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RESEARCH ARTICLE

Forecasting strength characteristics of concrete incorporating nano-silica, alccofine and fly ash as partial replacement of cement using artificial neural network

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Abstract

Concrete is a fundamental building material, and efforts are continually made to enhance its properties, sustainability, and performance. This study investigates the influence of incorporating nano-silica (1-5%), alccofine (10%), and fly ash (20%) as partial replacements of cement on the strength characteristics (compressive strength, tensile strength, and flexural strength) of concrete by performing experiments at various curing periods in the laboratory. The objective of the current study is to develop a predictive model using Artificial Neural Network (ANN) to forecast the compressive strength of concrete with varying combinations of these supplementary cementitious materials. Subsequently, an ANN-based predictive model was trained using the collected data to establish a relationship between the composition of the concrete mix and its strength characteristics. The ANN model takes into account various input parameters, including the percentage replacements of nano-silica, alccofine, and fly ash, as well as other relevant mix design parameters. The trained model aims to provide accurate predictions of compressive strength based on the selected input variables. The findings of this research contribute to a better understanding of the synergistic effects of nano-silica, alccofine, and fly ash on the strength properties of concrete. Moreover, the co-efficient of the correlation value comes out to be 0.924, revealing that observed and predicted values are in agreement with each other. Additionally, the developed ANN model serves as a valuable tool for engineers and researchers to efficiently forecast the strength characteristics of concrete with different combinations of these supplementary materials, facilitating more informed decision-making in concrete mix design and optimization.

Keywords Concrete · Nano-silica · Alccofine · flys ash · Artifical Neural Network

1 Introduction

Concrete, a versatile and widely used construction material, plays a crucial role in shaping the infrastructure of our modern world. Its adaptability, durability, and strength make it an indispensable component in the construction industry. Over the years, researchers and engineers have sought innovative ways to enhance the properties of concrete, addressing challenges such as sustainability, environmental impact, and performance. Concrete production faces a myriad of challenges that span environmental, economic, and social dimensions. Cement is an indispensable material, second only to water, and its global production and consumption are enormous, reaching 4.37 and 4.27 billion metric tonnes in 2021. Cement manufacturing accounts for between 5% and 7% of human-made CO_2 emissions [23]. The construction industry is a significant contributor to global carbon emissions, accounting for about 23% of greenhouse gas emissions worldwide [15]. Cement production is a significant contributor to these emissions, accounting for 8% of global carbon emissions [2]. Therefore, reducing the carbon footprint of the construction industry requires finding alternatives to cement that are sustainable, eco-friendly, and cost-effective. To address the environmental impact of the construction industry and mitigate carbon emissions further, various strategies and alternatives have been pursued. Researchers and engineers are actively investigating the development of

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alternative binding materials that can replace or reduce the use of cement in concrete. These alternative binders may include materials like fly ash, blast furnace slag, silica fume, and metakaolin, which have lower carbon footprints compared to cement. In addition to material alternatives, adopting sustainable construction practices can contribute to reducing the carbon footprint of the industry. Optimizing building designs for energy efficiency, utilizing renewable energy sources during construction, promoting modular and prefabricated construction methods, and incorporating recycling and waste management strategies all fall under the umbrella of sustainable construction practices. However, cement production heavily relies on natural resources, which can have significant environmental impacts, such as releasing CO_2 emissions. Cement is a crucial ingredient in concrete because it is most comprehensively used construction material in the world. Therefore, reducing the carbon footprint of the construction industry requires finding alternatives to cement that are sustainable, eco-friendly, and cost-effective. To address this issue, researchers have been exploring the use of mineral admixtures as partial replacements for cement, such as alccofine materials. The use of SCMs as partial replacements for Portland cement in concrete is necessary due to the environmental, economic, and technical benefits they offer. One of the potential alternatives to cement is the use of supplementary cementitious materials (SCMs), such as alccofine, fly ash, and nano-silica. These materials can partially replace cement in concrete, reducing its environmental impact without compromising its mechanical properties and durability. This paper aims to review the existing literature on the use of these SCMs as partial replacements for cement in concrete. The use of these SCMs in concrete has been extensively studied in the literature, and several studies have shown that the addition of these SCMs to concrete improves the compressive strength, flexural strength, and durability of concrete [10, 13, 14, 16, 18, 19]. The use of these SCMs reduces the waste generated by industrial processes, contributing to sustainable development.

One particular mineral admixture is Alccofine, which is a micro-fine level admixture that lowers the heat of hydration and enhances the strength of the concrete as well as its durability. Alccofine is a pozzolanic material that is produced from the calcination of kaolinite clay. It is a by-product of the manufacturing process of aluminum. Alccofine has high pozzolanic activity, which means that it reacts with calcium hydroxide to form calcium silicate hydrate gel (C-S-H), contributing to the strength and durability of concrete [17, 20]. Alccofine can help concrete achieve higher strength at an early stage, improve durability and workability, and balance out the slow early-stage strength-gaining ability of fly ash. Moreover, alccofine and NS work as pore-filling materials that compact concrete and increase its durability [3]. It can replace cement in two ways: by reducing the cement concentration and by being added to concrete to improve its properties. Alccofine's low calcium silicate content raises the pH of the concrete, protects it from corrosion, and improves its pumpability, shuttering removal, durability, and permeability.

