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Advancing Compressive Strength Prediction in Self-Compacting Concrete via Soft Computing: A Robust Modeling Approach

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ABSTRACT

Self-Compacting Concrete (SCC) is a unique type of concrete that can flow and fill spaces without the need for vibrating compaction, resulting in a dense and uniform material. This article focuses on estimating the compressive strength of SCC utilizing Artificial Neural Networks. Specifically, the study employs multilayer perceptrons with back-propagation learning algorithms, which are commonly used in various problem-solving scenarios. The study covers essential components such as structure, algorithm, data preprocessing, over-fitting prevention, and sensitivity analysis in MLPs. The input variables considered in the research include water, fine aggregate, super-plasticizer, fly ash, coarse aggregate, ground granulated blast furnace slag, limestone powder, viscosity-modifying admixtures, cement, silica fume, and rice husk ash. The target variable is the compressive strength. Through a sensitivity analysis, the study evaluates the relative importance of each parameter. The results indicate that the AI-based model accurately predicts the compressive strength of self-compacting concrete.

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1. Introduction

Self-compacting concrete (SCC) has emerged as a widely favored high-performance concrete in the construction sector, owing to its distinct attributes and benefits. Nevertheless, the design and fine-tuning of SCC mixtures can be intricate and time-intensive, often demanding extensive experimentation and trial-and-error procedures. To tackle this challenge, Artificial Intelligence (AI) methodologies have been increasingly employed in diverse engineering domains, including concrete technology. By leveraging AI-based techniques, the optimization of SCC mix design can be enhanced, leading to improved properties and cost reduction in production.

Several studies have been conducted to investigate the application of AI to SCC, including artificial neural networks (ANNs), genetic algorithms (GAs), Fuzzy logic, and swarm intelligence. These techniques have been applied to various aspects of SCC, such as mix design, rheology, workability, strength, and durability. The use of AI in SCC can also help in reducing the environmental impact of the production process by reducing cement consumption and waste. The application of AI to SCC is an emerging research area that has attracted the attention of researchers and practitioners worldwide. The following references provide valuable insights into the application of AI to SCC.

In the study by Kou and Poon (2009), the properties of self-compacting concrete (SCC) prepared with coarse and fine recycled concrete aggregates (RCA) were investigated. The researchers aimed to assess the potential use of RCA in SCC production and determine its impact on the concrete properties. Through experimental work, various proportions of coarse and fine RCA were incorporated into SCC mixes. The results showed that as the RCA content increased, the workability of the SCC decreased, necessitating adjustments in water content and superplasticizer dosage. However, by using appropriate mix design and superplasticizer, satisfactory workability and flowability could still be achieved with higher RCA content. The compressive strength of SCC decreased slightly with increasing RCA content, but the reduction remained within acceptable limits for certain applications. Moreover, the durability properties of the SCC, such as water absorption and chloride ion penetration resistance, were not significantly affected by the presence of RCA. Therefore, they concluded that coarse and fine RCA can be effectively utilized in SCC production, emphasizing the importance of adjusting mix proportions and incorporating suitable additives to maintain desired workability and achieve satisfactory performance in terms of strength and durability [1]. In their study, Grdić et al. (2010) examined the properties of self-compacting concrete (SCC) prepared with coarse recycled concrete aggregate (RCA). The aim was to assess the feasibility of incorporating coarse RCA into SCC and evaluate its impact on concrete properties. Through experimental investigations, various proportions of coarse RCA were incorporated into SCC mixes. The study found that as the content of RCA increased, the workability of the mixes decreased, necessitating adjustments in water content and superplasticizer dosage. However, by optimizing the mix proportions and utilizing suitable superplasticizers, satisfactory workability and flowability could still be achieved even with higher RCA content. The compressive strength of the SCC decreased with the addition of coarse RCA, but remained within acceptable limits for certain applications. Furthermore, the durability properties of the SCC, including water absorption and chloride ion penetration resistance, were not significantly affected by the presence of coarse RCA. Overall, the study concluded that coarse RCA can be effectively utilized in SCC production, emphasizing the importance of proper mix design and appropriate superplasticizer utilization to achieve desired workability and ensure acceptable performance in terms of strength and durability [2].

