Innovative Infrastructure Solutions (2021) 6:222
https://doi.org/10.1007/s41062-021-00588-9

TECHNICAL PAPER

Impact of nano ZnO particles on the characteristics of the cement mortar

Hiteshkumar Patil[1] · Arunkumar Dwivedi[2]

Received: 16 April 2021 / Accepted: 8 July 2021 / Published online: 24 July 2021

Abstract
In practice, it is very common to estimate the strength of concrete by destructive or by partial non-destructive testing on concrete. However, it is a very challenging task to estimate the correct value of the strength of concrete or cement as it is depending on various factors. The present research work is focussed on the impact of zinc oxide (ZnO) nano-particles on the compressive strength of the cement mortar. To investigate the modified compressive strength of the mortar incorporated with ZnO nano-particles, four different types of mixes were prepared with 0%, 0.25%, 0.5%, and 0.75% of the ZnO nanoparticle by the weight cement, respectively. Experimental results show the enhancement in compressive strength up to 0.5%, later on, strength is slightly decreased. By considering the experimental results of cement strength, three different models are proposed to predict the strength of cement mortar as analysis of covariance (ANCOVA), neural network (NN), and principal component regression (PCR). These models also validate the results of experimentation by showing the optimum results at 0.5% of the addition of ZnO nano-particles. These models are trained and tested in excel programming for thirty-six standard cement specimens. At the end of the work, each model is compared with others. Out of three models, the NN model can predict the reliable results for the compressive strength. However, the PCR model is in second place after the NN model though its value of R^2 is lesser than the ANCOVA model. PCR gives less residue as compared to ANCOVA. For the prediction of the strength of mortar, ANCOVA is not so significant as compared to the other two models due to the residuals of ANCOVA models are the largest value, though its R^2 value is more than the PCR model.

Keywords Compressive strength · Nano-particles · Analysis of covariance · Neural network model · Principal component regression

Introduction

Cement is one of the most often used materials by humans, and the compressive strength of structural concrete is determined by the concrete's numerous constituents. It is also one of the most important components that provide concrete its strength. The strength of the cement determines the concrete's performance. Standard specimens were created and cured at various days for the curing in the laboratory to test the strength of cement. Some concrete factors, such as cement, aggregates, water-cement ratio, curing period, have an impact on the strength of the concrete. The various regression [1, 2] approaches are used to calculate the strength of cement using known procedures. The trend of evaluating cement strength using models that are only based on data has been expanding over the last few years. Many researchers are currently considering various approaches to estimate cement and concrete strength, such as artificial neural networks (ANN)) [3–5], principal component regression [6–8], fuzzy logic [9, 10], and machine learning methods [11].

Many researchers have looked at estimating the particular properties of concrete. Using design of experiment analysis, Salem Alsanusi and Loubna Bentaher evaluated the compressive strength of concrete [12]. Moutassem et al. [13] anticipated theoretical and phenomenological models for predicting concrete qualities. ANN is also used to

✉ Hiteshkumar Patil
hitusp@gmail.com

Arunkumar Dwivedi
akd321@gmail.com

1 KBC North Maharashtra University, Umavi Nagar, Jalgaon, MS 425001, India

2 School of Engineering and Technology, Sandip University, Nasik, MS 422002, India

investigate displacement in a concrete reinforced building [14]. Joseph Mwati Marangu researched the use of machine learning (support vector machine) to estimate the strength of concrete [15].

Hamid Eskandari-Naddaf et al. [16] used an artificial neural network (ANN) to forecast the compressive strength of mortar mixtures with various cement strength classes. With improvements in cement class, ANN exhibits an improvement in mortar compressive strength. Because cement is made up of random, complicated, multi-scale composites, predicting its elastic characteristics is difficult. Finite element approaches, in combination with knowledge of individual phase modulus and a cement paste microstructure development model, are utilised by Haecker [17] to quantitatively predict elastic modulus as a function of degree of hydration as determined by loss on ignition. For degrees of hydration of 50% or greater, and for a range of water cement ratios, comparisons between model predictions and experimental results are good. Kavita Verma et al. [18] offer a finite element model for cement strength prediction. They also utilise the ANN to forecast the strength of cement mortar in various sorts of environmental conditions, confirming that the ANN model's prediction is the best. The amount of sodium chloride, chemical admixtures, and cement grade all have an impact on the compressive strength of cement mortar. As a result, Hamid Eskandari et al. [19] devised an artificial neural network model to estimate the compressive strength of mortar for various cement grades and sodium chloride (NaCl) percentages. Additionally, Shaqadan et al. [20] proposed the Relevance Vector Machine (RVM) and Random Forest (RF) models, and the study found that RVM predicts cement mortar strength better than RF. The ANN, correct orthogonal decomposition, and regression analysis models were compared to the created mathematical model by Kisan Bidkar et al. [21]. Akbar Ghanbari et al. [22] employ micromechanical parametric models to estimate the plastic viscosity of self-compacting steel fibre reinforced concrete (SCFRC) based on the observed plastic viscosity of the mixture. The study of Naresh Kumar Nagwani et al. [23] utilizes the cluster regression approach to estimate the concrete's compressive strength. Clustering and regression together will guarantee that the dependent and independent variables' curves are more accurately fitted. Huaicheng Chen et al. [24] deploy a support vector machine (SVM) model to estimate the compressive strength of mortars subjected to sulphate assault. The possibility of utilising artificial neural networks (ANNs) modelling to forecast the characteristics of self-compacting concrete (SCC) incorporating fly ash as a cement substitute is investigated by Omar Belalia Douma et al. [25].

The current investigation is focussed on the estimation and comparision of the strength of cement mortar incorporated with nano ZnO particles by using different types of models such as analysis of covariance (ANCOVA), artificial neural network (ANN), and principal component regression (PCR). The outline of the research work is shown in Fig. 1c.

Materials and methods

Materials

Cement: Pozzolana Portland Cement confirming to IS 1489:1991 [26] is used in this investigation. Table 1(a) and Table 1(b) show the chemical and physical properties of cement, respectively.

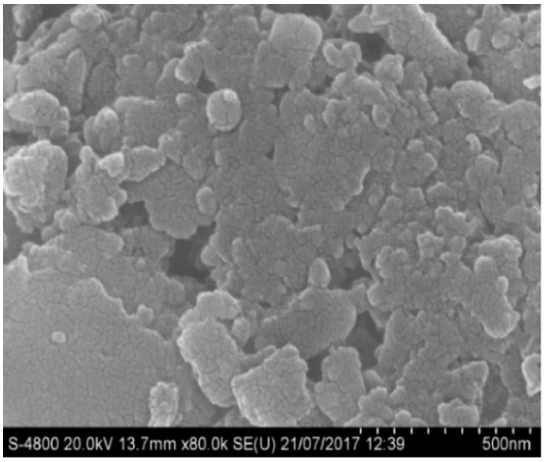
Fine aggregate: Locally available fine aggregate in the river is used for the experimentation, it is confirming to IS 383: 1970 [27] with Zone II utilizes for the experimentation. The properties of cement and fine aggregate shown in Table 1(c).