Another mineral admixture that shows promising results is nano-silica (NS). NS can enhance the mechanical qualities by compacting concrete micro and nanostructures, preventing water penetration, and improving durability by controlling the breakdown of the calcium silicate hydrate reaction. It also interacts with calcium hydroxide to produce additional C-S-H in concrete, which is a nanoporous, nanostructured substance that controls most of the mechanical characteristics of concrete [4]. Also, fly ash (FA) is an increasingly popular substitute for Portland cement in concrete production due to its positive effects on technology and the economy. A byproduct of coal combustion is FA, collected from the chimneys of power plants, and bottom ash, which is taken from the base of the furnace [22]. The use of NS as a partial replacement for cement in concrete has shown promising results in improving the mechanical properties and durability of concrete. Studies have shown that NS can significantly improve the compressive strength, tensile strength, and flexural strength of concrete. This is due to its high pozzolanic activity and its ability to fill the voids in the concrete matrix, leading to the formation of additional C-S-H gel. One of the key benefits of using NS as a partial replacement for cement in concrete is its ability to enhance the durability of concrete. nano-silica improves the durability of concrete by reducing the permeability of the concrete matrix, thereby reducing the ingress of harmful substances such as chloride ions and sulfates. Additionally, the use of NS in concrete production can reduce the risk of alkali-silica reaction (ASR), a chemical reaction that can cause concrete to crack and deteriorate over time [24]. Overall, mineral admixtures such as alccofine and NS and the use of FA as a substitute for cement show promising results in reducing cement's environmental impact while enhancing concrete's properties.

Artificial Neural Networks (ANNs) have emerged as a valuable tool in the field of concrete technology, offering a versatile approach for modeling and predicting various properties and behaviors of concrete. Researchers have extensively applied ANN models to address diverse challenges in concrete engineering, including the prediction of compressive strength, assessment of durability properties, optimization of mix designs, and modeling of fresh and hardened concrete properties. Studies have demonstrated the effectiveness of ANN models in accurately predicting concrete performance under different curing conditions, considering factors such as mix proportions, aggregate properties, and environmental exposures. The processes involved in producing ANN models are divided into several sections: selecting inputs and outputs, dividing and pre-processing data, selecting a model architecture, training the model, selecting preventing criteria, and validating the model [11–13, 21]. The feed-forward neural network was the initial and simplest artificial neural network design, and it is applied in the current study. The primary reason for selecting this architecture was because information in this network is only transmitted in a single direction ahead, from the inputs of the nodes to the output nodes, passing through any hidden nodes that may exist. There are no loops or cycles in the network. It is important to note that because feed-forward neural network structures lack connections for feedback, they are limited in their ability to store time-dependent variables or handle sequential input.

2 Research significance

The research proposed in this study holds paramount significance within the realm of construction and civil engineering. Cement production is known to be a major contributor to greenhouse gas emissions and environmental degradation. By investigating the replacement of conventional cement with the innovative combination of alccofine, fly ash, and nano-silica, this research seeks to address a pressing concern of adding all these additives together to concrete. Thus, the potential of alccofine, fly ash, and nano-silica as sustainable alternatives presents a promising opportunity to mitigate the adverse effects of traditional cement use. Furthermore, this research will have practical implications for builders, engineers, and policymakers who are seeking sustainable construction materials and practices. The findings of this study may offer an economically viable and environmentally responsible alternative, thereby reducing the industry's carbon footprint and dependence on finite resources.

3 Experimental program

3.1 Materials

3.1.1 Cement

Cement of grade 43 (OPC) was used in the current study for all concrete mixes as per IS: 8112-1989 [8] and was brough from local vendor from Kharar, Mohali, India. The physical properties and chemical composition of cement used in the current study are shown in Table 1.

3.1.2 Aggregates

River sand was used as fine aggregate that passed via a 4.75 mm screen and lying into grading zone 2 of BIS: 383-2016. The coarse aggregates were procured from rocks left after passing through a 16 mm sieve and meeting BIS 383-2016 requirement.

3.1.3 Fly ash (FA)

An amount of 20% by dry weight of cement of fly ash which was obtained from Lehragaga Powerplant, Punjab, India, was used in present study. Class F, fly ash was used for all mix types in accordance with IS 3812-2013 [6]. The physical properties and chemical compositions of FA are presented in Tables 1 and 2.

3.1.4 Alccofine (ALC)

Alccofine was obtained from Ultracon Infrachem Pvt Ltd., Gurugram, India and was added to concrete specimen by adding 10% by dry weight of cement. The characteristics of ALC-1203 conforming to ASTM C989-1999 are presented in Tables 1 and 2.

Table 2 Chemical properties of various materials

Chemical analysis	Cement	Alccofine	Nano-silica	Fly ash
Cao	62.7	33.2	-	5.12
SiO_2	19.29	36.5	99.98	58.91
Al_2O_3	6.7	24.6	0.005	24.8
MgO	3.2	5.2	-	0.6
Fe_2O_3	5.6	0.32	0.001	6.2
SO_3	2.5	0.18	-	0.28
Na_{2O}	0.02	-	-	0.16
TiO_2	-	-	0.001	2.1
LOI	-	-	-	1.8

Table 1 Physical properties of various materials

Property	Cement	Fine aggregate	Coarse aggregate	Fly Ash	Alccofine	Nano-silica
Particle size	16 nm			70 microns	4–6 microns	17 nm
Bulk density ($Kg/m^{3)}$	1440		1540	900	600–700	1220
Specific gravity	3.16	2.64	2.70	2.1	2.7	2.2–2.4
Water absorption (%)	-	1.22	0.936			
Fineness modulus	-	3.11	7.061			
Specific surface (m^2/Kg)	300–350			3500–4000	12,000	250–500
Particle shape	Spherical			Spherical	Irregular	Spherical

3.1.5 Nano-silica (NS)

Nano-silica used for this research work was obtained from Fiber Region, Chennai, India. For this experiment, NS with a particle size of 17 nm was used. The nano silica used in the current research was varied from 1%, 2%, 3% and 4% respectively by dry weigh of cement and further testing were carried out. All the characteristics related to NS are tabulated in Tables 1 and 2 and confirming to IS 15388-2003.