Uysal and Yilmaz (2011) investigated the effect of mineral admixtures on the properties of self-compacting concrete (SCC). Their objective was to examine the influence of mineral admixtures, such as fly ash and silica fume, on various characteristics of SCC. Through experimental work, SCC mixes with varying proportions of mineral admixtures were prepared and evaluated for their fresh and hardened properties. The findings revealed that the inclusion of mineral admixtures had a positive impact on the workability and flowability of SCC, enhancing its ability to self-compact. Moreover, the mineral admixtures contributed to improved compressive strength and reduced permeability of the concrete. The study emphasized the importance of determining the optimal dosage of mineral admixtures to achieve the desired performance of SCC in terms of workability, strength, and durability. As a result, they concluded that the incorporation of suitable mineral admixtures can significantly enhance the properties of SCC, making it a favorable choice for a wide range of construction applications [3]. In their analytical study, Aslani and Nejadi (2012) focused on evaluating the mechanical properties of conventional concrete and self-compacting concrete (SCC). The researchers aimed to compare and analyze the mechanical behavior of both types of concrete. Through their comprehensive investigation, various mechanical properties, including compressive strength, tensile strength, modulus of elasticity, and flexural strength, were examined. The results revealed that SCC generally displayed comparable or even superior mechanical properties in comparison to conventional concrete. This finding emphasizes the potential advantages of using SCC in construction applications. The study emphasized the significance of factors such as mix design, aggregate properties, and curing conditions in influencing the mechanical properties of SCC. Overall, the research provides valuable insights into the mechanical characteristics of both conventional and self-compacting concrete, serving as a useful reference for engineers and practitioners seeking to optimize the performance of concrete structures [4].

In their study, Ramanathan et al. (2013) investigated the performance of self-compacting concrete (SCC) containing various mineral admixtures. The objective was to evaluate the influence of mineral admixtures, including fly ash, silica fume, and metakaolin, on the properties of SCC. Through comprehensive experimentation, the researchers assessed the fresh and hardened properties of SCC mixes with different mineral admixture contents. The results revealed that the inclusion of mineral admixtures had a significant impact on the workability, flowability, and mechanical properties of SCC. The use of fly ash and silica fume improved the workability and flowability of SCC, while metakaolin contributed to enhanced compressive strength. The study highlighted the potential benefits of incorporating mineral admixtures in SCC, such as increased strength and improved performance. These findings provide valuable insights for the optimization and utilization of SCC in various construction applications [5]. Ponikiewski and Gołaszewski (2014) focused on investigating the influence of high-calcium fly ash on the properties of fresh and hardened self-compacting concrete (SCC) as well as high-performance self-compacting concrete (HPSCC). Their objective was to assess the impact of high-calcium fly ash, used as a mineral admixture, on the workability, compressive strength, and durability of both SCC and HPSCC. Through comprehensive experimental work, SCC and HPSCC mixes with varying proportions of high-calcium fly ash were prepared and evaluated. The findings revealed that the inclusion of high-calcium fly ash significantly improved the workability and compressive strength of both SCC and HPSCC. Moreover, the addition of high-calcium fly ash had a positive impact on the durability properties of the concrete, enhancing resistance to chloride ion penetration and reducing water absorption. These results underscored the potential benefits of incorporating high-calcium fly ash in SCC and HPSCC, suggesting its effective utilization for achieving desirable fresh and hardened properties. The study contributes valuable insights to the optimization and application of self-compacting concrete with high-calcium fly ash in sustainable construction practices [6].

Carro-López et al. (2015) conducted a study to investigate the rheology of self-compacting concrete (SCC) incorporating fine recycled concrete aggregates (FRCA). The researchers aimed to understand the flow behavior and workability of SCC with FRCA and evaluate its potential as a sustainable alternative. Through their experimental work, SCC mixes with different proportions of FRCA were prepared and tested for rheological properties. The results revealed that the incorporation of FRCA had a noticeable effect on the rheological behavior of SCC, particularly in terms of viscosity, yield stress, and plastic viscosity. The study found that the workability and flowability of SCC with FRCA were influenced by the water-to-cement ratio, FRCA content, and superplasticizer dosage. The findings indicated that SCC with FRCA can exhibit suitable rheological properties, making it a viable option for sustainable construction practices. The research contributes to the understanding of SCC incorporating FRCA, providing valuable insights for the development of environmentally friendly concrete solutions [7]. Al-Hadithi and Hilal (2016) conducted a study to explore the potential of enhancing certain properties of self-compacting concrete (SCC) by incorporating waste plastic fibers. The researchers aimed to assess the impact of waste plastic fibers on the workability, compressive strength, and flexural strength of SCC. Through experimental investigations, SCC mixes with varying proportions of waste plastic fibers were prepared and tested. The results indicated that the addition of waste plastic fibers improved the workability of SCC, enhancing its ability to self-compact. Additionally, the incorporation of waste plastic fibers led to increased compressive strength and flexural strength of the concrete. The study demonstrated the feasibility of using waste plastic fibers as a means to enhance the performance of SCC, providing potential benefits in terms of workability and mechanical properties. These findings contribute to the development of more sustainable and durable concrete materials [8].