Zinc oxide (ZnO) nano-particles: Zinc ash or zinc oxide is a by-product of the coating industry, which occurs as a fine powder and grey in colour. Figure 1a shows an average particle size of ZnO is 50 nm and a density of 263 kg/cm^3. The Chemical composition of the ZnO nano-particles is shown in Table 1(d).

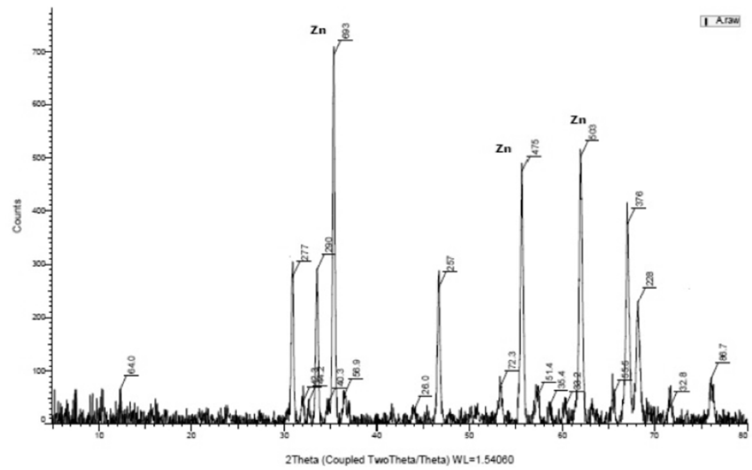
Characterisation of Zno particles: XRD figure of ZnO nanoparticles given in Fig. 1b. The XRD peaks show the materials in the nano-scale series. From these peak intensity, width and position, full width at half maximum data (FWHM) can be determine. The peaks situated at 30.88°, 33.539°, 35.364°, 46.659°, 55.718°, 61.988°, 67.076°, 68.213°.

$$D = (0.9 \times \lambda)/(\beta \times \cos\,\theta) \quad \text{Scherrer equation [28],}$$

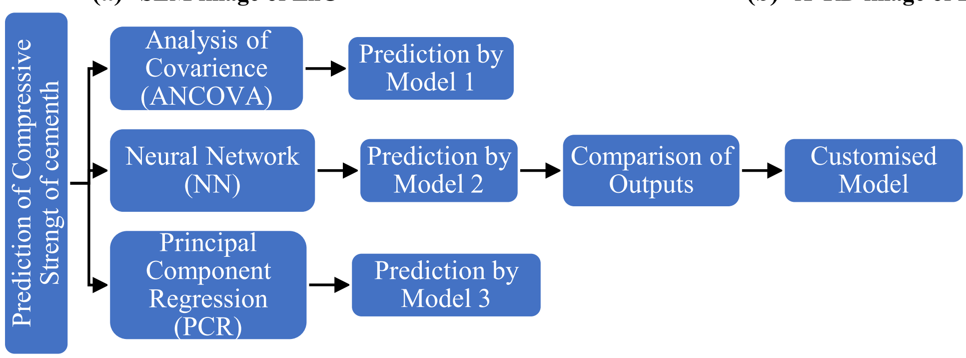
where λ = wavelength, β = full width at half maximum (FWHM)of diffraction peak. The average practical size is 48.69 nm at an angle 35.36°, it is calculated as Scherrer Equation. The widening of XRD peaks shows the presence of nanoscale particles in the materials. XRD pattern analysis may be used to identify peak intensity, location, and breadth-full width at half maximum data. SEM pictures demonstrate the formation of ZnO nano-particles. SEM confirms the approximately spherical form, and most particles have some faceting. The selected region electron diffraction pattern confirms nano-crystals preferred orientation over conventional crystals [29, 30]. SEM images, which reveal the formation of ZnO particles, also confirm the hexagonal plane.



(a) SEM image of ZnO



(b) X-RD image of ZnO



(c) Outline of research work

(d) Nano ZnO

Fig. 1 **a** SEM image of ZnO **b** X-RD results of ZnO **c** Outline of the research work **d** Nano ZnO

Methods

Experiments start with the preparation of 4 types of mixes. In these mixes, the amount of addition of ZnO nano-particles varies from 0%, 0.25%, 0.5% and 0.75% by weight of the cement. The mix proportions and its details are shown in Table 2. The compressive strength of cement mortar was checked as per IS 4031 (part 6) [31].

The outline of the research work is shown in Fig. 1c. After testing the specimens of all mixes, three types of models were prepared for the prediction of the strength of cement. Table 3(a) shows the input parameters for the various models and Table 3(b) shows the characteristics of specimens after casting. At the end of the work, results of all models were compared with each other and find out the best model fit for further experimentation. The predicted values from models and experimental values were calculated. The residuals of each model were again compared and based on this, the best-fitted model was customized for this work.

Table 1 (a) Chemical and physical properties of the cement (b) properties of fine aggregates (c) chemical composistion of zinc oxide (%)

Cement	Notation	% Mass
(a) *Chemical composition of cement*		
Calcium oxide	Cao (C)	65%
Silicon dioxide	SiO_2 (S)	21%
Aluminium oxide	Al_2O_3(A)	5%
Ferric oxide	Fe_2O_3(F)	2%
Sulfer trioxide	SO_3 ($\overline{S}$)	2
(b) *Physical properties of cement*		
Specific gravity:		3.15
Fineness (%):		0.89
Consistency (%):		32
Initial setting TIME (IST) Min:		143
Final setting time (FST) Min:		205
Soundness (mm):		0.6
(c) Properties of fine aggregates		
Fineness modulus (%)		3.46
Specific gravity		2.71
Bulk density (kg/m^3)		1549
Water absorption (%)		0.22

(d) *Chemical composition of zinc oxide (%)*

Zinc	Fe	Pb	Cd	Cu	Mg	Sn	Al
63	0.66	0.24	0.0011	0.08	0.02	0.12	1.62

Table 2 Mix proportions

Mortar	Notation	Cement (kg)	Sand (kg)	ZnO (gm)
C + FA + ZnO 0	CM1	1.5	4.5	0
C + FA + ZnO 0.25	CM2	1.5	4.5	3.75
C + FA + ZnO 0.5	CM3	1.5	4.5	7.5
C + FA + ZnO 0.75	CM4	1.5	4.5	11.25

Models

Analysis of covariance (ANCOVA)

ANCOVA is used for the assessment of the main effect of categorical variables on the main (dependent) variables. It is also used for limiting the effect of continuous variables on the dependent variables. ANCOVA is blended with linear regression (LR) and analysis of variance (ANOVA) as the same type of dependent variables is there, so the model alters linearly and the hypothesis becomes identical. If p is the number of quantitative variables, and q the number of factors (the qualitative variables including the interactions between qualitative variables), the ANCOVA model is written as [32]:

$$y_i = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} + \sum_{j=1}^{q} \beta_{k(i,j),j} + \varepsilon_i \tag{1}$$

where y_i is the value observed for the dependent variable for observation i, xij is the value taken by quantitative variable j for observation i, $k(i,j)$ is the index of the category of factor j for observation i and ε_i is the error of the model. By ANCOVA, here we wanted to determine the compressive strength. Use of this model to predict compressive strength as the dependent variable and zinc ash, cement to zinc ash ratio, water to cement ratio as quantitative variables, and curing days as qualitative variables as the portion of multiple linear models.

