Application of fuzzy logic in the prediction of compressive strength of cement mortar containing nano and micro silica

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***Abstract*- A fuzzy logic (FL) prediction model for the 28-day compressive strength of cement mortar containing Micro and Nano silica under standard curing conditions was create. Pre-collected data were used in model construction and testing. The input variables of FL model were W/C, S/C, Ns/C, Ms/C, cement content, and porosity values of cement mortar hardened specimens, while the output variable were 28-day cement mortar compressive strength. The Mamdani fuzzy rules relating the input variables to the output variable were created by the FL model and were laid out in the if-then format. It was demonstrated that properties of cement mortar containing micro and Nano silica could be determined without attempting any experiments by using FL models. The obtained results with FL were compared with the experimental methods and found remarkably close to each other the results show that the FL can be used to predict the compressive of cement mortar compressive strength containing nano and micro silica.**

Keywords - Modeling; Compressive strength; Fuzzy Logic

1. Introduction

Prediction compressive strength cement mortar containing additives such as Nano and Micro silica is a complex process that involves the effect of several processing parameters on the quality control parameter examples for processing parameters are ratio W/C, M/C, Na/C and amount of cement and porosity. These factors are all effective in producing single strength quantity of 28-day compressive strength. Such effects have been the subject of several different studies[1, 2]. Prediction modeling studies, like regression and other mathematical models, were also proposed[3, 4]. Recently, artificial neural networks (ANNs) were used to create a prediction model [5-8]. The benefits of using ANN models are the ease of application, robustness, etc. They are, however, black-box models. They do not yield an explicit relation between input and output variables, which makes them more difficult to interpret. All that the model offers is a weight matrix that defines the weights of interlayer connections, which are optimized after thousands of iterations .Considering the type of data used in cement strength modeling, FL may prove to be a better modeling tool [9]. Pre-collected data are always associated with some error, which makes the FL approach more suitable[10]. First of all, the FL approach provides possible rules relating to input variables to the output variable; hence, it is more in-line with human thought. Therefore operators can rapidly develop their own set of rules to test for their fit for the FL model. This makes the fuzzy approach more user-friendly. In this article, the water to cement ratio (W/C), micro silica to cement ratio (Ms/C), and nano silica to cement ratio (Ns/C), cement content, and porosity values are the input parameters of cement mortar which used as a feed to a FL model. Process control data which were used in a previous publication [6],are employed in this article for model construction.

1.2 Fuzzy logic approach

We come across FL as an expression of ambiguity. It is known that these ambiguities gain certainty only after a series of experimental studies and some acknowledgments. Indeed, it is acknowledged that some acceptances, which are seen as certain, contain some degree of proximity and are in definite boundaries [11]. Hence, generally speaking, such approaches are always needed. One of the methods of solving such approaches is FL [12, 13]. Although there are many formal works about FL, fuzziness was first proposed as a faster and cheaper method to model human reasoning in order to control highly complex and non- linear systems. The main goal of designing a fuzzy system is to provide a cost-effective solution that utilizes uncertainties instead of trying to resolve them. Fuzziness is a way to represent uncertainty, possibility, and approximation. If something is fuzzy, it means that we are unable to define precisely its boundaries. In FL, constraints become elastic, limits are relaxed and values have distributions instead of being unique. FL is a good tool for situations where uncertainty is somewhat intrinsic to the system. This uncertainty can appear in a variety of ways [14]. Fuzzy set theory was developed by Lotfi Zadeh in 1965 to deal with the imprecision and uncertainty that is often present in real-world applications [15]. Fuzzy concepts and systems attracted attention after a real control application in 1974 conducted by Mamdani [16]. A general fuzzy system is presented in Fig. 1. According to Fig. 1, the system has basically four components: Fuzzification, fuzzy rule base, Fuzzy output engine, and Defuzzification.

Fuzzification contains all the rules that can be written as logical IF– THEN rules that connect the inputs in the database to out-put variables. While writing these rules, the interval between input and output data is considered as fuzzy set links. In other words, In other words, Fuzzification converts each piece of input data to degrees of membership by a lookup in one or more several membership functions. Generally, the situations of ambiguity in FL are defined via giving membership functions to the elements of the set that represent the situation. If the highest level elements are given the value 1, then the values occur between 0 and 1. Thus, the value of the variation between 0 and 1 for each element is called a membership degree and its value in the subset is called membership function [11, 13, 15, 17, and 18]. Fuzzy membership functions may take many forms but in practical applications simple linear functions such as triangular and trapezoidal are preferred because they provide fast computation time. In this study, the FL model was used to assign the membership functions for the input variables including W/C, S/C, Ms/C, Na/C, cement, and porosity values of 28-days compressive strength of cement mortar as the output variable.