Ahmad et al. (2017) conducted an experimental study to investigate the properties of normal concrete, self-compacting concrete (SCC), and glass fiber-reinforced self-compacting concrete (GFSCC). The researchers aimed to compare and analyze the key characteristics of these three concrete types. Through their experimental work, they evaluated various properties, including workability, compressive strength, flexural strength, and water absorption. The results showed that SCC and GFSCC exhibited improved workability compared to normal concrete. The addition of glass fibers in GFSCC further enhanced the mechanical properties, resulting in increased compressive strength and flexural strength compared to SCC. Additionally, GFSCC demonstrated lower water absorption compared to both SCC and normal concrete. The study emphasized the potential benefits of incorporating glass fibers in self-compacting concrete to enhance its performance in terms of workability and mechanical properties. The research provides valuable insights into the properties of normal concrete, self-compacting concrete, and glass fiber-reinforced self-compacting concrete, which can aid in the development of optimized concrete mixes for various engineering applications [9]. Niewiadomski et al. (2018) conducted a study to investigate the properties of self-compacting concrete (SCC) modified with nanoparticles. The researchers aimed to assess the impact of nanoparticles on the fresh and hardened properties of SCC. Through their experimental work, SCC mixes with varying proportions of nanoparticles were prepared and tested. The results revealed that the addition of nanoparticles had a significant influence on the workability and flowability of SCC. The nanoparticles improved the dispersion of cement particles, resulting in enhanced filling ability and passing ability of the concrete. Additionally, the inclusion of nanoparticles contributed to improved compressive strength and durability properties of SCC. The study highlighted the potential benefits of using nanoparticles as a modifier in SCC, offering opportunities to enhance its mechanical performance and durability [10]. Singh et al. (2019) conducted a review to examine the behavior of high-volume fly ash-based self-compacting concrete (HVFA-SCC). The researchers aimed to evaluate the properties and performance of HVFA-SCC by analyzing relevant literature. HVFA-SCC is a type of self-compacting concrete that incorporates a high volume of fly ash as a partial replacement for cement. The review highlighted that HVFA-SCC exhibits improved workability, reduced segregation, and enhanced flowability compared to conventional concrete. Additionally, HVFA-SCC demonstrated enhanced mechanical properties, including compressive strength and flexural strength. The use of fly ash in HVFA-SCC contributed to improved sustainability by reducing carbon dioxide emissions and utilizing industrial by-products. The review emphasized the potential of HVFA-SCC as a sustainable and high-performance concrete for various construction applications [11].

The study conducted by Rezazadeh Eidgahee et al. (2019) examined the assessment of shear strength parameters in granulated waste rubber through the application of artificial neural networks (ANNs) and the group method of data handling (GMDH). The primary focus of the research was to utilize ANNs and GMDH as computational tools for evaluating these parameters. The authors aimed to provide an efficient approach for predicting shear strength parameters, ultimately enhancing the knowledge and practical utilization of granulated waste rubber materials in civil engineering applications [12]. Naderpour et al. (2020) conducted a study on estimating the shear capacity of FRP-reinforced concrete beams using computational intelligence. The research focuses on the application of computational intelligence techniques to evaluate the shear capacity of these beams. By employing computational methods, the authors aim to provide a reliable approach for predicting the shear capacity and enhancing the understanding of FRP-reinforced concrete structures. The study contributes to the advancement of structural engineering practices by providing insights into the design and analysis of FRP-reinforced concrete beams [13].

Naderpour and Mirrashid (2020) proposed the use of soft computing models to predict the moment capacity of reinforced concrete columns. The study, published in Soft Computing, focuses on the development of these models, which leverage computational intelligence techniques to accurately estimate the moment capacity. The authors aim to enhance the understanding and analysis of reinforced concrete column behavior by providing a reliable approach for predicting moment capacity. The findings contribute valuable insights to the field of structural engineering, particularly in the design and assessment of reinforced concrete columns [14]. In another research, Naderpour and Mirrashid (2020) conducted a study on the estimation of moment capacity in spirally reinforced concrete columns using Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The research, focuses on the development and application of ANFIS models to accurately predict the moment capacity of spirally reinforced concrete columns. The authors aim to provide a reliable approach for estimating the moment capacity, enhancing the understanding and analysis of these structural elements. The findings presented in this study contribute to the field of structural engineering by offering valuable insights into the design and assessment of spirally reinforced concrete columns [15]. Recent advancements in computing methodologies have resulted in the successful implementation of soft computing methods within the context of civil engineering [16–20].

