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## CIVIL & ENVIRONMENTAL ENGINEERING | RESEARCH ARTICLE

# Use of triangular membership function for prediction of compressive strength of concrete containing nanosilica

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**Abstract:** In this paper, application of fuzzy logic technique using triangular membership function for developing models for predicting compressive strength of concrete with partial replacement of cement with nanosilica has been carried out. For this, the data have been taken from various literatures and help in optimizing the constituents available and reducing cost and efforts in studying design to develop mixes by predefining suitable range for experimenting. The use of nanostructured materials in concrete can add many benefits that are directly related to the durability of various cementitious materials, besides the fact that it is possible to reduce the quantities of cement in the composite. Successful prediction by the model indicates that fuzzy logic could be a useful modelling tool for engineers and research scientists in the area of cement and concrete. Compressive strength values of concrete can be predicted in fuzzy logic models without attempting any experiments in a quite short period of time with tiny error rates.

**Subjects:** Composites; Civil, Environmental and Geotechnical Engineering; Concrete & Cement; Structural Engineering; Mathematics & Statistics for Engineers; Nanoscience & Nanotechnology

**Keywords:** Fuzzy Logic; Nanosilica; Concrete; Compressive strength; prediction; Triangular membership function; Modelling

### ABOUT THE AUTHOR

Sakshi Gupta is working as an assistant professor, Civil Engineering Department, ASET, Amity University, Manesar, Gurgaon, Haryana, India. Her areas of interest include the use of nanosilica in paste, mortar and concrete, its study of mechanical and durability properties, use of data mining techniques such as ANN and Fuzzy logic to correlate different properties of concrete and high-strength concrete, their performance and durability aspects, incorporating waste materials. In order to predict the effects of nanosilica on compressive strength values of concrete, models were carried out in fuzzy logic system. Successful prediction by the model indicates fuzzy logic could be a useful modelling tool for engineers and research scientists in the area of cement and concrete. Compressive strength values of concrete can be predicted without attempting any experiments in quite short period of time with tiny error rates. The present research work is one such effort towards attaining above goal.

### PUBLIC INTEREST STATEMENT

This work deals with the optimization of the constituents available and reducing cost and efforts in studying design to develop mixes by predefining suitable range for experimenting. This has been done using the Fuzzy Logic tool in MATLAB where the parameters have been chosen from different literatures which are used in the prediction of the compressive strength of concrete containing nanosilica. This will help to know the best possible use and the amount of replacement of nanosilica with cement in concrete and knowing the optimized percentage replacement for a high compressive strength of concrete. This will in turn reduce the cost of the structure when the concrete containing nanosilica is employed in construction work.

## 1. Introduction

Concrete being one of the oldest materials in the construction industry is a mixture of paste and aggregates. It is the most widely used construction material due to its flowability in most complicated forms and its strength development characteristics when it hardens.

The necessity of the cementitious materials in the construction industry is nowadays beyond any doubt; however, their variety of applications must not hide their complexity. They are indeed composite materials with truly multi-scale internal structures that keep evolving over centuries. With the onset of nanotechnology, it allows engineers and architects to use various materials in structural applications that were once impossible. Nanotechnology creates new prospects to improve the material properties for civil construction. Attracting civil engineers to adopt nanotechnology could enable them to provide pioneering elucidation to the complicated problems of construction today. It is well known that materials such as concrete, being the core elements of construction industry, could be developed using nanotechnology. Nanosilica is typically a highly effective pozzolanic material consisting of very fine vitreous particles approximately 1,000 times smaller than the average cement particles. nS has proven to be an excellent admixture for cement to improve strength and durability and decrease permeability (Aitcin, Hershey, & Pinsonneault, 1981; ARI News, 2007).

The present study was envisaged to develop a relationship between various input parameters and an output parameter, i.e. 28-day compressive strength, using triangular membership function in fuzzy logic technique. The objective was to use the triangular membership function for prediction of compressive strength of concrete containing nanosilica, with data obtained from literature (Gupta, 2014).