Fuzzy rule base, each part of the input space is logically connected to an output space. These connections constitute the rule base. As mentioned that all these relationships are based on the If-Then rules. There are basically two kinds of fuzzy rules [19].

Fuzzy output engine takes into account all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs and in simpler terms, the kind of processor that collects all the relations among input and output fuzzy sets in the fuzzy rule base and enables the system to act as if it was a single output system. There are basically two kinds of inference operators: minimization (min) and product (prod). That both methods, in general, work well [19].

Defuzzification is the unit where fuzzy set outputs of the fuzzy output engine are converted to real numbers changing their scale. Output data, are the values obtained through the interaction of data and fuzzy rule bases with fuzzy output engine [9, 15, 20-22].

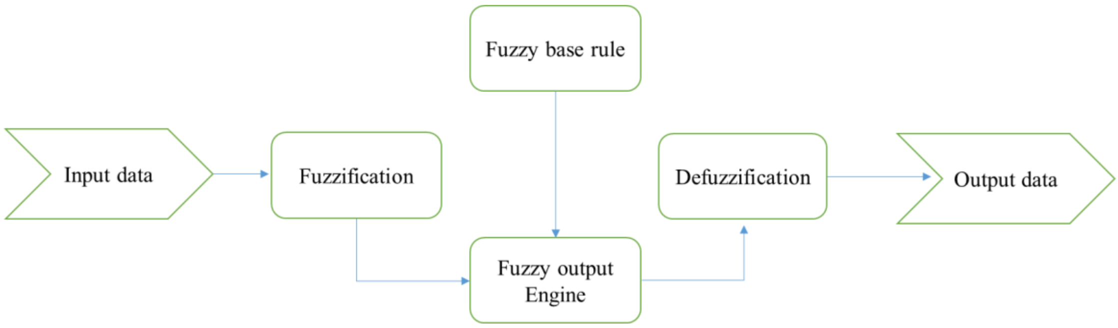

Fig 1. The structure of a fuzzy controller

2. Model construction

In the present study, we used the results of 32 experimental tests in the development of a Mamdani type fuzzy inference model in the FL system. The total number of data sets was 160 but selected 32 data of 28day for model testing. The same data sets were also used in a previous study [6]. The Mamdani method in MATLAB was used for modeling. The developed model has 6 input parameters with compressive strength as the model output. Input parameters were W/C, S/C, Ms/C, Na/C, cement, and porosity. A schematic representation of the model inputs and output is illustrated in Fig. 2. Triangular membership functions were considered for model inputs and output, as demonstrated in Fig 3. Relevant fuzzy rules were written after entering membership functions, some of which are presented in Fig.4