3.1.6 Superplasticizer

Forsoc Conplast P211 plasticizer was used for every concrete mix group, conforming to BIS 5075 (Part 1), having specific gravity 1.17. The dosage of plasticizer was taken as 0.75% by replacing water content.

3.1.7 Water

When preparing the concrete, water was used from the tap available at the concrete laboratory (at room temperature) that complies with BIS 456-2000 guidelines.

4 Methodology

4.1 Blend proportions

The mix proportions play a vital role in determining the overall characteristics of the concrete, and the utmost attention was given to ensuring that the mix design met the required standards. The standards outlined in IS 10262:2019 [5] were followed for M-30 concrete grade mix design in this study. The proportions of the mix were determined based on the information provided in Table 3. Careful consideration was given to select the appropriate mix proportions to achieve the desired concrete properties. Adhering to the guidelines of IS 10262:2019, it was ensured that the mix design for M-30 concrete grade was suitable for the experimental work.

4.2 Mix preparation

For conducting compression tests, moulds of dimensions 150 mm x 150 mm x 150 mm were used; for conducting tensile strength tests, moulds of dimensions 150 mm x 300 mm were used, while moulds having dimensions 100 mm x 100 mm x 500 mm were casted for determining flexural strength. All the samples were mixed thoroughly by taking water-cement ratio as 0.42 for all the combinations shown in Table 3. After the concrete was mixed, it was poured into pre-oiled moulds to facilitate easy removal of the hardened samples and ensure a smooth and even surface finish (Fig. 1).

4.3 Curing

The curing process plays an important role in the production of concrete samples. The samples were cured in large tanks, and tap water was utilized without the presence of any chemicals to prevent potential chemical reactions. The curing durations for the samples were carefully followed: 7, 14, 28, and 56 days, respectively. Upon the completion of the curing process, the samples were deemed ready for testing to assess various mechanical properties of concrete such as compressive strength, tensile strength, flexural strength, and other relevant parameters.

Fig. 1 Casted samples

Table 3 NS, FA and ALC Mix proportions in Kg/m^3

Mix Id	Cement	NS	Fly Ash	ALC	Sand	Coarse aggregates	Water
NS0	253.4	0	72.4	36.2	683.2	1209	152
NS1	252.2	3.62	71.2	35	683.2	1209	152
NS2	250.9	7.24	69.9	33.78	683.2	1209	152
NS3	249.8	10.86	68.78	32.58	683.2	1209	152
NS4	248.5	14.48	67.57	31.37	683.2	1209	152

Mix Proportion = 1: 1.88: 3.34: 0.42

5 Experimental results

5.1 Workability

Workability is a critical factor as it determines how easily the concrete can be placed, compacted, and finished. The workability test was conducted using the slump cone method, following the guidelines provided by BIS 1199–1959. The findings of the slump test for each concrete mixture are presented in Fig. 2. It was observed that the inclusion of fine aggregate (FA) in the concrete mix resulted in a delay in the pozzolanic reactivity, which affected the early strength development of the concrete. To improve both strength and workability, various additives were added by replacing cement. Notably, the results of the slump test exhibited slight variations among the different groups of mixtures. These variations in slump values may be attributed to differences in consistency after adding water to the mixtures, underscoring the significance of precise measurements in the process of concrete mixing. In this particular study, a plasticizer (Forsoc Conplast P21) admixture was employed to enhance the workability of the concrete by decreasing the water-cement ratio. By reducing the water-cement ratio, the plasticizer improved the flowability and ease of handling of the concrete mixture, resulting in a higher slump value. Similar results on adding plasticizer on workability of concrete have been obtained in the past [1, 9].

5.2 Pulse velocity of ultrasound

Non-destructive evaluation of concrete structures plays a crucial role in construction and maintenance. In this study, Ultrasonic Pulse Velocity (UPV) test was conducted on concrete samples that complied with the BIS 13311-1 (1992) standards. The UPV test involved placing a transmitter and a receiver against two faces of the concrete, creating the UPV testing device. The equipment generated an electronic ultrasonic wave that was transmitted through the concrete by the transmitter. In this study, the direct method was employed, using an UPV meter for the test. The velocity of the ultrasonic wave was determined using the formula:

$$V = L/T$$

where 'V' represents the pulse velocity (in Km/s), 'T' denotes the effective time (in microseconds), and 'L' indicates the length (in mm) of the cube sample (Table 4).

The results of the UPV tests indicated that the NS1 group exhibited the highest pulse velocity, followed by NS0, NS3, NS4, and NS2 (Fig. 3). These findings demonstrate the effectiveness of admixtures in improving the quality of the concrete structure and enhancing its resistance to flaws and cracks. The NS1 series demonstrated the fastest ultrasonic pulses, while the NS4 group exhibited slower transitions. Overall, the UPV test proved to be an effective non-destructive method for evaluating the quality of concrete structures and detecting any flaws or defects. It provides valuable insights into the performance and integrity of the concrete, helping to ensure the durability and reliability of the structure (Fig. 4).