Over the last two decades, different data mining methods, such as the fuzzy logic and artificial neural network, have become popular and have been used by many researchers for a variety of engineering applications. In daily life, information obtained is used to understand the surroundings to imbibe new things and to make plans for the future. Over the years, the ability to reason has been developed on the basis of evidence available to achieve the required goals. To deal with the problem of uncertainty, the theory of probability had been established and successfully applied to many areas of engineering and technology. The principal catalyst for introducing fuzzy theory is to represent the uncertain concepts. It does not need to handle the laborious mathematical models but only need to set a simple controlling method based on the engineering experiences. It is convenient and easy to use fuzzy logic models for numerical experiments to review the effects of each variable on the mix proportions (Akkurt, Tayfur, & Can, 2004; Demir, 2005; Topcu & Saridemir, 2008; Ünal, Demir, & Uygunoğlu, 2007).

## 2. Fuzzy logic

The concept of “fuzzy set” was preliminarily introduced by Zadeh (1965), who pioneered the development of fuzzy logic (FL) replacing Aristotelian logic which has two possibilities only. FL concept provides a natural and atypical way of dealing with the problems in which the origin of imprecision/unreliability is the absence of sharply defined criteria rather than the presence of random variables (Demir, 2005; Sen, 1998). Herein, the uncertainties do not mean random, probabilistic and stochastic variations, all of which are based on the numerical data. Fuzzy set theory provides a methodical calculus to deal with such information linguistically. Fuzzy approach performs numerical computation using linguistic labels stimulated by membership functions. Therefore, Zadeh introduced linguistic variables as variables whose values are sentences in a natural or artificial language. Although FL was brought forward by Zadeh (1965), the fuzzy concepts and systems attracted attention after a real control application conducted by Mamdani and Assilian in the year 1975 (Demir, 2005).

A general fuzzy inference system (FIS) has basically four components:

- (1) Fuzzification
- (2) Fuzzy rule base
- (3) Fuzzy output engine
- (4) Defuzzification

In Fuzzification, each piece of input data is converted to degrees of membership by a lookup in one or more several membership functions. Fuzzy rule base includes rules that have all possible fuzzy relation between inputs and outputs. These rules are expressed in the IF-THEN format. There are primarily two type of rule base: (1) Sugeno type and (2) Mamdani type. Fuzzy inference engine takes into consideration all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to the corresponding outputs. There are essentially two kinds of inference operators: minimization (min) and product (prod). Defuzzification converts the resulting fuzzy outputs from the fuzzy inference engine to a number. There are many defuzzification methods such as weighted average (wtaver) or weighted sum (wtsum). In the present study, the fuzzy model used is of Mamdani fuzzy rule type and the prod method was employed because of its more precise result methodology. For the defuzzification in the fuzzy model, weighted average method has been applied (Akbulut, Hasiloglu, & Pamukcu, 2004; Bouzoubaa & Lachemi, 2001; Ho & Zhang, 2001; Jang & Sun, 1995; Passino, 1998; Takagi & Sugeno, 1985).

The key idea in FL is the allowance of partial belongings of any object to different subsets of the universal set instead of belonging to a single set totally. Partial belonging to set can be described numerically by a membership function which assumes values between 0 and 1 contain. All the available inputs to a parameter are used to form their respective membership functions assigning a membership value of 1 to the crisp input in the database. The base of all the membership functions has been chosen to be the entire range of values to ensure that no region is left out of the functions. For convenience, functions have been assigned names on the basis of values of nodal points for the functions.

The accuracy of the predictions of a network was quantified by the root mean squared error difference (RMSE), between the measured and the predicted values and mean absolute error (MAE).

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (actual - predicted)^2}$$

$$MAE = \frac{1}{N} \sum_{n=1}^N (actual - predicted)$$

### 3. Database

The database for the FIS models was collected from available literature on concrete containing nanosilica, as summarized in Table 1.