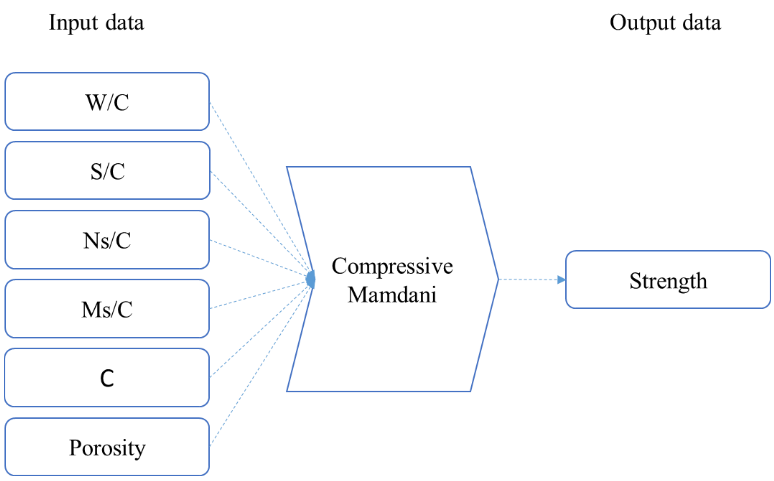

Fig 2. A schematic view of the FL model

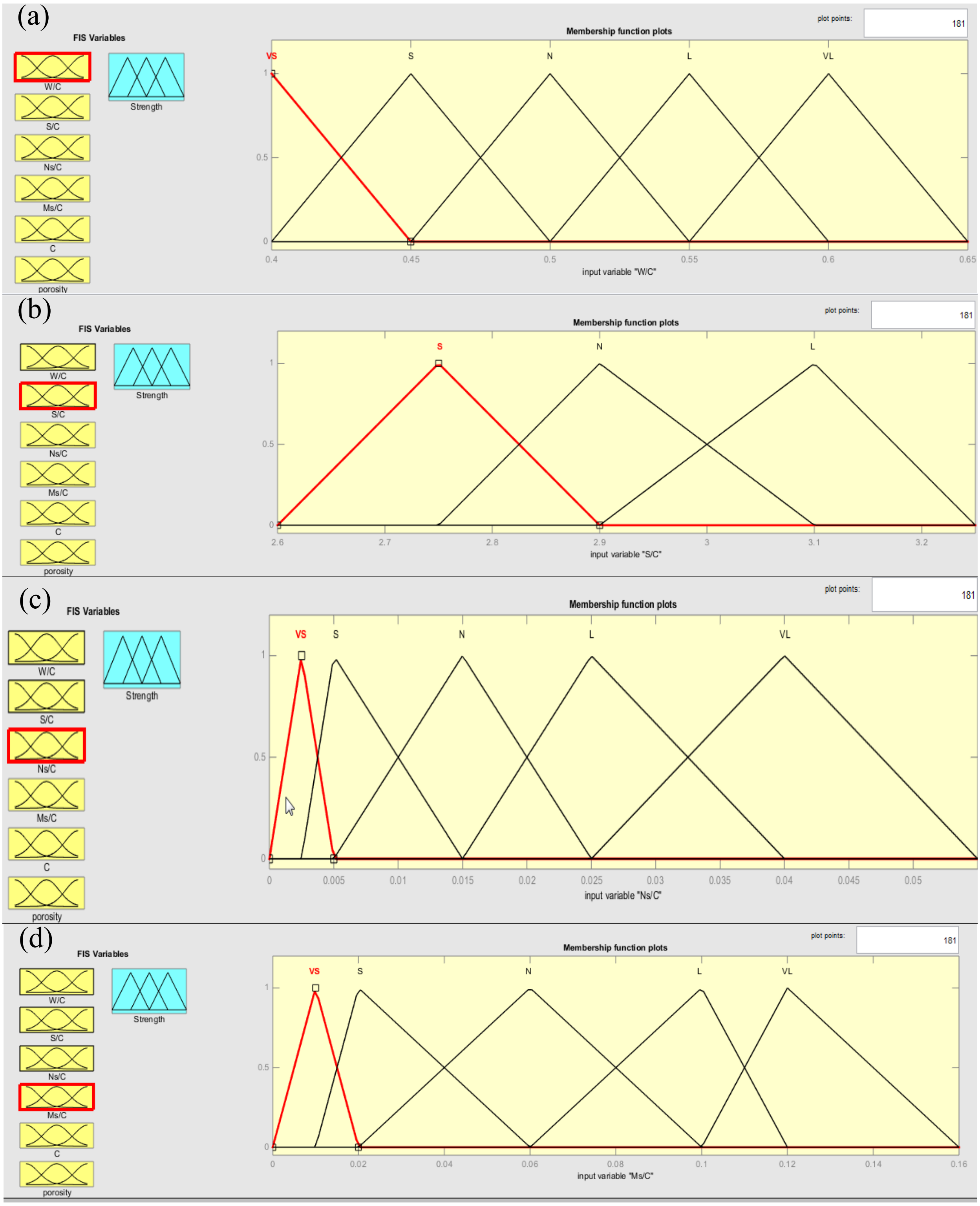

Fig 3. Triangular membership functions were considered for model (a-f) inputs: a) W/C, b) S/C, c) Ns/C, d) Ms/C, e) C, f) Porosity and (g) output: Fc

