 1.38 RMSE = 0.38. |
RMSE = 2.12. The group 3 samples were made and tested for the permeability validation of the CSS analysis, the results of which are presented in table 9, where the mean value of permeability is 1.38 cm and RMSE = 0.38.

6. Concluding remarks

This study aimed to find the effect of nano-MgO on the durability of normal concrete in the freeze and thaw condition. To this end, we used 98 cubic 10 × 10 × 10 samples for the compressive strength test and 78 cylindrical 10 × 20 samples for the tensile strength and permeability tests. All the samples were under 300 cycles of freeze and thaw. The variables of this study were the w/c ratio (0.44, 0.49, and 0.62), percentage of nano-MgO (0, 0.5%, 1%, and 1.5%), and curing period (7, 28, and 56 days). The findings of this study have been summarized below:

- The effect of nano-MgO was different when the value of the w/c ratio was changed. For example, 1.5% of nano-MgO increased the compressive strength by 7.7% for w/c = 0.44, while it was 17.1% for w/c = 0.49, for the same curing period of 56 days.
- The maximum compressive strength was observed in samples with w/c = 0.44, cured for 56 days by the addition of 1% nano-MgO. The respective compressive strength was 61.78 MPa that is 9.1% more than those of the control samples.
- The results of the splitting test showed that the maximum effect of nano-MgO occurred in samples with 1% nano-MgO, 56 days curing time, and w/c = 0.44. These properties could increase the mean tensile strength of samples by around 10.6% more than the control samples.
- The measurement of permeability of cylindrical samples showed that the least values could be gained for samples with w/c = 0.44, cured in 56 days with 1% nano-MgO. The respective value was 1.3 cm, whereas it was 3.6 cm in the control samples.

Moreover, from the results of the CSS algorithm, we can conclude the following:

- The best compressive strength can be achieved in samples with w/c = 0.44 and 1% nano-MgO cured in 34 days.
- For tensile strength, the result of the CSS analysis showed that the convergence value was 4.6 MPa. The properties of the samples which led to this result were w/c = 0.44, 1% nano-MgO, and a curing period of 34 days.
- The convergence value of permeability was 1.1 cm, which could be achieved with w/c = 0.44, 1% nano-MgO, and a curing period of 30 days.

It can be concluded that the optimized results were obtained in the samples containing 1% nano-MgO with the w/c ratio of 0.44 and curing period of 34 days.

For the verification of the CSS results, the following additional samples with the same properties were made: 5 cubic samples for compressive strength, 5 cylindrical samples for tensile strength, and 5 cylindrical samples for permeability. The experimental results turned out to be in good agreement with those obtained by the CSS algorithm. The mean value of compressive strength was 61.6 MPa with RMSE = 3.04, the mean value of tensile strength was 4.58 MPa with RMSE = 2.12, and the mean value of permeability was 1.38 cm with RMSE = 0.38.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.
Disclosure statement

No potential conflict of interest was reported by the authors.

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