Compressive strength = Function (zinc ash, cement to zinc ash ratio, water to cement ratio and curing days).

Neural network (NN)

Due to the strength, the user-friendly approach and the elasticity of Neural Network model is widely preferred model for the prediction. This is most useful under the multifaced circumstances. Radial basis function (RBF) [33, 34] and multilayer perceptron (MLP) [35, 36] applications are used

Table 3 Input details

Blends	Cement (Kg)	Sand (kg)	Water (Kg)	X1	X2	X3	X4	Load (KN)	Strength (Mpa)
(a) *Input parameters for the models*									
CM1	1.50	4.50	0.45	0.00	0	0.30	3	142	28.50
CM1	1.50	4.50	0.45	0.00	0	0.30	3	144	28.90
CM1	1.50	4.50	0.45	0.00	0	0.30	3	146	29.30
CM1	1.50	4.50	0.45	0.00	0	0.30	7	204	40.94
CM1	1.50	4.50	0.45	0.00	0	0.30	7	205	41.14
CM1	1.50	4.50	0.45	0.00	0	0.30	7	209	41.95
CM1	1.50	4.50	0.45	0.00	0	0.30	28	309	62.02
CM1	1.50	4.50	0.45	0.00	0	0.30	28	308	61.82
CM1	1.50	4.50	0.45	0.00	0	0.30	28	310	62.22
CM2	1.50	4.50	0.71	3.75	400	0.47	3	152	30.51
CM2	1.50	4.50	0.71	3.75	400	0.47	3	153	30.71
CM2	1.50	4.50	0.71	3.75	400	0.47	3	154	30.91
CM2	1.50	4.50	0.71	3.75	400	0.47	7	214	42.95
CM2	1.50	4.50	0.71	3.75	400	0.47	7	216	43.35
CM2	1.50	4.50	0.71	3.75	400	0.47	7	219	43.95
CM2	1.50	4.50	0.71	3.75	400	0.47	28	319	64.02
CM2	1.50	4.50	0.71	3.75	400	0.47	28	321	64.43
CM2	1.50	4.50	0.71	3.75	400	0.47	28	320	64.23
CM3	1.50	4.50	0.95	7.50	200	0.63	3	157	31.51
CM3	1.50	4.50	0.95	7.50	200	0.63	3	158	31.71
CM3	1.50	4.50	0.95	7.50	200	0.63	3	160	32.11
CM3	1.50	4.50	0.95	7.50	200	0.63	7	219	43.95
CM3	1.50	4.50	0.95	7.50	200	0.63	7	222	44.56
CM3	1.50	4.50	0.95	7.50	200	0.63	7	220	44.15
CM3	1.50	4.50	0.95	7.50	200	0.63	28	324	65.03
CM3	1.50	4.50	0.95	7.50	200	0.63	28	326	65.43
CM3	1.50	4.50	0.95	7.50	200	0.63	28	325	65.23
CM4	1.50	4.50	1.17	11.25	133	0.78	3	145	29.10
CM4	1.50	4.50	1.17	11.25	133	0.78	3	146	29.30
CM4	1.50	4.50	1.17	11.25	133	0.78	3	149	29.90
CM4	1.50	4.50	1.17	11.25	133	0.78	7	207	41.55
CM4	1.50	4.50	1.17	11.25	133	0.78	7	210	42.15
CM4	1.50	4.50	1.17	11.25	133	0.78	7	209	41.95
CM4	1.50	4.50	1.17	11.25	133	0.78	28	312	62.62
CM4	1.50	4.50	1.17	11.25	133	0.78	28	310	62.22
CM4	1.50	4.50	1.17	11.25	133	0.78	28	315	63.22

Variables	Units	Minimum	Maximum	Median	Mean	Variance	Standard deviation
(b) *Characteristics of the specimens*							
X1	gm	0.00	11.25	5.63	5.63	18.08	4.25
X2	–	0.00	400.00	166.50	183.25	21,437.16	146.41
X3	–	0.30	0.78	0.55	0.55	0.03	0.18
X4	Days	3.00	28.00	7.00	12.67	123.66	11.12
Strength (Mpa)	N/mm^2	28.50	65.43	42.55	45.49	195.95	14.00

Where X1 = ZA (gm); X2 = C/ZA; X3 = W/C; X4 = Curing Days

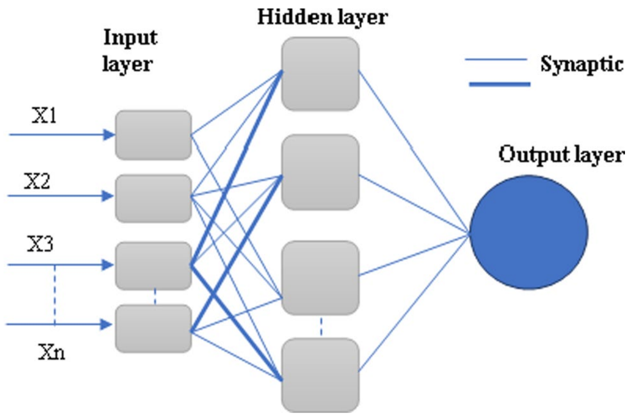


Fig. 2 General architecture of neural networks

to predict. The target values are compared with predicted values and this task is supervised by RBF & MLP models.

Figure 2 describes the architecture of neural network. In this first layer is input layers which include the predictors. The second layer (hidden layer) includes the units or ignored nodes. The value of each node is the function of the predictors, MLP, and RBF extracted required function value as per their requirement. The third (output) layer includes the reply or output of the model. MLP involved a second hidden layer in which each node is the function of first layer nodes. In this work zinc ash, cement to zinc ash ratio, water to cement ratio & curing days are the input parameters and compressive strength is the output parameter.

Principal component regression (PCR)

Generally, the Principal component Regression technique is adopted when there is a multicollinearity problem is arising in data for the linear regression. Multicollinearity causes estimation of least squares neutral values with big variance, so its values are so far from its true values and create more standard errors. In such a case, PCR reduces the standard values and gives accurate prediction values. PCR [37] is divided into three parts. In first step, principal component factors are extracted from the variables and in second step ordinary least square regression is performed between dependent parameters and the component which were extracted from the first step. The following Eq. (2) is the basic regression equation for the PCR model [38].

$$Y = BX + e \tag{2}$$

where Y = Dependent variables, X = Independent Variables, B = regression coefficient and e = error or residuals. In this work, Zinc Ash, Cement to zinc ash ratio, water to cement ratio and curing days are the input parameters and compressive strength is the output parameter.

Results and discussion

In this section, the experimental results are compared with the ANCOVA, NN, and PCR models prediction. These results showed that ZnO nano-particles enhance the compressive strength of the cement mortar significantly, the detailed discussion about the result is given below.