Table 4 UPV test results

Mix Id	TIME (ms)	LENGTH (mm)	UPV(Km/s)
NS0	34.2	150	4.38
NS1	33.4	150	4.68
NS2	34.9	150	4.49
NS3	32	150	4.29
NS4	37.2	150	4.03

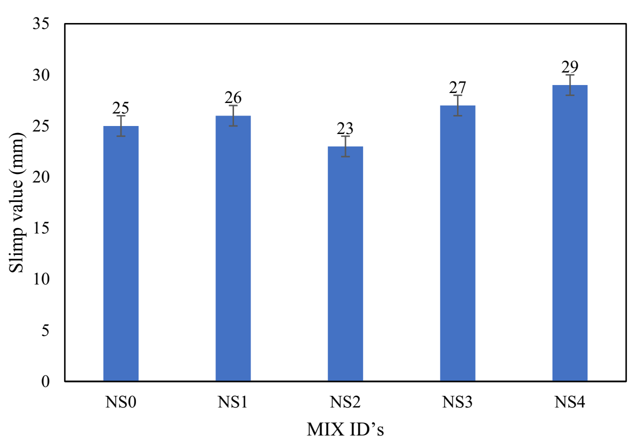

Fig. 2 Slump Cone Test values (in mm)

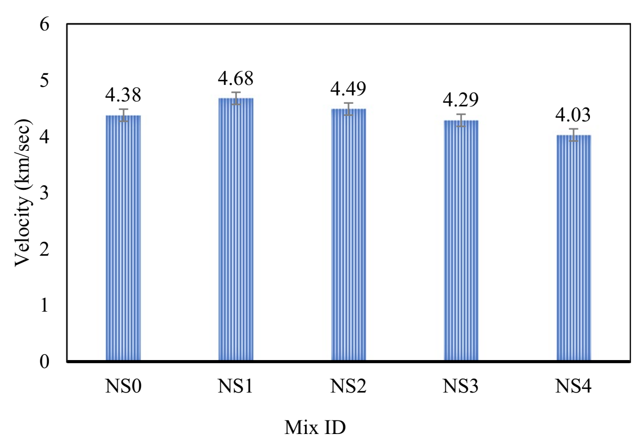

Fig. 3 UPVT results are shown in the column graph

Fig. 4 Machine used for UPV test

5.3 Compression strength

The compressive strength test (CST) was conducted on a compression testing machine (CTM) with a capacity of 2000 KN, following the guidelines specified in IS 14858 (2000). The test was performed with a precision of ± 1% as per the requirements of the 1828 (class 1) standard at different ages: 7, 14, 28, and 56 days. The results presented in Fig. 5, indicated that the NS1 group exhibited the highest compression strength among all the other groups at each of the four ages, while the remaining groups displayed lower strength values. In previous studies these supplementary materials had a positive impact on the compressive strength of concrete [19, 20]. At 7 days, the compression strength values of NS0, NS1, NS2, NS3, and NS4 were 24.3, 25.68, 23.64, 23.73, and 22.79 MPa, respectively. NS1 exhibited higher compressive strength than NS0, indicating that the addition of 1% NS had a favorable impact on early strength development. The NS1 group showed approximately 5.6% higher strength than the NS0 group at 7 days. At 14 days, the compression strength values of NS0, NS1, NS2, NS3, and NS4 were 32.5, 33.96, 32.13, 31.73, and 31.84 MPa, respectively. Once again, NS1 demonstrated higher compression strength values compared to NS0, indicating the advantageous impact of including 1% NS on strength development. The NS1 group exhibited approximately 4.5% higher strength than the NS0 group at 14 days. At 28 days, the compression strength values of NS0, NS1, NS2, NS3, and NS4 were 35.53, 36.07, 34.62, 34.04, and 34.1 MPa, respectively. NS1 continued to show higher compressive strength values than NS0 at this age. The NS1 group displayed approximately 1.5% better strength than the NS0 group at 28 days. At 56 days, the compression strength values of NS0, NS1, NS2, NS3, and NS4 were 36.9, 37.52, 35.3, 35.1, and 34.7 MPa, respectively. NS1 once again exhibited higher compressive strength values compared to NS0 at this age. The NS1 group showed approximately 1.7% greater strength than the NS0 group at 56 days.

The results of the compression strength tests demonstrated that including 1% NS in the concrete mixtures improved early strength development. The NS1 group consistently displayed higher compression strength values than the NS0 group at all ages. However, the increase in compressive strength was relatively small, with a maximum percentage increase of approximately 5.6% at 7 days. Overall, the results suggest that the compression strength of concrete is enhanced with the inclusion of 1% nano-silica content.