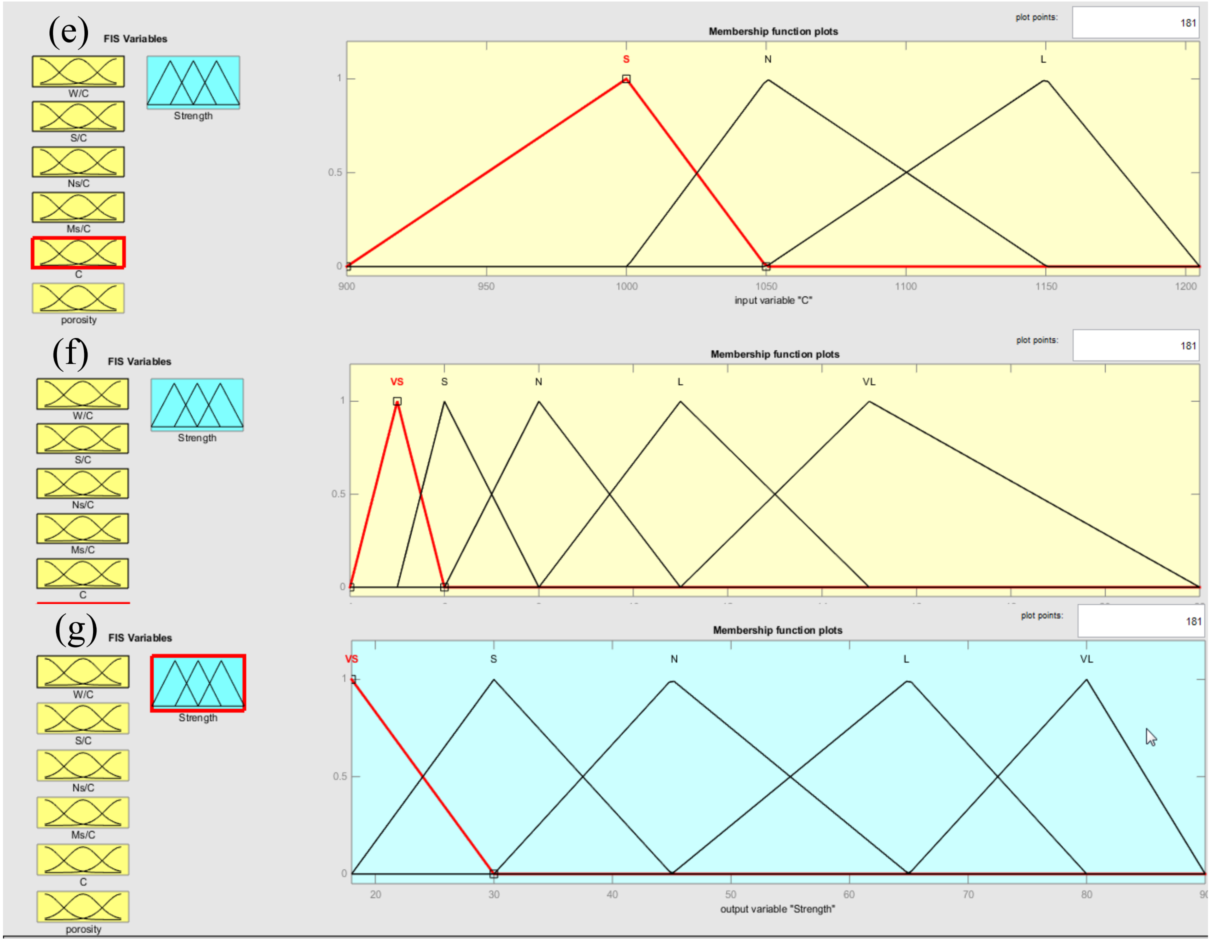

Fig 3. Continued.