Thus, large varieties of data were collected and in total 32 data-sets have been used with the following input and output variables (Beigi, Javad, Lotfi, Sadeghi, & Iman, 2013; Givi, Rashid, Aziz, & Salleh, 2010; Heidari & Tavakoli, 2013; Li, 2004; Li, Xiao, Yuan, Ou, & Ou, 2004; Ji, 2005; Jo, Kim, Tae, & Park, 2007; Nili, Ehsani, & Shabani, 2010; Said, Zeidan, Bassuoni, & Tian, 2012; Zhang & Li, 2010). The basic parameters considered in this study were cement content, fine aggregate content, coarse aggregate content, nanosilica content, diameter of nanosilica, water-to-binder ratio and superplasticizer dosage. The exclusion of one or more of concrete properties in some studies and the ambiguity of mixtures proportions and testing methods in others was responsible for setting the criteria for identification of data. The successful model to predict the 28-day compressive strength depends upon the magnitude of the training data using Triangular and Gaussian membership functions. The predicted results were compared with the values obtained experimentally.

**Table 1. Details of data used in modelling**

S. No.	Cement (kg/m <sup>3</sup> )	FA (kg/m <sup>3</sup> )	CA (kg/m <sup>3</sup> )	W/b ratio	SP (kg/m <sup>3</sup> )	nS (kg/m <sup>3</sup> )	D (nm)	28-d CS (MPa)	Researcher (Year)
1	396.6	826	722	0.37	7	16.5	15	75.2	Beigi et al. (2013)
2	380	826	722	0.35	7	33	15	86.1	
3	363.5	826	722	0.33	7	49.6	15	85.4	
4	318.4	840	1040	0.5	2.71	1.6	15	36.8	Heidari and Tavakoli (2013)
5	316.8	840	1040	0.5	4.75	3.2	15	40.2	
6	390	783	1175	0.4	1.78	23.4	35	70	Said et al. (2012)
7	390	774	1162	0.4	3.56	46.8	35	76	
8	390	769	1154	0.4	1.27	23.4	35	60	
9	390	762	1143	0.4	2.54	46.8	35	66	
10	356.4	650	1260	0.42	5.4	3.6	10	66.36	Zhang and Li (2010)
11	349.2	650	1260	0.42	7.2	10.8	10	61.16	
12	447.75	492	1148	0.4	0	2.25	80	39.2	Givi et al. (2010)
13	445.5	492	1148	0.4	0	4.5	80	40.3	
14	443.25	492	1148	0.4	0	6.75	80	41.2	
15	441	492	1148	0.4	0	9	80	38.1	
16	447.75	492	1148	0.4	0	2.25	15	42.7	
17	445.5	492	1148	0.4	0	4.5	15	43.6	
18	443.25	492	1148	0.4	0	6.75	15	42.9	
19	441	492	1148	0.4	0	9	15	39.7	
20	394	811	915	0.45	1.68	12	15	53.8	
21	388	811	915	0.45	2.32	24	15	56.5	
22	382	811	915	0.45	3	36	15	60	Nili et al. (2010)
23	247.5	625	0	0.5	4.5	7.5	40	54.3	Jo et al. (2007)
24	240.6	626	0	0.5	5.8	14.4	40	61.9	
25	241.8	627	0	0.5	7	23.2	40	68.2	
26	227.7	628	0	0.5	7.5	27.3	40	68.8	
27	370	647	1088	0.49	13.5	13.9	15	44	Ji (2005)
28	568.36	1757.8	0	0.5	8.85	17.5	15	32.9	Li et al. (2004)
29	556.64	1757.8	0	0.5	14.58	29.3	15	33.8	
30	527.34	1757.8	0	0.5	29.3	58.59	15	36.4	
31	556.64	1757.8	0	0.5	10.28	11.71	15	35.4	
32	480	647	1140	0.28	10	20	10	75.8	Li (2004)

Note: All types of SP have been considered to be same.