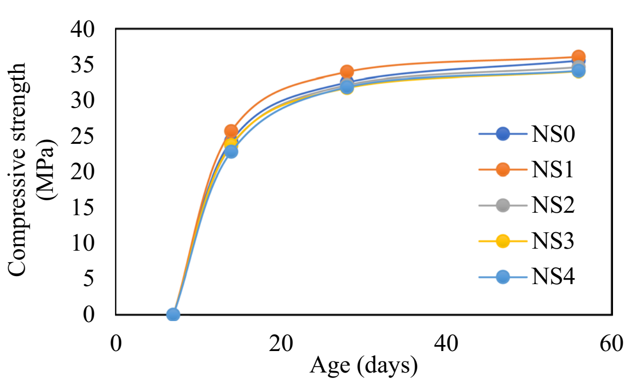

Fig. 5 Compressive strength of samples at 7, 14, 28 and 56 days

5.4 Tensile strength

The STST (Split Tensile Strength Test) is another test that was conducted using the same compression testing machine (CTM) specified in IS 516–1959 to determine the split tensile strength (STS) of concrete at 7, 14, 28, and 56 days (Fig. 6). The cured specimens were removed and sun-dried before being placed in the compression testing equipment. The split tensile strength of

Fig. 6 CTM with samples before testing

the concrete cylinder specimens was calculated by measuring the load. The results of the STST indicated that the NS1 group exhibited superior endurance compared to the NS0 group at 7, 14, 28, and 56 days. At 7 days, the STS of the NS1 group was 29.1% higher than that of the NS0 group. At 14, 28, and 56 days, the NS1 group's split tensile strength was 6.4%, 9.3%, and 7% higher than the NS0 group, respectively shown in Fig. 7. Nano-silica and alccofine outperforms the control group in STS characteristics of the concrete in previous studies as well [19, 20]. The enhanced tensile strength observed in the NS1 group can be attributed to the pore-filling effect of ultra-fine particles and accelerated hydration, resulting in denser and more compact concrete. The fine particles of NS and ALC filled the small pores of the concrete, contributing to a denser and more compact structure. The use of a plasticizer aided in filling the air voids in the concrete and reducing water absorption, further enhancing the strength of the NS1 group.

Overall, the results of the STSS demonstrated that the addition of NS and ALC to the concrete mixture had a significant positive impact on its tensile strength, with the NS1 group identified as the optimal mixture. The higher tensile strength exhibited by the NS1 group makes it a suitable choice for structures that require high tensile strength, such as bridges, roads, and high-rise buildings.

5.5 Flexural strength

The Flexural Strength Test (FST) was performed to determine the ability of the concrete specimens to withstand bending forces. The test was conducted using a two-point flexural testing machine with a maximum capacity of 100 KN, following the guidelines specified in IS 516-1959. The FST was conducted on all concrete mix groups at 28 days of age after the specimens had been cured according to the standard procedure. The FS (flexural strength) of the concrete beam specimens was determined by measuring the load and calculating it using the equation,

$$f_{cr} = PL/bd^2 \tag{1}$$

Here, 'f_{cr}' represents the flexural strength of the samples, 'P' indicates the applied force on the test specimen, and the specimen's width and depth are denoted by "b" and "d," respectively.

The results of the FST revealed that the NS4 group exhibited the highest flexural strength at 28 days, whereas the control group (NS0) displayed the lowest strength as shown in Fig. 8. As the proportion of NS in the mix increased, the FS of the concrete samples also increased. The NS4 group demonstrated a 10.06% improvement in flexural strength compared to the control group. The higher flexural strength observed in the NS4 group can be attributed to the improved microstructure and denser packing of the concrete matrix due to the presence of nano-SiO_2. The reduction in voids and pores in the matrix leads to enhanced inter-facial bonding and a greater load-carrying capacity, resulting in higher flexural strength.

The outcomes of the FST align with previous studies that have reported the beneficial effects of nano-silica on flexural strength [19]. The improved flexural strength in the NS4 group suggests that the addition of nano-silica to be the mix at an optimal dosage that can effectively enhance the bending performance of concrete structures. The 28-day period for flexural strength tests is a standard practice because it allows concrete to reach a significant portion of its ultimate strength due to the completion of major hydration reactions; while, 7-day and 14-day strength tests can provide valuable early indications of concrete performance, they are often used for quality control purposes rather than design purposes.

5.6 Standard deviation and coefficient of variance

The standard deviation is a statistical measure that indicates the spread of data around the mean value. In the case of compressive strength, a smaller standard deviation indicates