This article presents the prediction of the compressive strength of self-compacting concrete using a well-known machine learning technique. Through a thorough examination of existing approaches and available experimental datasets, the input variables were carefully chosen, including water, fine aggregate, super-plasticizer, fly ash, coarse aggregate, ground granulated blast furnace slag, limestone powder, viscosity-modifying admixtures, cement, silica fume, and rice husk ash. The target variable considered in the study was the compressive strength. Furthermore, a sensitivity analysis was conducted to assess the relative importance of each parameter.

2. Artificial neural networks

Artificial Intelligence (AI) is a discipline within computer science and engineering that concentrates on developing machines and software applications capable of executing tasks that traditionally necessitate human intelligence. These tasks encompass reasoning, problem-solving, learning, perception, and natural language comprehension. The overarching objective of AI is to fabricate intelligent machines that can mimic human intelligence and undertake complex tasks that may be arduous, hazardous, or time-intensive for humans to accomplish.

Artificial Neural Networks (ANNs) are machine learning models that draw inspiration from the intricate structure and functionality of the human brain. ANNs are composed of interconnected nodes, often referred to as "neurons," which are arranged in layers. The input layer receives the data, while the hidden layers carry out intricate computations and transformations on the information. Finally, the output layer produces the network's resulting output based on the processed data. This layered architecture enables ANNs to effectively learn and make predictions from complex datasets.

Artificial Neural Networks (ANNs) are mathematical models, and therefore, they can be represented by various equations depending on the specific formulation of the network. Here are some equations commonly used in ANNs:

Perceptron equation:

$$Output = sign(W * X + b) \tag{1}$$

where W is the weight vector, X is the input vector, b is the bias term, and sign is the sign function that outputs 1 if the input is positive or 0 if the input is negative.

Multilayer Perceptron (MLP) equation:

$$Output = g(W2 * g(W1 * X + b1) + b2) \tag{2}$$

where W1 and W2 are the weight matrices of the first and second layers, b1 and b2 are the bias vectors, X is the input vector, and g is the activation function that introduces nonlinearity to the network.

Radial Basis Function (RBF) Network equation:

$$Output = \sum_{N}^{i=1} wi * \varphi(||X - ci||) \tag{3}$$

where N is the number of neurons, wi is the weight associated with the ith neuron, ci is the center of the ith neuron, and φ is the radial basis function.

Back-propagation algorithm equations:

$$Error = Target - Output \tag{4}$$

$$Delta = Error * g'(Input) \tag{5}$$

where Error is the difference between the target output and the predicted output, Delta is the error signal that is propagated through the network, g' is the derivative of the activation function, and Input is the weighted sum of the inputs to a neuron.

Convolutional Neural Network (CNN) equation:

$$Output = g(W * I + b) \tag{6}$$

where W is the filter kernel, I is the input image, b is the bias term, and g is the activation function.

These equations provide a basic overview of the mathematical foundations of ANNs, but the exact equations used in practice can be much more complex depending on the specifics of the network architecture and training algorithm.

Artificial neural networks (ANNs) are increasingly being used in civil engineering for a variety of applications. Some examples include:

Structural engineering: ANNs can be used to predict the behavior of complex structures, such as bridges or buildings, under different loads and conditions. This can help engineers optimize the design and ensure safety.

Geotechnical engineering: ANNs can be used to predict soil behavior, such as settlement or stability, based on various input parameters such as soil properties, loading conditions, and environmental factors. This can help engineers design more effective foundations and retaining structures.

Water resources engineering: ANNs can be used to predict water levels and flows in rivers, lakes, and reservoirs based on rainfall, runoff, and other inputs. This can help with flood forecasting and management.

Transportation engineering: ANNs can be used to predict traffic patterns and travel times based on historical data, as well as to optimize traffic signal timings and route planning. This can help reduce congestion and improve safety.

Construction management: ANNs can be used to optimize construction schedules and resource allocation based on various input parameters, such as project scope, budget, and available resources. This can help reduce costs and improve project efficiency.

Overall, ANNs offer a powerful tool for civil engineers to analyze and model complex systems and optimize designs for better performance and safety.