1. If (W/C is N) and (S/C is S) and (Ns/C is VS) and (Ms/C is VS) and (C is L) and (porosity is VL) then (Strength is VS) (1)
2. If (W/C is N) and (S/C is S) and (Ns/C is S) and (Ms/C is VS) and (C is L) and (porosity is VL) then (Strength is S) (1)
3. If (W/C is N) and (S/C is S) and (Ns/C is L) and (Ms/C is VS) and (C is L) and (porosity is VL) then (Strength is S) (1)
4. If (W/C is N) and (S/C is S) and (Ns/C is VL) and (Ms/C is VS) and (C is N) and (porosity is VL) then (Strength is S) (1)
5. If (W/C is VS) and (S/C is S) and (Ns/C is VS) and (Ms/C is VS) and (C is S) and (porosity is VL) then (Strength is VS) (1)
6. If (W/C is N) and (S/C is S) and (Ns/C is N) and (Ms/C is S) and (C is N) and (porosity is VL) then (Strength is N) (1)
7. If (W/C is N) and (S/C is S) and (Ns/C is L) and (Ms/C is S) and (C is N) and (porosity is VL) then (Strength is S) (1)
8. If (W/C is N) and (S/C is N) and (Ns/C is VL) and (Ms/C is S) and (C is N) and (porosity is VL) then (Strength is S) (1)
9. If (W/C is N) and (S/C is N) and (Ns/C is VS) and (Ms/C is N) and (C is N) and (porosity is VL) then (Strength is S) (1)
10. If (W/C is L) and (S/C is N) and (Ns/C is N) and (Ms/C is L) and (C is N) and (porosity is VL) then (Strength is S) (1)
11. If (W/C is L) and (S/C is N) and (Ns/C is L) and (Ms/C is L) and (C is N) and (porosity is L) then (Strength is N) (1)
12. If (W/C is L) and (S/C is N) and (Ns/C is VL) and (Ms/C is L) and (C is S) and (porosity is VL) then (Strength is S) (1)
13. If (W/C is L) and (S/C is N) and (Ns/C is VS) and (Ms/C is VL) and (C is S) and (porosity is VL) then (Strength is S) (1)
14. If (W/C is L) and (S/C is L) and (Ns/C is N) and (Ms/C is VL) and (C is S) and (porosity is VL) then (Strength is S) (1)
15. If (W/C is L) and (S/C is L) and (Ns/C is L) and (Ms/C is VL) and (C is S) and (porosity is VL) then (Strength is S) (1)
16. If (W/C is VL) and (S/C is L) and (Ns/C is VL) and (Ms/C is VL) and (C is S) and (porosity is VL) then (Strength is N) (1)
17. If (W/C is VS) and (S/C is S) and (Ns/C is VS) and (Ms/C is VS) and (C is L) and (porosity is VL) then (Strength is VS) (1)

Fig4. Some of the relevant fuzzy rules

3. Error estimation

In the present study, three norms were used to comparative evaluation of the performance of the Mamdani-type fuzzy inference model. These norms are root-mean-squared (RMS) error, coefficient of determination (R^2) and mean absolute percentage error (MAPE) between the prediction model and experimental results which are calculating through the following equations, respectively. Where A is the target value, P is the output value; n is the total number of data points in each set of data.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(A_i - P_i\right)^2} \tag{1}$$

$$R^2 = \frac{(n\sum A_i P_i - \sum A_i * \sum P_i)^2}{(n\sum A_i^2 - (\sum A_i)^2)(n\sum P_i^2 - (\sum P_i)^2)} \tag{2}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - P_i}{A_i}\times 100\right| \tag{3}$$

4. Results

The FL model developed in this study is used to predict the compressive strength of cement mortar. As mentioned earlier, 32 experimental results have been used in the processes of the FL models. 6 parameters including W/C, S/C, Ms/C, Na/C, cement, and porosity used as input, while compressive strength (Fc) of the cement mortar set as output of the model. Furthermore, the Mamdani type fuzzy inference model used in the FL system. The comparison between the FL model results and experimental data are presented in Figs. 5 and 6 so the performance of the model could be evaluated. The vertical-axis of these figures is the sample testing records and horizontal ones are their corresponding predicted compressive strength in MPa. Fig.5 presents the measured compressive strengths versus predicted compressive strengths which obtained by FL and the respective R^2 coefficients. According to Fig 5, R^2 coefficient of the FL prediction model is 0.9724. Since indicate clearly in fig 6, the results predicted by FL are very close to the experimental results. The results of these figures indicate that the FL model was successful in learning the relationship between the different input parameters and output and finally, the results of the testing phase show that this model had good potential for predicting the compressive strength of cement mortar contain Nano and Micro silica. The findings obtained from the created prediction model using FL were evaluated in view of root-mean-squared (RMS) error, coefficient of determination (R^2) and mean absolute percentage error (MAPE). The statistical performance values (MAPE, RMSE, and R2) values of proposed FL model for predicting the compressive strength of cement mortar are 1.92, 0.2724, and 0.9724 respectively. Therefore, the FL approach is well suited for such samples. Another advantage of the FL is that all the rules are written verbally, much like human thought while ANN models are black-box models and are not immediately visible to the user.