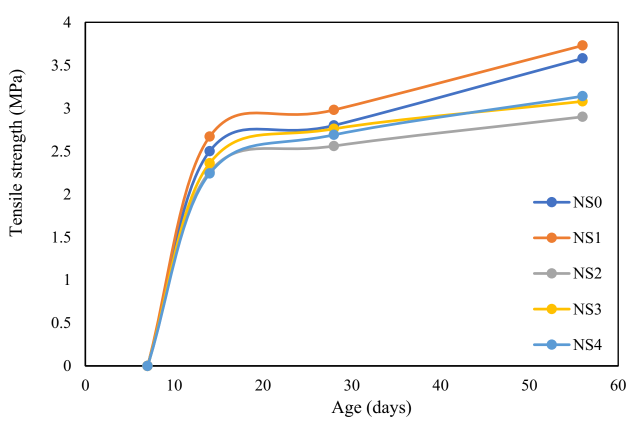

Fig. 7 Tensile strengths at 7, 14, 28, and 56 days

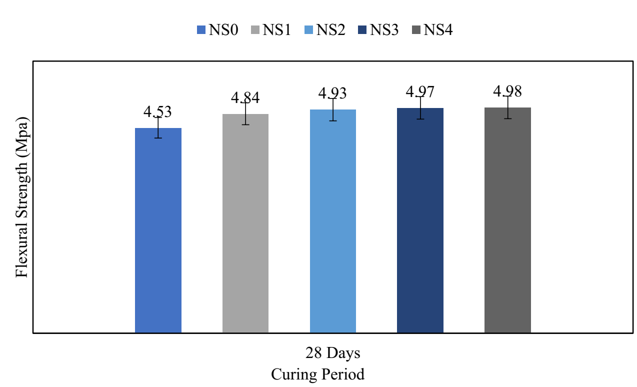

Fig. 8 Flexural strength after 28 days of curing

that the concrete samples are more consistent in terms of their strength. The coefficient of variation (COV) is the ratio of the standard deviation to the mean value, expressed as a percentage. It is a statistical indicator that quantifies the relative variation of the data under consideration. Similar measures of standard deviation and COV can be calculated for tensile and flexural strength tests as well. These statistical measures are important for evaluating the reliability of the test results and comparing the strength of different concrete mixes. A lower standard deviation and coefficient of variance value indicate that the test results have been evaluated for reliability and consistency, indicating a uniform and predictable concrete quality.

The calculations were performed according to the guidelines specified in IS 456:2000 [7]. These measures helped assess the uniformity and consistency of the concrete strength across the different mixes and ages. The bending strength, split tensile force, and compression strength tests were conducted on all five concrete mixes at the age of 28 days. The statistical analysis was conducted to assess the consistency and variability of the strength data for each mix. The standard deviation and coefficient of variation values were also found to decrease with increasing NS content. The addition of NS to the concrete enhanced its mechanical properties, improving strength and reducing variability. The results overall suggest that NS can be used as an effective and sustainable supplementary cementitious material (SCM) to enhance the endurance and strength of concrete (Tables 5, 6 and 7).

6 Database for ANN models

The ANN-based models are created utilizing a small data set containing 80 comprehensive experimental data from the compressive strength testing mentioned in prior parts. The database covers compressive strength tests on cubical specimens. Table 8 provides a detailed description of the whole information that was obtained. The experimental data was divided into two groups: The confirmation error can be determined by using the method's leftover data from the selection. The training subset contains 70% of the data needed to train the network. Following each learning phase, the average square error of prediction and an estimate of compressive strength from test data are computed. If the error continues to develop during ten epochs in a row, the training is terminated. (This strategy reduces the impact of overfitting). Subset of tests: Once trained, the neural network may be used to forecast the compressive strength values of the test subset.

To evaluate the performance of an ANN model, the correlation coefficient (r) and root mean squared error (RMSE) were determined using the following formulae:

$$R = \frac{\sum_{i=1}^{n}\left(h_i - \bar{h}_i\right)(t_i - \bar{t}_i)}{\sqrt{\sum_{i=1}^{n}(h_i - \bar{h}_i)^2 \sum_{i=1}^{n}(t_i - \bar{t}_i)^2}}$$

$$RMSE(MPa) = \sqrt{\frac{\sum_{i=1}^{n}(h_i - \bar{t}_i)^2}{n}}$$

6.1 ANN models results and sensitivity analysis

After the training procedure was completed, a set of connections biases and weights was formed. The hidden layer number has a significant influence on the MSE and the coefficient of efficiency (R^2). Figure 9a, b shows how MSE changes as the total number of neurons in the layer that is hidden grows. MSE drops while R^2 increases until the fourth neuron in the hidden layer, when this pattern reverses (Table 9). A crucial research methodology for categorizing input factors and elucidating their sequential influence on the outcome of a physical problem is sensitivity analysis. In this particular study, we employ a weighted approach technique to assess the relative significance of all input factors. The analysis method utilized in this study is weight magnitude analysis. The arrangement of input values in this technique is determined by the relative weights assigned to the input layer and the hidden layer. The initial step involves normalizing the weight

Table 5 Standard deviation and coefficient of variance for compressive strength

Mix code	S.D (σ)	C.O.V (%)
NS0	0.54	2.05%
NS1	0.73	1.49%
NS2	0.77	2.22%
NS3	0.70	2.05%
NS4	0.72	2.11%

Table 6 Standard deviation and coefficient of variance for tensile strength

Mix code	S.D (σ)	C.O.V (%)
NS0	0.08	4.90%
NS1	0.11	2.90%
NS2	0.19	6.80%
NS3	0.18	6%
NS4	0.20	6.30%

Table 7 Standard deviation and coefficient of variance for flexural strength

Mix code	S.D (σ)	C.O.V (%)
NS0	0.019	0.42%
NS1	0.077	1.59%
NS2	0.073	1.49%
NS3	0.065	1.32%
NS4	0.078	1.56%

Table 8 Descriptive statistics of the parameters used to build the ANN-based model

Descriptive statistics					
Variables	N	Minimum	Maximum	Mean	Std. Deviation
Cement	80	248.50	253.40	250.9600	1.77064
Alccofine	80	31.37	36.20	33.7860	1.75276
Fly Ash	80	67.57	72.40	69.9700	1.75312
nano-silica	80	0.00	14.48	7.2400	5.25245
Time	80	7.00	56.00	26.2500	19.25419
Compressive Strength	80	22.79	37.52	31.8090	4.8804
Valid N (listwise)	80				