3. Dataset

One of the important steps in presenting a machine learning model is gathering experimental data by which the training could be conducted. In this regard, after collecting so many references, 148 data were selected for creating the networks [21–40]. By exploring the data, some input variables and one target variable were considered. The input data are: Viscosity-modifying admixtures, Rice husk ash, Fly ash, Superplasticizer, Ground granulated blast furnace slag, Limestone powder, Water-to-Cement Ratio, Silica fume, Fine aggregate, and Coarse aggregate, while the target is Compressive strength. Table 1 summarizes the statistical data for the selected 148 sets of data.

Table 1
Summary of dataset utilized in training the ANNs

Parameters	Max	Min	Mean	Standard Deviation
Water to Cement Ratio	0.7	0.35	0.51	0.08
Coarse aggregate (kg/m^3)	1600	500	745.03	170.24
Fine aggregate (kg/m^3)	1135	337	845.21	146.7
Fly ash (kg/m^3)	275	0	98.32	88.65
Superplasticizer (kg/m^3)	22.5	0	6.05	4.57
Viscosity-modifying admixtures (kg/m^3)	1.23	0	0.15	0.34
Limestone powder (kg/m^3)	272	0	32.24	68.63
Ground granulated blast furnace slag (kg/m^3)	220	0	9.13	32.55
Silica fume (kg/m^3)	250	0	9.79	31.49
Rice husk ash (kg/m^3)	100	0	3.61	14.92
Compressive strength (MPa)	79.6	10.2	52.71	16.46

4. ANN modeling

In order to present an ANN model, the existing data was divided into three categories including training, test and validation. Then by changing the nodes of hidden layers and also the activation functions, the idealized network was found. Figures 1 to 3 show the procedures by which the training was completed.

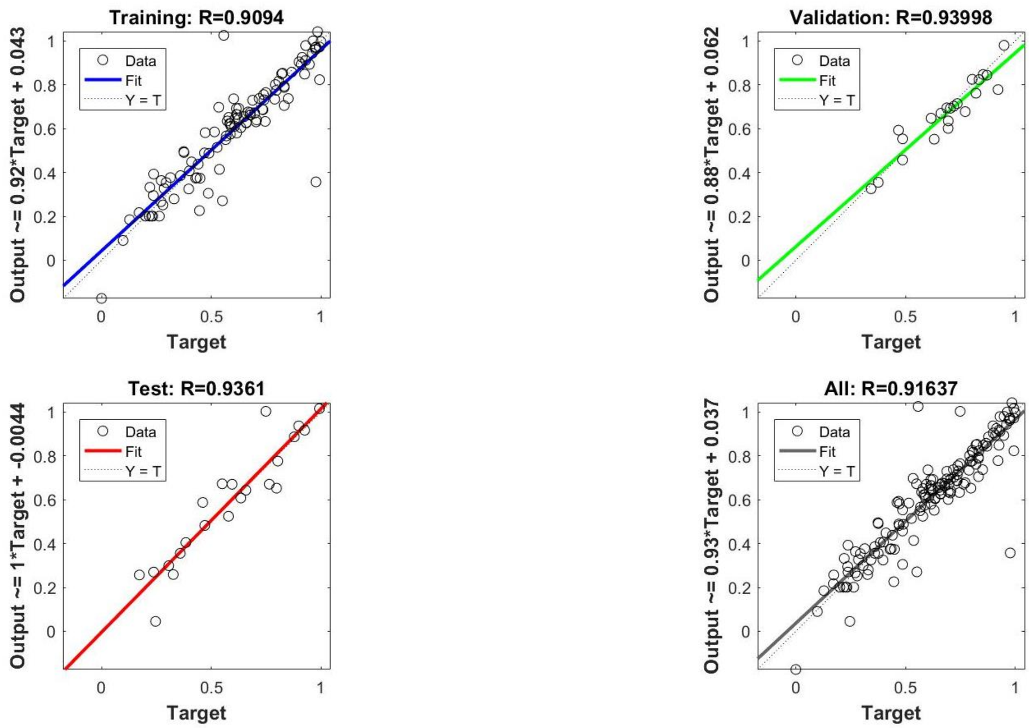

Fig. 1. R-Values for all sets of data in the idealized ANN.