The variables used are as follows:

- Cement
- FA (fine aggregates)
- CA (coarse aggregates)
- W/b ratio
- SP (superplasticizer)
- nS (nanosilica)
- Diameter of nanosilica

The ranges of various input and output parameters used in FL technique are given in Table 2.

**Table 2. Input and output variables**

Variables	Parameter	Abbreviation	Database range	
			Minimum	Maximum
Input	Cement (kg/m <sup>3</sup> )	Cement	227.70	568.36
	Fine aggregate (kg/m <sup>3</sup> )	FA	492	1757.80
	Coarse aggregate (kg/m <sup>3</sup> )	CA	0	1260
	Water to binder ratio	W/b ratio	0.28	0.50
	Superplasticizer (kg/m <sup>3</sup> )	SP	0	29.30
	Nanosilica (kg/m <sup>3</sup> )	nS	1.60	58.59
	Diameter of nanosilica (nm)	D	10	80
Output	28-day compressive strength (MPa)	28-d CS	32.90	86.10

#### 4. Application of FL technique

Fuzzy modelling is a system identification task involving two phases: structure identification and parameter prediction. Structure identification consists of the issues such as selecting the relevant input variables, choosing a specific type of FIS, determining the number of fuzzy rules and their antecedents and consequents, and determining the type and number of membership functions. Parameter prediction is the determination of aimed values response to evident input values of embodied model. For this aim, in the study, 32 data results were used in the processes of Mamdani-type Fuzzy inference model in the FL system. Training meant to present the network with the experimental data and have it learn, or modify its weights, such that it correctly reproduces the strength behaviour of mix. However, training the network successfully required many choices and training experiences. It was observed that an individual’s membership in a fuzzy set admit some uncertainty and hence, it is said that its membership is a matter of degree of association.

#### 5. Results and discussions

The various membership functions for different parameters are presented in Figure 1 (a–d) and the ruler view is shown in Figure 2. The if–then rule base is applied in this case. Membership functions are the building blocks of the fuzzy set theory. Membership functions were first prepared for each input and output data depending upon their ranges and variability. According to the importance, the shape of the membership function here was decided to be triangular. Figure 3 gives the surface diagrams between various parameters. The Rule Viewer is used as a diagnostic; it can show, for example, which rules are active, or how individual membership function shapes are influencing the results to predict the model. The Surface Viewer in the form of surface diagrams is used to display the dependency of one of the outputs on any one or two of the inputs—that is, it generates and plots an output surface map for the system. The MATLAB FL toolbox is used in the modelling where it generates a plot of the output surface of a given FIS using the first two inputs and the output. To compare the performance of models, graph between actual and predicted values is plotted and is represented by Figure 4. Table 3 gives the actual and the predicted values of the 28-day compressive strength of concrete containing different percentage replacement of cement with nanosilica. Table 4 gives the statistical parameters for the FL model, i.e. the correlation coefficient (CC), the root mean squared error (RMSE) and the mean absolute error (MAE). The best measure of model fit depends on the researcher’s objectives, and more than one are often useful. The RMSE will always be larger or equal to MAE; the greater the difference between them, the greater the variance in the individual errors in the data-set. Since the correlation coefficient of the given set of data is 0.968581, i.e. it is near to 1, it indicates that the variables actual and predicted 28-day compressive strength have a positive correlation. This means that if one variable moves a given amount, the second moves proportionally in the same direction, with the strength of the correlation growing as the number approaches one. Minimizing the MAE is the key criterion of the development of the FL model and getting it close to zero which is an ideal condition, practically never possible. The MAE is representing the difference between the actual and the predicted observations of the model and is used to determine the extent to which the model fits the data and whether the removal or some