ANCOVA model

In Table 4, output parameters of the ANCOVA model are given. Using the Backward variables selection method, 4 variables have been retained in the model. Given the R^2, 99.40% of the variability of the dependent variable Strength (Mpa) is explained by the 4 explanatory variables. Given the p value of the F statistic computed in the ANOVA table, and given the significant level of 5%, the information brought by the explanatory variables is significantly better than what a basic mean would bring. Form Table 4(a), the ANCOVA model R^2 value is 0.9994. It means all variables correlated and significant for the prediction of the strength. As this value is closer to 1, the model is the best-fitted model. From the analysis of variance in Table 4(b) F value < 0.0001, it shows that all independent variables in the model are significant. Abhijit Chatterjee et al. [32] and Okan et al. [39] were also reported similar types of results.

Figure 3 shows the results of ANCOVA models in the graphical format. Figure 3a gives the value of $R^2 = 0.9994$ of predicted value and the observed value of the ANCOVA model. Figure 3b and Fig. 3c give the standard residue of the training and validation set, the value of the standard error is between − 1.4 and 2.1 for active data and − 2 to 2 for validation data for the ANCOVA.

Neural network model

For research work, 36 specimens were cast. Out of 36 the 28 specimens (77.8%) were considered as training specimens and 8 specimens (22.2%) were considered as testing purposes. The summary of the model processing is given in Table 5(a) and Table 5(b) shows the network information for the model. Results of model summary are displayed in Table 5(c) and the importance of the variables shows in Table 5(d). The architecture of the neural network model is shown in Fig. 4a. Figure 4b shows the plot of predicted vs observed values in this value for R^2 is 0.999 which shows the model best fitted. Figure 4c shows the residuals of the NN model which has a range between − 0.7 to 1. The obtained results in research work are similar to khademi et al. [9] and Sudarshan et al. [4]. As residues are less, so it is suggested that the model predicts the accurate values. This model also

Table 4 Output of ANCOVA

Statistic	Training set	Validation set
(a) *Goodness of fit statistics*		
Observations	25	11
Sum of weights	25	11
DF	19	5
R^2	0.9996	0.968
Adjusted R^2		**0.9994**
MSE	0.105	0.319
RMSE	0.324	0.565
MAPE	0.589	0.769
DW	2.250	
Cp	6.000	
AIC	−51.232	
SBC	−43.919	
PC	0.001	

Source	DF	Sum of squares	Mean squares	F	Pr > F
(b) *Analysis of variance*					
Model	5	4500.22	900.04	8580.98	**< 0.0001**
Error	19	1.99	0.10		
Corrected total	24	4502.22			

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
(c) *Model parameter*						
Intercept	−24.32	4.51	−5.39	**< 0.0001**	−33.76	−14.87
X1	−12.21	0.65	−18.90		−13.56	−10.86
X2	0.00	0.00	−4.25		0.00	0.00
X3	288.41	15.13	19.06		256.74	320.08
X4-3	−33.33	0.17	−192.41		−33.69	−32.97
X4-7	−20.93	0.14	−153.92		−21.21	−20.64
X4-28	0.00	0.00				

(d) Model equation

Strength (Mpa) = −24.32–12.21 × X1-3.061E-03 × X2 + 288.41 × X3-33.33 × X4-3–20.93 × X4-7

gives normalizes importance to each variable. The validation of the neural network models is its residuals as from Fig. 4b and c is very minimum means the prediction of the models is very accurate.

Principal component regression model

Figure 5a shows the scree plot for the PCR model. It shows that the model describes 50% of the variability, so it is possible to present variable on the one axis. Table 6 provides the information of output for the model of PCR. From Table 6(a) and Fig. 5b the goodness of the fit statistics, the value of R^2 is 0. 944, so that the PCR model is best fitted. The values of the standard residue of active and validation data are shown in Fig. 5b and c and the range of residue for active data is between − 1.17 and 1.8 and validation data is − 1.2 to 1.6. So, the prediction of the PCR models also gives accurate values. The same types of results also observed by Islam et al. [6] in their work. PCR models provide the equation given in Table 6(d) for the prediction of the compressive strength of mortar, this equation represents the 93.2% of the variability.

Table 7(a) shows the overall comparison between compressive strength by actual experimental testing and compressive strength predicted by different models. Table 7(a) and Fig. 6a display the compressive strength of all mixers enhances with ZnO nano-particles addition continue up to 0.5% in cement, later on, the strength of cement mortar is decreased. Table 7(b) shows the comparison of all models, in that R^2 and minimum and maximum residues are compared, the values of R^2 are very closer to 1 for each model but from this, it is not clear that which model is best fitted but with