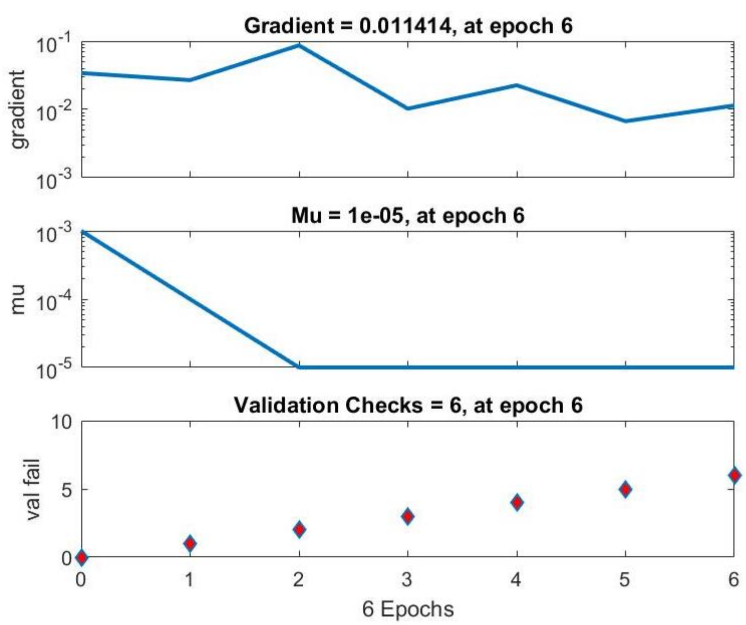

Fig. 2. Training procedure of the idealized ANN.

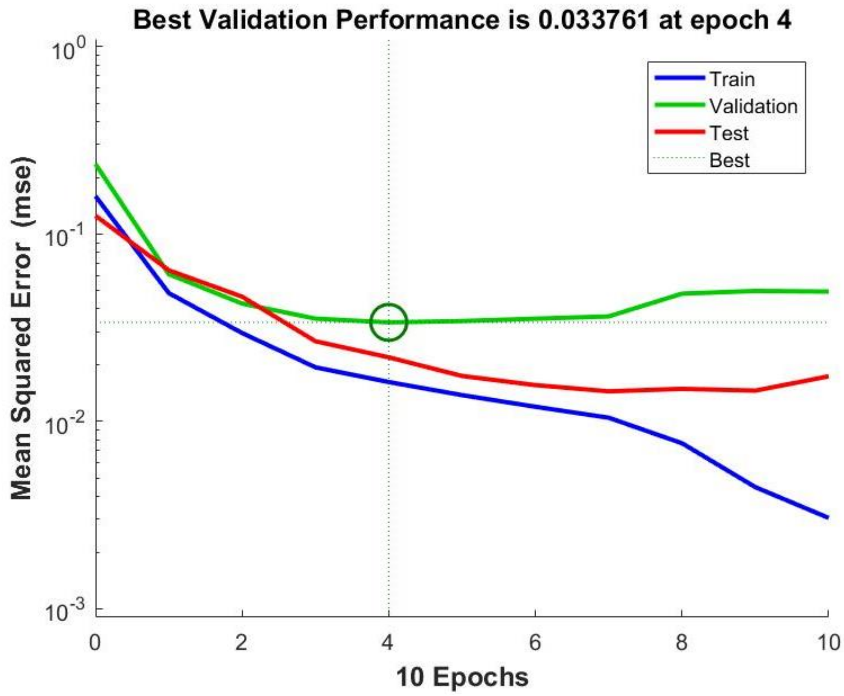

Fig. 3. Performance of the idealized ANN.

Then the idealized network was utilized for simulation. In this step, the network was examined using the input data and the outputs were obtained. Then in Fig. 4, the predicted values are compared against the experimental exact data. The more the spots are close to the line, the more precise the network is. As can be seen from the figure, the precision of the ANN is in a very good level.