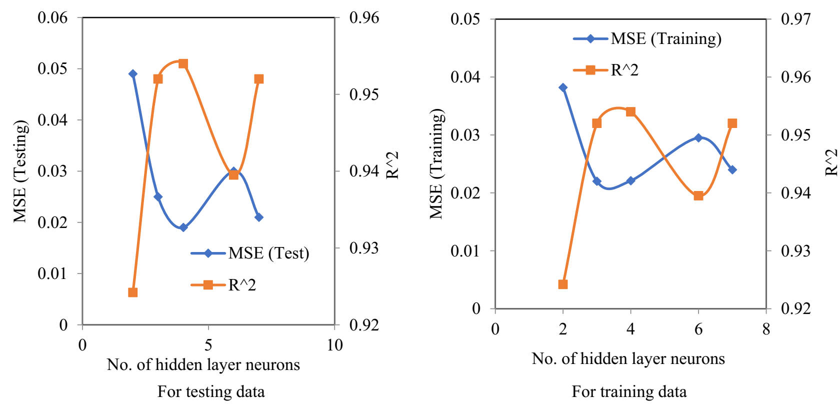

Fig. 9 Relationship between MSE and the number of hidden layer neurons

Table 9 The proposed model's statistical parameters

Hidden neurons	Rsqr	MSE (Training)	MSE (Test)
2	0.924	0.446	0.339
7	0.955	0.475	0.279
2	0.925	0.331	0.229
2	0.918	0.265	0.483
3	0.952	0.357	0.100
2	0.927	0.283	0.352
6	0.934	0.528	0.112
6	0.945	0.233	0.790
2	0.927	0.388	0.176
4	0.954	0.534	0.232

magnitude of each input node. During this normalization process, the weight of each input layer is divided by the largest weight between the input and hidden layers. For each input layer, we calculate the sum of weights after normalizing their values. The higher the order of a node, the greater its weight when serving as input to the node responsible for generating the output. The mathematical expression governing the process of summing up the normalized weights of the i_{th} input is as follows:

$$I_i = \sum_{j=1}^{4} \frac{x_{ji}}{max_{all,j,i}\left(x_{ji}\right)}$$

Figure 10 depicts the degree of sensitivity index for every input parameter. The analysis of Fig. 10 shows that the curing period has the greatest influence on the output, whereas fly ash has the least.

6.2 Neutral interpretation diagram (NID)

An approach called Neuronal Interpretation Diagram to illustrate the connection weights between neurons and to show the connections between input and output. The input layer, hidden layer, and output layer are the three network tiers that makeup NID. The weights are displayed as a line connecting input and hidden neurons, as well as hidden and output neurons. A schematic design of the ANN architecture is shown in Fig. 11. The color of the line in the current NID, depicted in Fig. 11, shows the relative importance of every link weight. The gray lines reflect a connection weight magnitude less than zero, whereas the blue line indicates a connection weight magnitude greater than zero. The output of the residual analysis is a residue map for the full data set. As can be seen from a close examination of the figure,