**Table 3. Actual and predicted values of 28-day compressive strength**

S. No.	Actual 28-d CS (MPa)	Predicted 28-d CS (MPa)
1	75.2	72.5
2	86.1	77.6
3	85.4	76.6
4	36.8	42.8
5	40.2	52.9
6	70	65.4
7	76	63.2
8	60	58.7
9	66	64.6
10	66.36	63
11	61.16	61.3
12	39.2	43.1
13	40.3	46.2
14	41.2	50.1
15	38.1	44.9
16	42.7	46.3
17	43.6	44.1
18	42.9	53.9
19	39.7	43.6
20	53.8	56.9
21	56.5	58
22	60	59.4
23	54.3	58.9
24	61.9	60.3
25	68.2	63.9
26	68.8	65
27	44	44.6
28	32.9	38
29	33.8	39.3
30	36.4	40.1
31	35.4	39.5
32	75.8	70.3

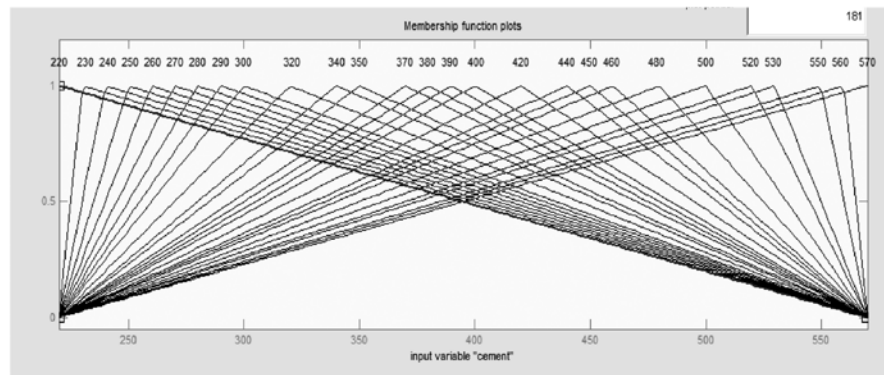
**Table 4. Statistical parameters for the fuzzy logic model**

S. No.	Statistical parameter	Value
1	Correlation coefficient (CC)	0.968581
2	Mean absolute error (MAE)	1.00875
3	Root mean square error (RMSE)	5.769963

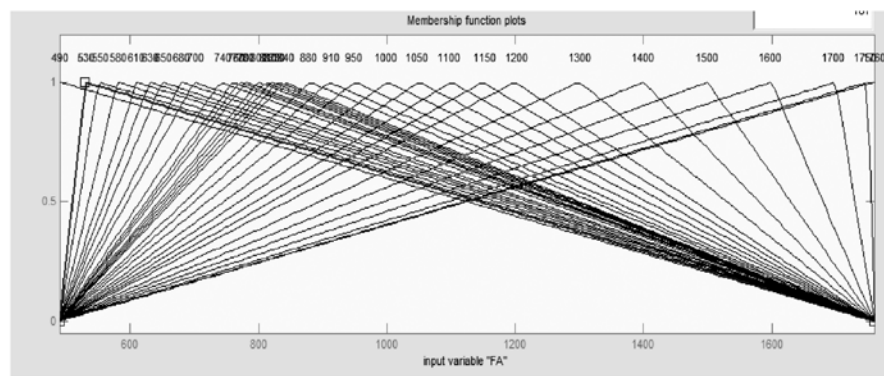
explanatory variables, simplifying the model, is possible without significantly harming the model's predictive ability. Compared to the similar MAE, RMSE amplifies and severely punishes large errors and can be used to distinguish model performance. The values of MAE and RMSE were found out to be 1.008750 and 5.769963, respectively. The two biggest advantages of MAE or RMSE are that they provide a quadratic loss function and that they are also measures of the uncertainty in forecasting. Lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response.