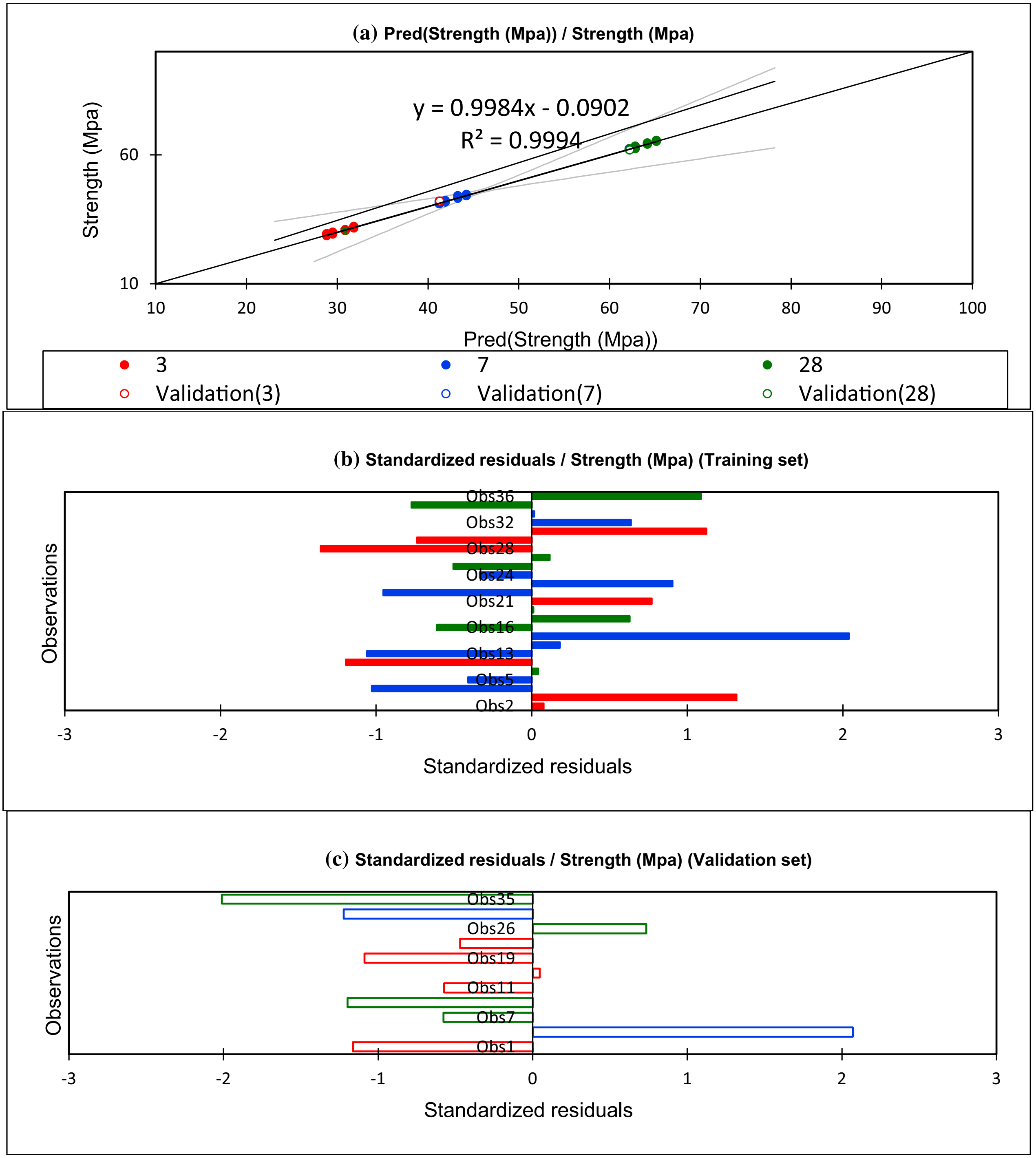


Fig. 3 Graphical results of ANCOVA models

the help of residuals plot given in Fig. 6b, it is possible to suggest the best model for the prediction of the compressive strength of the mortar.

Out of three models, the Neural Network produces the lesser value of the residue that means it is the best model for the prediction of the strength of cement mortar. It has minimum residue values as – 0.7 and 1. Figure 6b shows the comparison of overall performance by the models. This indicates that all models give the optimum response at 0.5% of addition afterwards it shows declination in the results of the compressive strength of the mortar. This is directly validated the outcomes of the research. The decreases in the strength of mortar may be causes due to ZnO nano-particles formed the crystalline layer of $CaZn_2(OH)_2 \cdot 2H_20$ around the cement

Table 5 Output for NN model

		N	Percent
(a) *Case processing summary*			
Sample			
Training		28	77.8
Testing		8	22.2
Valid		36	100.0
Excluded		0	
Total		36	
(b) *Network information*			
Input layer	Factors	1	ZA (gm)
		2	C/ZA
		3	Water (Kg)
		4	W/C
	Covariates	1	Age (days)
	Number of units[a]	17	
	Rescaling method for covariates	Standardized	
Hidden layers	Number of hidden layers	1	
	Number of units in hidden layer 1[a]	2	
	Activation function	Hyperbolic tangent	
Output layer	Dependent variables	1	Strength (Mpa)
	Number of units	1	
	Rescaling method for scale dependents	Standardized	
	Activation function	Identity	
	Error function	Sum of Squares	
a. Excluding the bias unit			
(c) *Model summary*			
Training			
Sum of squares error			.010
Relative error			.001
Stopping rule used			Training error ratio criterion (.001) achieved
Training time			0:00:00.01
Testing			
Sum of squares error			.007
Relative rrror			.001
Dependent variable: strength (Mpa)			

	Importance	Normalized importance (%)
(d) *Independent variable importance*		
ZA (gm)	.138	27.7
C/ZA	.107	21.5
Water (Kg)	.152	30.6
W/C	.106	21.4
Age (days)	.497	100.0