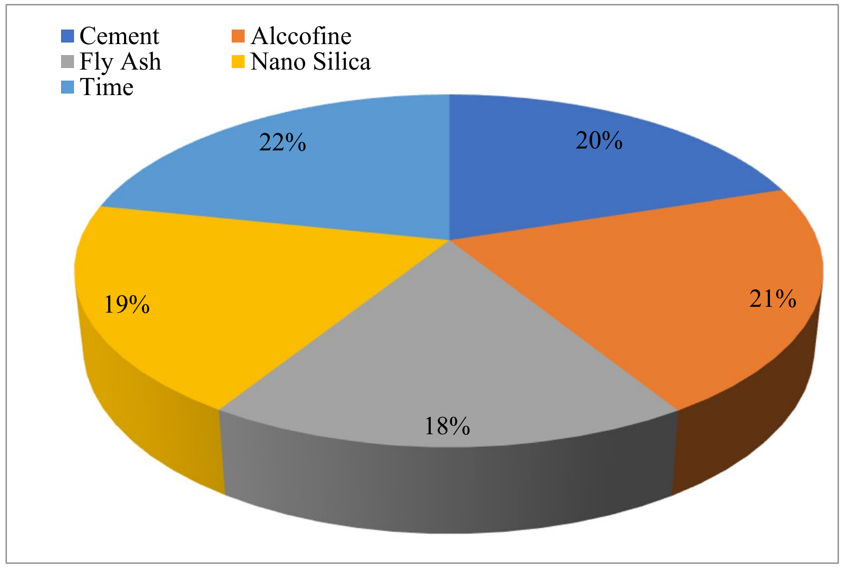

Fig. 10 Impact of a variable's disturbance on sensitivity index

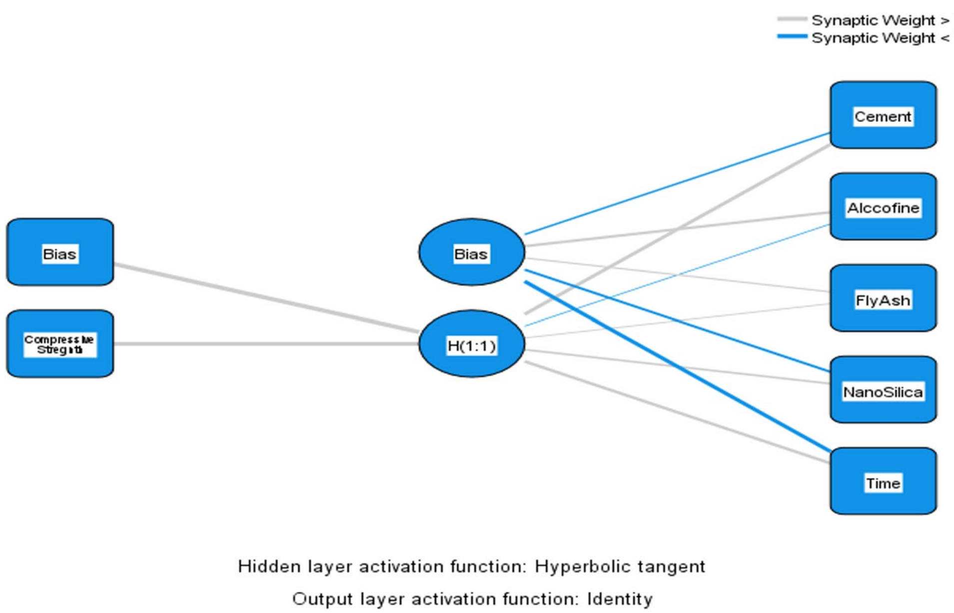

Fig. 11 Lines in the neuronal interpretation diagram indicate the weight of connections

residuals are evenly spaced around the plot's center line. This may indicate that the network has been correctly trained and is capable of producing reliable estimates.

6.3 ANN model formulation

The results show how the experimental compressive strength differs from the compressive strength obtained by using the ANN, as shown in Fig. 12. The efficiency coefficient (R^2) was discovered to be 0.924. The comparison's success is demonstrated in Fig. 12. An artificial neural network's predicted compressive strength and the experimental compressive strength were found to differ by roughly 12%. Rarely, and only in certain circumstances, does the

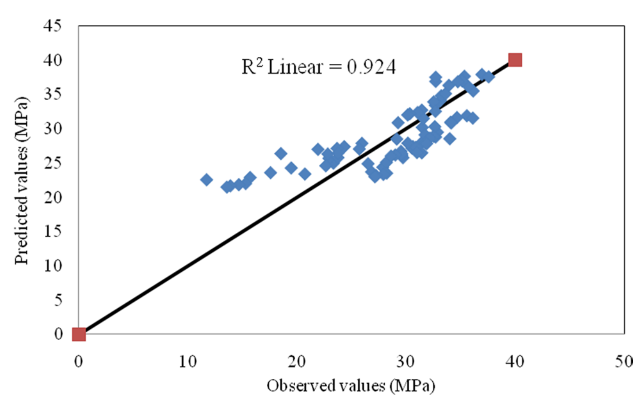

Fig. 12 Comparison of the obtained compressive strength with the experimental compressive strength using ANN

deviation approach 16%. As revealed by the results, the outcome of the ANN model accurately forecasts the compressive strength.

7 Conclusion

The feasibility of neural networks with artificial intelligence (ANN) for predicting the compressive strength of materials was investigated in this study. The constructed ANN model exhibited significant precision for estimating RAC strength when parameters such as water-to-cement ratio, materials, and curing age were considered. The ANN model also scored better than conventional regression models, highlighting its potential for capturing intricate interactions in the RAC system. These findings demonstrate the potential of ANN as an effective method for precisely forecasting compressive strength. Based on the experiments conducted with M30-grade concrete, the following conclusions were drawn:

- The inclusion of nano-silica and alccofine in the concrete had a positive effect on its density. The small particle sizes of nano-silica and alccofine helped fill small pores, resulting in denser concrete.
- Despite the use of a plasticizer, the low water-to-cement (W/C) ratio of 0.42 made it challenging to improve workability and pumpability. High-range water-reducing (HRWR) admixtures were found to be more effective in enhancing these properties. The addition of a plasticizer contributed to filling air pores in the concrete and reducing its water absorption capacity.
- The NS1 group outperformed the NS0 group in terms of both compressive and tensile strength at all tested ages (7, 14, 28, and 56 days). Based on the results, the NS1 mix was identified as the optimal group.
- The flexural strength (FS) of the concrete improved with increasing nano-silica content, along with the presence of fly ash and alccofine.
- Ultrasonic pulse velocity test proved to be a reliable, non-destructive method for assessing the quality and durability of concrete structures, with the NS1 mix displaying the highest pulse velocity.
- Predicting the strength of nano-silica, alccofine, and fly ash with an artificial neural network seems highly accurate.
- By examining additional factors, future research should try to improve the performance of neural network models. The durability of concrete with nano-silica, fly ash, and alccofine must also be investigated, as well as the effects of curing conditions. Improvements in concrete construction efficiency and durability can be accomplished by addressing these factors.

7.1 Limitation of the study

Overall, this study highlights the potential benefits of incorporating NS and ALC into concrete mixtures as well as the significance of selecting appropriate admixtures to achieve desired workability and strength properties. However, there are certain limitations of the study as follows:

The experiments are conducted under controlled laboratory conditions, which may not fully replicate real-world environmental factors such as temperature fluctuations, humidity, and exposure to various chemicals. The performance of the concrete mix in actual field conditions might differ. Further, the study does not address the environmental impact or sustainability metrics associated with using nano-silica, alccofine, and fly ash. While these materials can enhance concrete properties, their production, transportation, and lifecycle impacts need consideration for a holistic evaluation.

Author contributions All of the authors did their contribution in various ways. Mr. Tushar did the research work and prepared various versions of the manuscript. Prof. Jagdish chand reviewed the manuscript and prepared the final version. Dr. Abhishek Sharma applied artificial neutral network to the final version of manuscript.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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