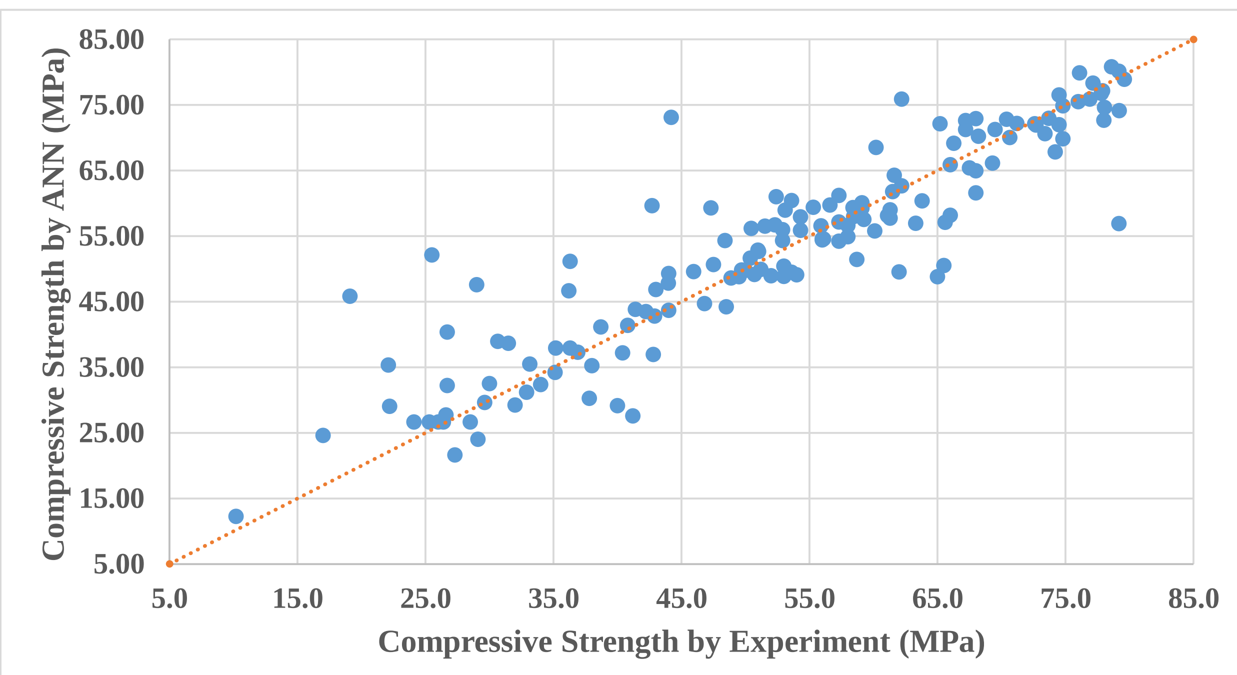

Fig. 4. ANN-predicted against experimental data for compressive strength of self-compacting concrete.

5. Sensitivity analysis

The following equation and accompanying code facilitate the assessment of the significance of input variables in relation to specific outputs. Within the equation, E_j symbolizes the relative importance of the j_{th} input variable, W represents the weighted coefficient, and N denotes the number of neurons. Subscripts k, t, and n correspond to input, hidden, and output neurons respectively, while superscripts i, h, and o refer to input, hidden, and output layers respectively.

$$E_j = \frac{\sum_{t=1}^{t=N_h}((\left|W_{jt}^{ih}\right| / \sum_{k=1}^{k=N_i}\left|W_{kt}^{ih}\right|) \times |W_{tn}^{ho}|)}{\sum_{k=1}^{N_i}\left\{\sum_{t=1}^{t=N_h}((\left|W_{jt}^{ih}\right| / \sum_{k=1}^{k=N_i}|W_{kt}^{ih}|) \times |W_{tn}^{ho}|)\right\}} \quad (7)$$

The weights for both layers of the hidden section of the idealized ANN are presented in Table 2. Further, the results of sensitivity analysis using the weights considering the Eq. (7) are shown as bar chart in Fig. 5.

Table 2
Weights of the idealized ANN for both hidden layers.

Weights of Layer 1										Weights of Layer 2
-1.288	1.468	-1.196	1.501	0.024	0.792	1.841	-0.939	0.415	-1.754	-1.504
0.477	1.323	-2.008	0.485	1.891	0.625	-1.287	-0.306	0.717	1.109	0.793
-0.877	-2.655	2.692	-3.133	2.916	2.010	-0.102	0.651	-0.229	-1.148	2.004
-2.611	2.568	0.183	-1.717	-1.008	-0.720	-1.374	0.688	1.408	1.234	1.034
1.843	-3.930	0.667	-1.697	2.797	-0.700	-1.311	1.789	1.184	1.452	-2.240
1.681	0.621	-0.307	-2.599	1.252	0.187	-2.897	-1.954	0.558	-0.752	2.582
0.967	-0.709	2.165	-1.609	0.351	-0.174	1.081	-2.122	-1.741	-1.137	1.718
0.991	-0.439	1.786	-1.060	0.515	-0.113	-1.309	-1.812	0.125	-1.532	0.702
1.011	-4.854	-0.081	-3.615	0.967	0.230	-0.482	1.027	0.707	-2.495	-2.719
2.134	0.430	-1.551	-0.107	-2.784	0.809	-0.924	1.646	1.097	-1.746	2.527
0.368	1.575	2.552	-0.080	-0.880	-0.482	0.046	1.459	-2.413	1.642	-1.481
1.573	1.737	-1.164	-1.568	-2.176	2.336	-2.113	-1.236	0.235	-2.879	-3.835
1.065	-1.133	-0.043	-1.107	3.241	0.085	-1.774	-0.796	0.518	1.697	-1.817
1.885	0.023	-0.371	0.330	-0.810	1.035	1.078	-1.548	-0.142	-2.397	-1.323
-0.917	-1.182	0.631	1.989	-0.385	1.920	-0.374	-0.339	0.839	1.544	1.313
-1.125	-0.909	-1.974	0.870	-0.194	0.159	2.131	1.550	0.079	-0.956	-0.998