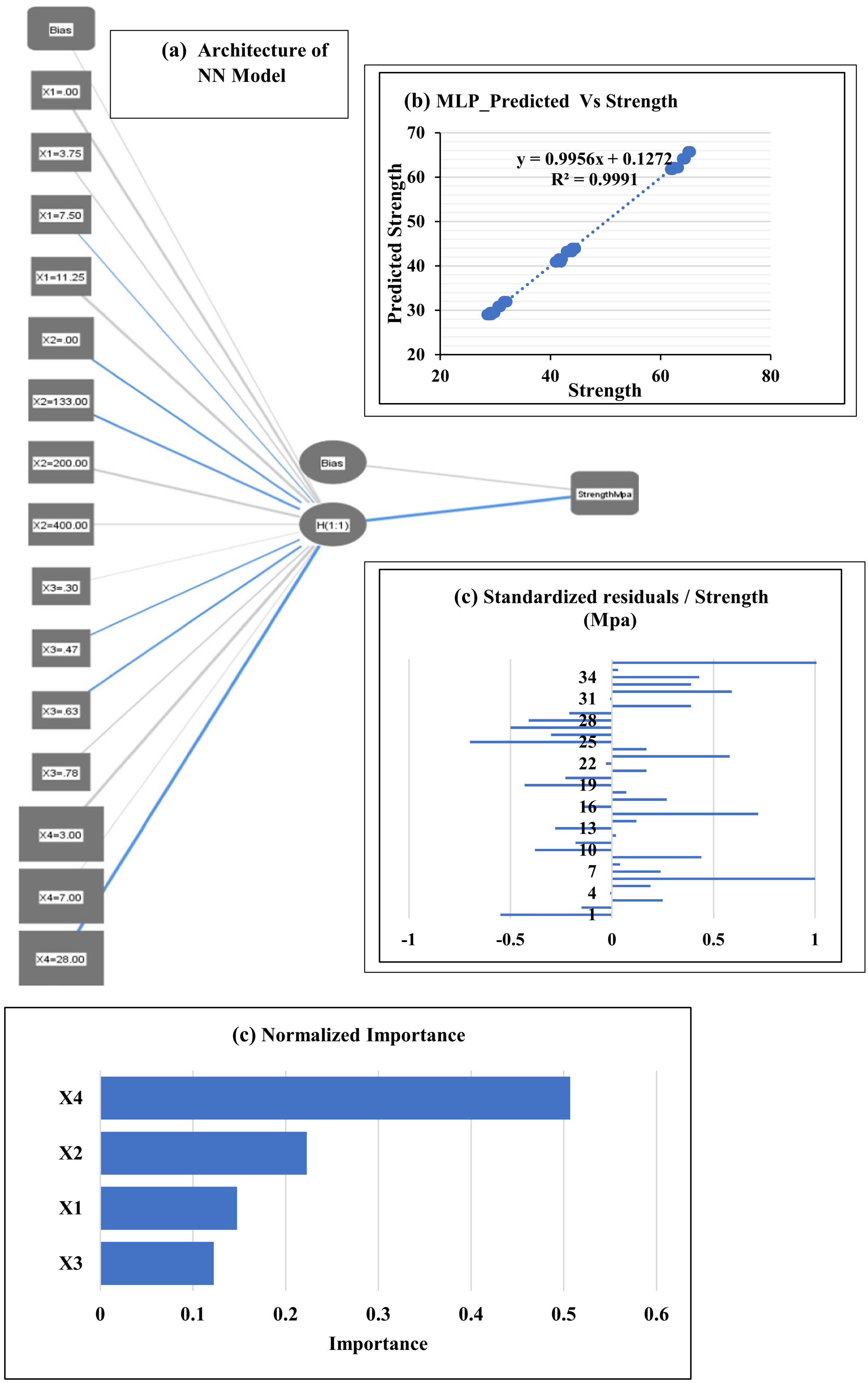


Fig. 4 Graphical outputs of the NN model

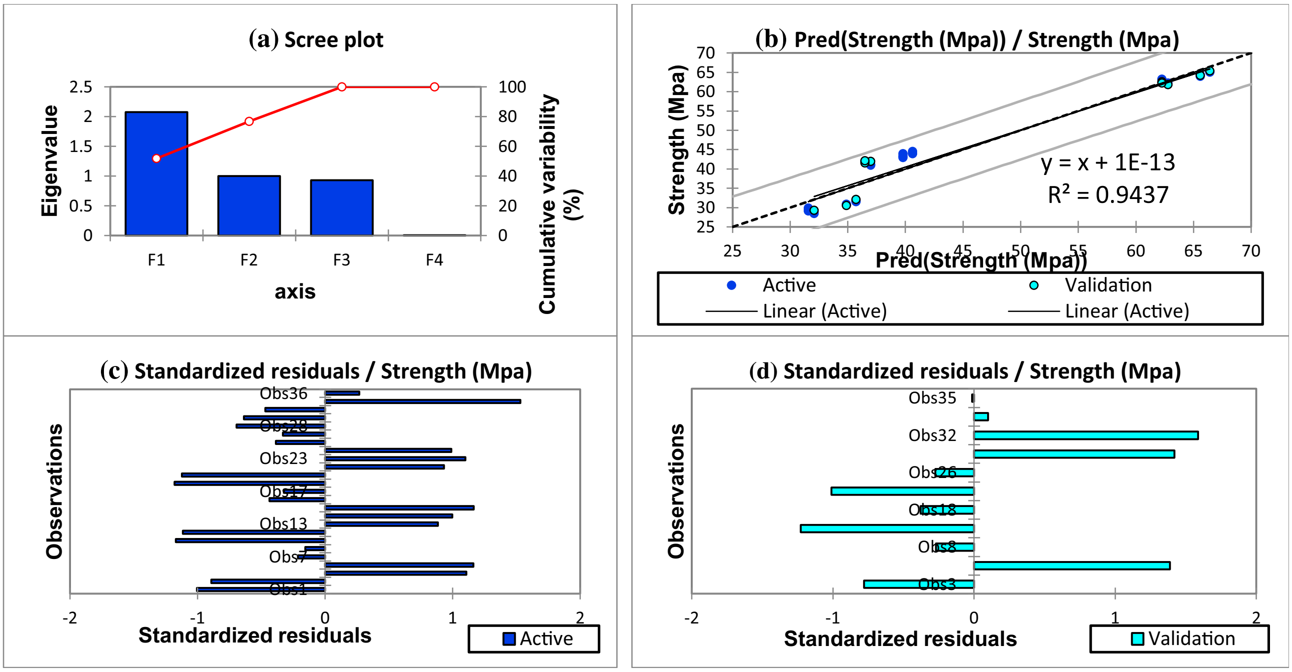


Fig. 5 Graphical representation of output of PCR model

particles. As per the available literature, some of reported that the analysis of X-ray diffraction (XRD) of calcium zinc hydrate is formed with ZnO nano-particles which restrict the hydration reaction and result in the formation of fewer hydrates and ultimately it decreases the compressive strength of the mortar. The similar types of results were reported by Riahi et al. [40] Kantharia et al. [41] and Arefi et al. [42].

Conclusions

The outcomes of the experimentation show that mortars containing ZnO nano-particles have expressively higher strength as compared with mortar without the ZnO. The optimum % of the addition of ZnO nano-particles is 0.5%. To validate and prediction of the experimental results, three different mathematical modelings reported. These three models based on Analysis of variance, Neural Network, and Principal Component Regression. Thirty-six standard specimens of cement paste with nanomaterials were casted. The compressive strength is considered as a function of the zinc oxide nano-particles, cement to zinc oxide ratio, water to cement ratio, and curing days. It is concluded that the neural network (NN) model is the best fitted and more accurate model than other models. Principal component regression (PCR) predicts an accurate value of the compressive strength as compared to the analysis of variance (ANCOVA) model. Although the R^2 value of the ANCOVA model is better than the PCR model, the residuals of the ANCOVA model are more than the PCR model. This shows that PCR gives accurate and better prediction than ANCOVA. In all NN and PCR models can be confidently customized to the estimation of the compressive strength of cement mortar instead of vast and costly methods. The results of NN and PCR models also helpful for material selection and its mixed design process.

Table 6 Outputs of PCR model

(a) The goodness of fit statistics

Observations = 25
Sum of weights = 25
DF = 25
R^2 = 0.944
Adjusted R^2 = 0.932
MSE = 12.72
RMSE = 3.566
MAPE = 7.672
DW = 1.311
Cp = 5.000
AIC = 67.996
SBC = 74.090
PC = 0.084

Source	DF	Sum of squares	Mean squares	*F*	Pr > *F*
(b) *Analysis of variance*					
Model	4	4265.67	1066.417	83.85	< 0.0001
Error	20	254.352	12.718		
Corrected Total	24	4520.02			

Source	Value	Standard error	*t*	Pr > |*t*|	Lower bound (95%)	Upper bound (95%)
(c) *Model parameters for the input variables*						
Intercept	− 104.47	1798.5	− 0.06	0.95	− 3856.09	3647.14
X1	− 18.90	10.46	− 1.81	0.09	− 40.71	2.92
X2	0.00	0.01	− 0.49	0.63	− 0.02	0.01
X3	442.93	245.50	1.80	0.09	− 69.18	955.04
X4	1.23	0.07	17.86	< 0.0001	1.08	1.37