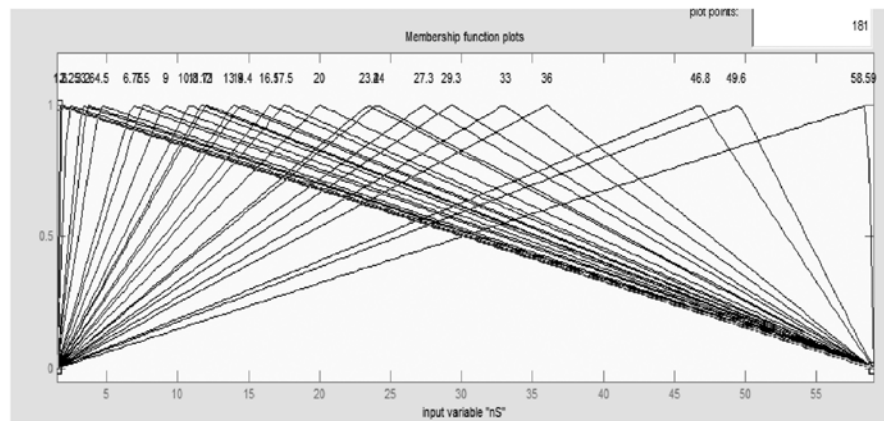
**Figure 1. Membership functions for inputs and output (a) cement (b) fine aggregates (c) nanosilica (nS) (d) 28-day compressive strength.**