The outcomes obtained through the sensitivity analysis indicate that the compressive strength of self-compacting concrete is primarily influenced by Limestone powder, Water-to-Cement Ratio, and Fine Aggregate, as they hold the highest significance among the input parameters. Conversely, Superplasticizer exhibits the least impact among all the considered input variables.

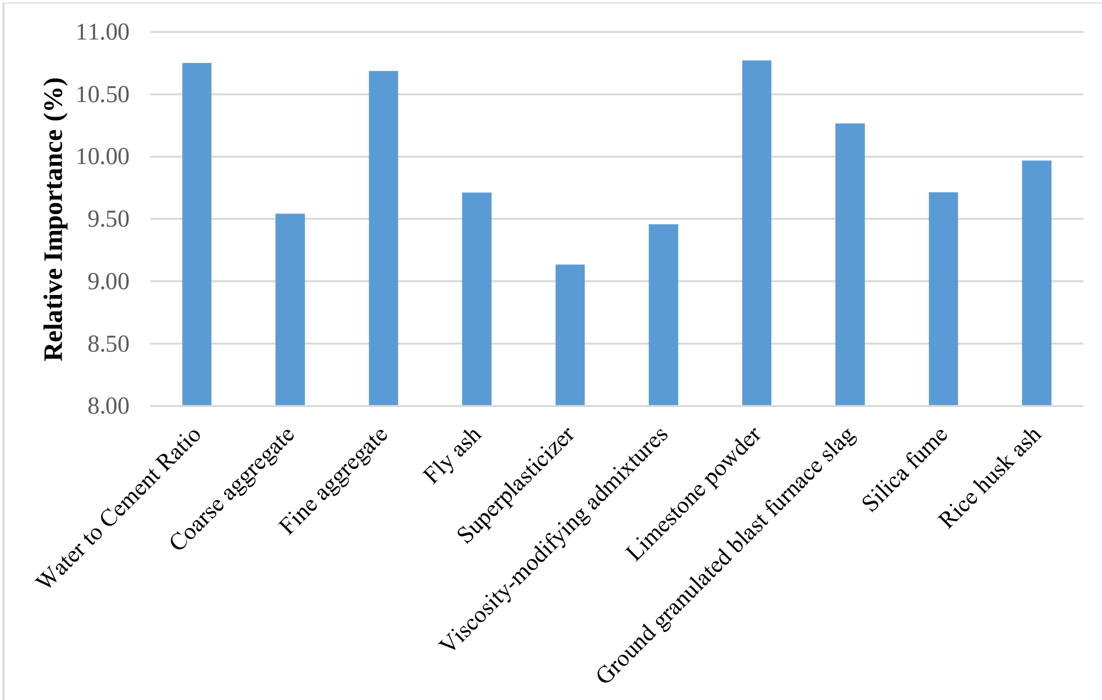

Fig. 5. Relative importance of the input data on compressive strength of self-compacting concrete.

6. Conclusions

In this article, the compressive strength of self-compacting concrete has been predicted in terms of one of the most famous machine learning techniques. After careful investigation of the existing approaches and available experimental datasets, the input variables were selected as: water, fine aggregate, super-plasticizer, fly ash, coarse aggregate, ground granulated blast furnace slag, limestone powder, viscosity-modifying admixtures, cement, silica fume, and rice husk ash while the target was considered as the Compressive strength. The relative importance of each parameter was also examined through a sensitivity analysis. The results indicated that Limestone powder and Water to Cement Ratio and the Fine Aggregate are the most important input parameters influencing the compressive strength of the self-compacting concrete. Further, Superplasticizer was found as the least important parameter. Finally, the results showed that the machine learning could predict the compressive strength of self-compacting concrete with a good level of precision which help us to utilize it instead of spending time and money in laboratories.

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