(d) *Equation of the model*

Strength = − 104.47–18.90 × X1-4.1E-03 × X2 + 442.93 × X3 + 1.233 × X4

Table 7 Strength comparison of the experimentation and models

% ADD	Experimental Strength	ANCOVA		NN		PCR	
		Prediction	Resid	Prediction	Residual	Prediction	Resid
(a) *Model output summary*							
0.00	28.50	28.88	−0.38	29.05	−0.55	32.09	−3.59
0.00	28.90	28.88	0.03	29.05	−0.15	32.09	−3.19
0.00	29.30	28.88	0.43	29.05	0.25	32.09	−2.78
0.00	40.94	41.28	−0.33	40.95	−0.01	37.00	3.95
0.00	41.14	41.28	−0.13	40.95	0.19	37.00	4.15
0.00	41.95	41.28	0.67	40.95	1.00	37.00	4.95
0.00	62.02	62.21	−0.19	61.78	0.24	62.78	−0.76
0.00	61.82	62.21	−0.39	61.78	0.04	62.78	−0.96
0.00	62.22	62.21	0.01	61.78	0.44	62.78	−0.56
0.25	30.51	30.89	−0.39	30.89	−0.38	34.89	−4.38
0.25	30.71	30.89	−0.19	30.89	−0.18	34.89	−4.18
0.25	30.91	30.89	0.02	30.89	0.02	34.89	−3.98
0.25	42.95	43.29	−0.34	43.23	−0.28	39.80	3.15
0.25	43.35	43.29	0.06	43.23	0.12	39.80	3.55
0.25	43.95	43.29	0.66	43.23	0.72	39.80	4.16
0.25	64.03	64.22	−0.20	64.16	−0.14	65.58	−1.55
0.25	64.43	64.22	0.20	64.16	0.27	65.58	−1.15
0.25	64.23	64.22	0.00	64.16	0.07	65.58	−1.35
0.50	31.51	31.86	−0.35	31.94	−0.43	35.72	−4.21
0.50	31.71	31.86	−0.15	31.94	−0.23	35.72	−4.01
0.50	32.11	31.86	0.25	31.94	0.17	35.72	−3.61
0.50	43.95	44.26	−0.31	43.98	−0.03	40.63	3.32
0.50	44.56	44.26	0.29	43.98	0.58	40.63	3.93
0.50	44.16	44.26	−0.11	43.98	0.17	40.63	3.53
0.50	65.03	65.19	−0.16	65.73	−0.70	66.41	−1.38
0.50	65.43	65.19	0.24	65.73	−0.30	66.41	−0.98
0.50	65.23	65.19	0.04	65.73	−0.50	66.41	−1.18
0.75	29.10	29.54	−0.44	29.51	−0.41	31.58	−2.47
0.75	29.30	29.54	−0.24	29.51	−0.21	31.58	−2.27
0.75	29.91	29.54	0.36	29.51	0.39	31.58	−1.67
0.75	41.55	41.94	−0.40	41.56	−0.01	36.49	5.06
0.75	42.15	41.94	0.21	41.56	0.59	36.49	5.66
0.75	41.95	41.94	0.01	41.56	0.39	36.49	5.46
0.75	62.62	62.87	−0.25	62.19	0.43	62.27	0.35
0.75	62.22	62.87	−0.65	62.19	0.03	62.27	−0.05
0.75	63.22	62.87	0.35	62.19	1.03	62.27	0.96

Model	R^2	Minimum residue	Maximum residue
(b) *Models output summary*			
ANCOVA	0.9994	−1.4	2.1
NN	0.9991	−0.7	1
PCR	0.944	−1.17	1.8

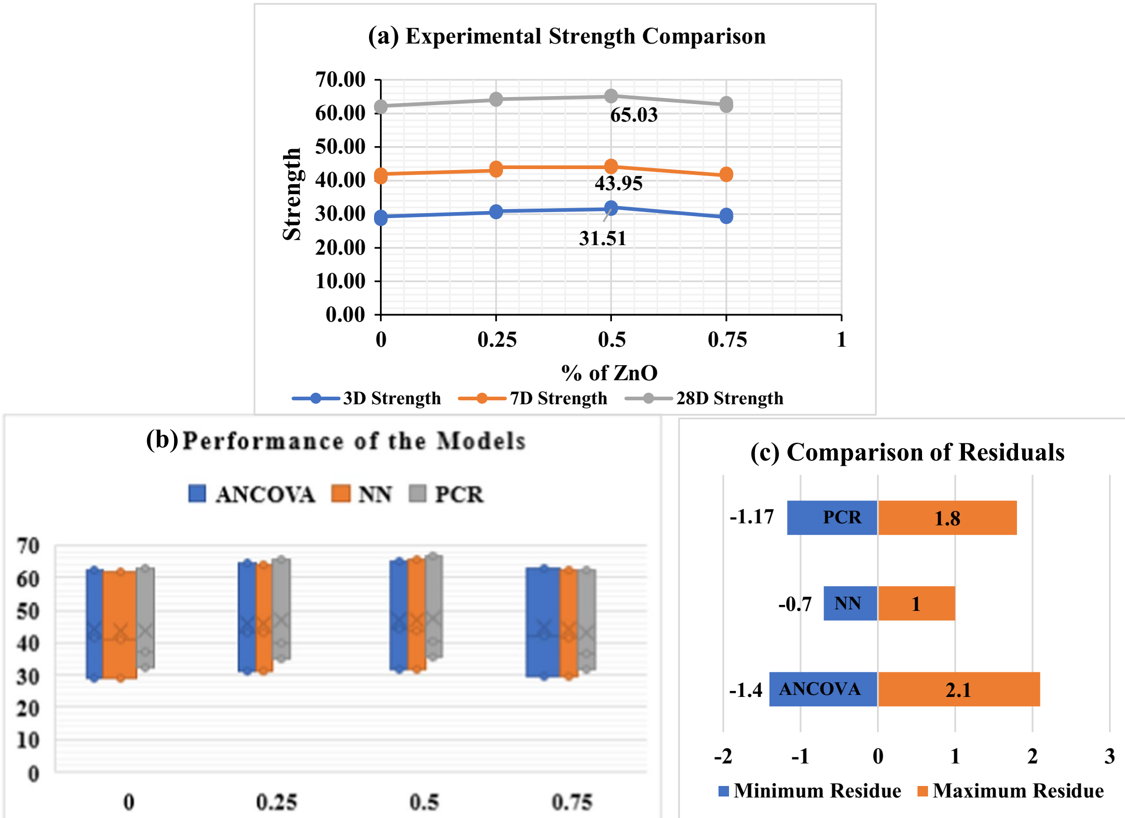


Fig. 6 Comparison of overall performance of the mixes and models

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. Abdi H, Chin WW, Vinzi VE et al (2013) New perspectives in partial least squares and related methods. Springer Proc Math Stat 56:65–78. https://doi.org/10.1007/978-1-4614-8283-3
2. Borucka-Lipska J (2016) Acid resistance, water permeability and chloride penetrability of concrete containing crushed basalt as aggregates. Neural Comput Appl 31:137–150. https://doi.org/10.1007/s00521-017-3007-7
3. Asteris PG, Ashrafian A, Rezaie-Balf M (2019) Prediction of the compressive strength of self-compacting concrete using surrogate models. Comput Concrete 24:137–150. https://doi.org/10.12989/cac.2019.24.2.137
4. Raman SN, Salam A, Jumaat MZ (2016) Modeling of compressive strength for self-consolidating high-strength concrete incorporating palm oil fuel ash. Materials 9:1–13. https://doi.org/10.3390/ma9050396
5. Al-Khatib MI, Al-Martini S (2019) Predicting the rheology of self-consolidating concrete under hot weather. Proc Inst Civil Eng Constr Mater 172:235–245. https://doi.org/10.1680/jcoma.16.00055
6. Islam MS, Alam S (2013) Principal Component and Multiple Regression Analysis for Steel Fiber Reinforced Concrete (SFRC) Beams. 7:303–317. https://doi.org/10.1007/s40069-013-0059-7
7. Manoj A, Babu Narayan KS (2019) Proper orthogonal decomposition for generation of organized data in concrete technology. Ukieri concrete Congress, concrete. The Global Builder
8. Naizot T, Auda Y, Dervieux A et al (2004) A new multi-temporal analysis of satellite images using principal componenet analysis: a case studt using landsat TM images of the Camargue, France. Int J Remote Sens. https://doi.org/10.1080/01431160310001642313
9. Khademi F, Akbari M, Mohammadmehdi S, Nikoo M (2017) Multiple linear regression, artificial neural network, and fuzzy logic prediction of 28 days compressive strength of concrete. Front Struct Civ Eng 11:90–99. https://doi.org/10.1007/s11709-016-0363-9
10. Douma OB, Boukhatem B, Ghrici M (2014) Prediction compressive strength of self-compacting concrete containing fly ash using fuzzy logic inference system. Int J Civil Environ Struct Constr Arch Eng 8:1285–1289
11. Cook R, Lapeyre J, Ma H, Kumar A (2019) Prediction of compressive strength of concrete: critical comparison of performance of a hybrid machine learning model with standalone models. J Mater Civ Eng 31:1–15. https://doi.org/10.1061/(ASCE)MT.1943-5533.0002902
12. Alsanusi S, Bentaher L, Salem A, Loubna B (2015) Prediction of compressive strength of concrete from early age test result using design of experiments (RSM). Int J Civil Environ Struct Constr Arch Eng 9:1559–1563. https://doi.org/10.13140/RG.2.1.3270.7684