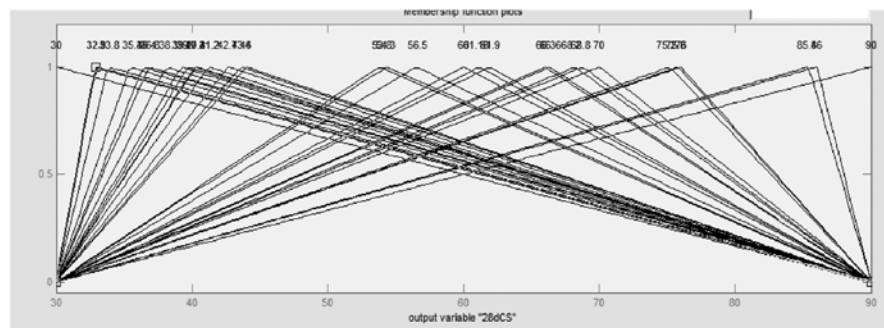
**(a) Cement**



**(b) Fine aggregates**



**(c) nS**



**(d) 28-days Compressive strength**

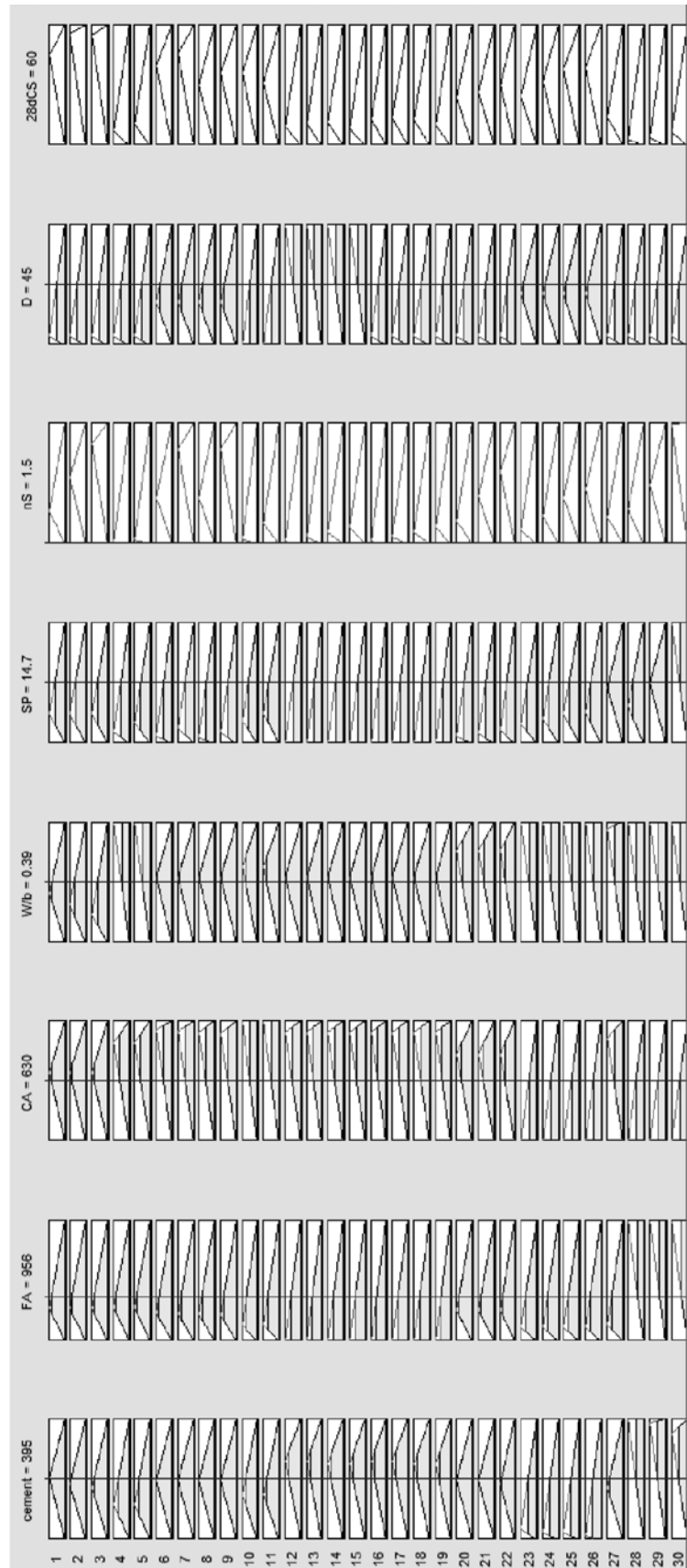
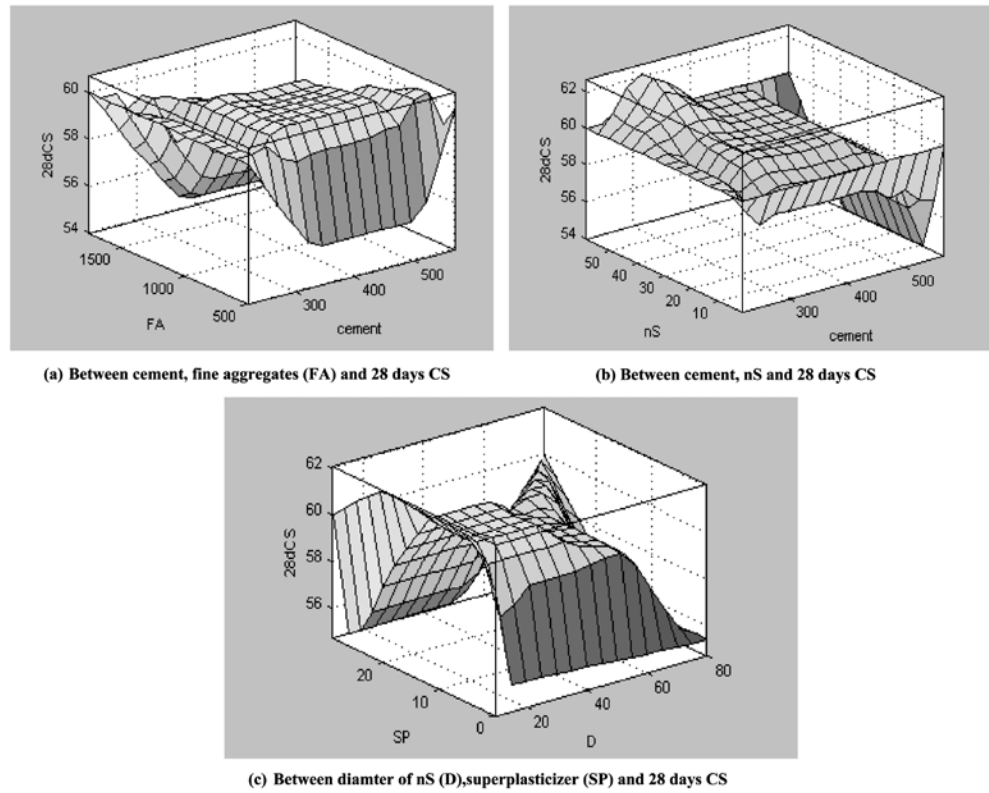


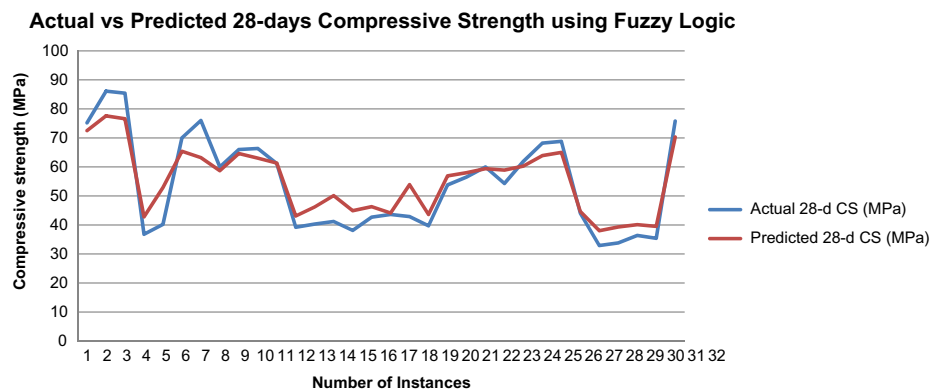
Figure 2. Rule viewer.



**Figure 3. Surface diagrams (a) between cement, fine aggregates (FA) and 28-day CS (b) between cement, nS and 28-day CS (c) between diameter of nS (D) superplasticizer (SP) and 28-day CS.**



**Figure 4. Actual vs. predicted results of the 28-day compressive strength using fuzzy logic approach.**



## 6. Conclusions

In the present study, an FL prediction model for 28-day compressive strength has been developed. In order to predict the effects of nanosilica on compressive strength values of concrete without attempting any experiments, the models were carried out in FL system. A successfully trained model is characterized by its ability to predict strength values for the data it was trained on. The models were trained with input and output experimental data. The values are very closer to the experimental data obtained from FL models. CC, RMSE and MAE are statistical values that are calculated for comparing experimental data with FL model. The correlation coefficient is 0.968581 which is approaching 1 indicates that the correlation between actual and predicted values is strong. As a result, compressive strength values of concrete can be predicted in FL models without attempting any experiments in a quite short period of time with tiny error rates. The values of MAE and RMSE were found out to be

1.008750 and 5.769963, respectively. The difference between MAE and RMSE values is small indicating lesser variance in the individual errors in the data-set chosen. The FL technique could be improved upon by combining it with another method, i.e. artificial neural network and genetic algorithm for its optimization purpose. Also, the FIS could be further improved on using larger data-sets and more parameters. Also, in this work, the triangular membership function is used in the prediction of compressive strength of concrete containing nanosilica. This can be further done by considering other membership functions such as Gaussian, two-sided Gaussian,  $\pi$ -shaped, S-shaped, trapezoidal, sigmoid and bell shaped and also different rule base. As the number of data increases, there will be more accurate prediction and have a better correlation of the actual and predicted values of the compressive strength.

Thus, Successful prediction by the model indicates that FL could be a useful modelling tool for engineers and research scientists in the area of cement and concrete.

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