13. Moutassem F, Chidiac SE (2015) Assessment of concrete compressive strength prediction models. KSCE J Civ Eng 00:1–16. https://doi.org/10.1007/s12205-015-0722-4
14. Sadowski Ł, Nikoo M, Nikoo M (2015) Principal component analysis combined with a self organization feature map to determine the pull-off adhesion between concrete layers. Constr Build Mater J 78:386–396. https://doi.org/10.1016/j.conbuildmat.2015.01.034
15. Marangu JM (2020) Prediction of compressive strength of calcined clay based cement mortars using support vector machine and artificial neural network techniques. J Sustain Constr Mater Technol 5:392–398. https://doi.org/10.29187/jscmt.2019.43
16. Eskandari-Naddaf H, Kazemi R (2017) ANN prediction of cement mortar compressive strength, influence of cement strength class. Constr Build Mater 138:1–11. https://doi.org/10.1016/j.conbuildmat.2017.01.132
17. Haecker CJ, Garboczi EJ, Bullard JW et al (2005) Modeling the linear elastic properties of Portland cement paste. Cem Concr Res. https://doi.org/10.1016/j.cemconres.2005.05.001
18. Verma K, Ram S, Verma A (2019) Prediction of compressive strength of cement mortar in normal and aggressive environment using artificial neural network. Int J Appl Eng Res 14:3435–3441
19. Eskandari H, Gharouni M, Mahdi M (2016) Prediction of mortar compressive strengths for different cement grades in the vicinity of sodium chloride using ANN. Proc Eng 150:2185–2192. https://doi.org/10.1016/j.proeng.2016.07.262
20. Shaqadan AA, AL-Rawashdeh, (2018) Prediction of concrete mix compressive strength using statisticallearning models. J Eng Sci Technol 13:1916–1925
21. Bidkar KL, Jadhao PD (2019) Prediction of strength of remixed concrete by application of orthogonal decomposition, neural analysis and regression analysis. Open Eng 9:434–443. https://doi.org/10.1515/eng-2019-0053
22. Ghanbari A, Karihaloo BL (2009) Prediction of the plastic viscosity of self-compacting steel fibre reinforced concrete. Cem Concr Res 39:1209–1216. https://doi.org/10.1016/j.cemconres.2009.08.018
23. Nagwani NK, Deo SV (2014) Estimating the concrete compressive strength using hard clustering and fuzzy clustering based regression techniques. Sci World J. https://doi.org/10.1155/2014/381549
24. Chen H, Qian C, Liang C, Kang W (2018) An approach for predicting the compressive strength of cement-based materials exposed to sulfate attack. PLoS ONE. https://doi.org/10.1371/journal.pone.0191370
25. Belalia Douma O, Boukhatem B, Ghrici M, Tagnit-Hamou A (2017) Prediction of properties of self-compacting concrete containing fly ash using artificial neural network. Neural Comput Appl 28:707–718. https://doi.org/10.1007/s00521-016-2368-7
26. Indian Standard (1991) IS:1489 (Part 1):1991 Portland Pozzolona Cement Specification. In: Bureau of Indian Standards, New Delhi, THIRD. Bureau of Indian Standards, INDIA, p 57
27. Indian Standard (2016) IS:383 (2016) Coarse and fine aggregate for concrete-specification. In: Bureau of Indian Standards, New Delhi
28. Cullity BD (1967) Elements of X-ray diffraction, 3 rd. Addison-Wesley, New York
29. Khoshhesab ZM, Sarfaraz M, Asadabad MA (2011) Preparation of ZnO nanostructures by chemical precipitation method. Synth React Inorg Met-Org Nano-Met Chem 41:814–819. https://doi.org/10.1080/15533174.2011.591308
30. Zhou J, Zhao F, Wang Y et al (2007) Size-controlled synthesis of ZnO nanoparticles and their photoluminescence properties. J Lumin 122–123:195–197. https://doi.org/10.1016/j.jlumin.2006.01.089
31. Indian Standard (2005) IS: 4031 (Part 6)-1988 Determination of compressive strength of hydraulic cement other than masonry cement. In: Bureau of Indian Standards, New Delhi. pp 1–3
32. Chatterjee A, Das D (2013) Assessing flow response of self-compacting mortar by Taguchi method and ANOVA interaction. Mater Res 16:1084–1091. https://doi.org/10.1590/S1516-14392013005000083
33. Lin CJ, Wu NJ (2021) An ann model for predicting the compressive strength of concrete. Appl Sci (Switzerland). https://doi.org/10.3390/app11093798
34. Tang CW (2006) Using radial basis function neural networks to model torsional strength of reinforced concrete beams. Comput Concrete 3:335–355. https://doi.org/10.12989/cac.2006.3.5.335
35. Mazloom M (2013) Application of neural networks for predicting the workability of self-compacting concrete. J Sci Res Rep 2:429–442
36. Charhate S, Subhedar M, Adsul N (2018) Prediction of concrete properties using multiple linear regression and artificial neural network. J Soft Comput Civil Eng 2:27–38
37. Hameed MM, AlOmar MK, Baniya WJ, AlSaadi MA (2021) Incorporation of artificial neural network with principal component analysis and cross-validation technique to predict high-performance concrete compressive strength. Asian J Civil Eng. https://doi.org/10.1007/s42107-021-00362-3
38. Fadzillah NA, Rohman A, Rosman AS et al (2016) Differentiation of fatty acid composition of butter adulterated with lard using gas chromatography mass spectrometry combined with principal componenet analysis. Jurnal Teknologi. https://doi.org/10.11113/jt.v78.3818
39. Karahan O, Tanyildizi H, Atis CD (2008) An artificial neural network approach for prediction of long-term strength properties of steel fiber reinforced concrete containing fly ash. J Zhejiang Univ Sci A 9:1514–1523. https://doi.org/10.1631/jzus.A0720136
40. Riahi S, Nazari A (2011) Physical, mechanical and thermal properties of concrete in different curing media containing ZnO_2 nanoparticles. Energy Build 43:1977–1984
41. Kantharia M, Mishra P, Trivedi MK (2019) Strength of cement mortar using nano oxides : an experimental study. Int J Eng Adv Technol 8:294–299
42. Arefi MR, Rezaei-zarchi S (2012) Synthesis of zinc oxide nanoparticles and their effect on the compressive strength and setting time of self-compacted concrete paste as cementitious composites. Int J Mol Sci 13:1–12. https://doi.org/10.3390/ijms13044340