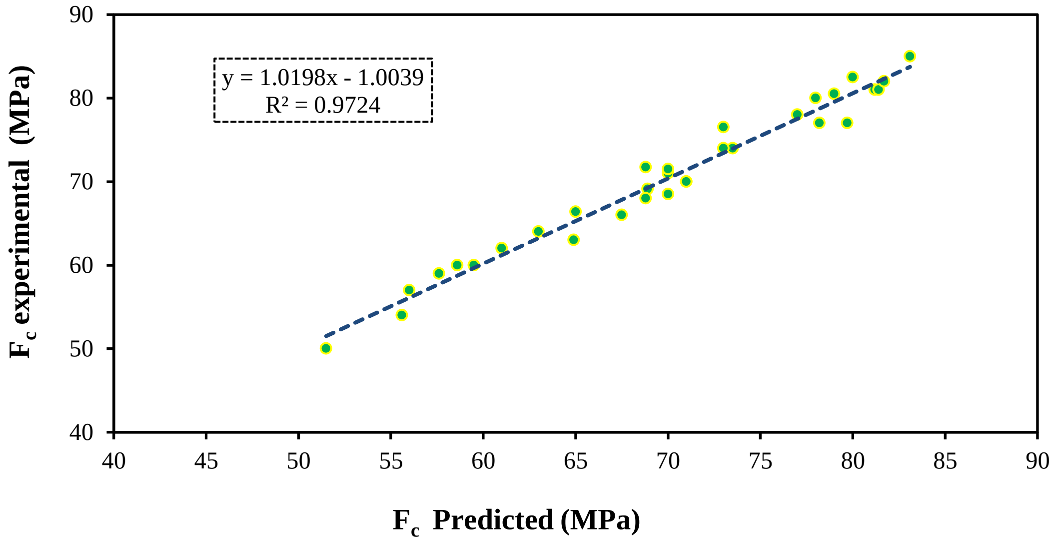

Fig 5. Correlation of experimental results and FL

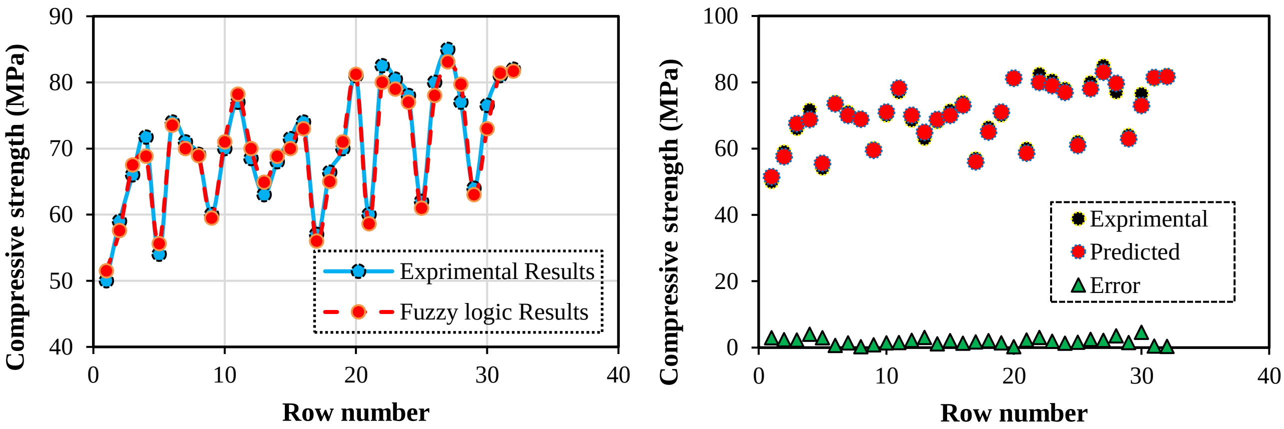

Fig6. Comparison compressive strength of experimental results with predicted values of FL approach model

5. Conclusions

A FL model was created to predict the compressive strength of the 28-day cement mortar. Input parameters used in the model creation process included W/C, S/C, Ms/C, Na/C, cement, and porosity.The model was created from process control data which were used in a previous publication data.

- Successful predictions of the observed cement mortar strength by the model indicate that FL could be a useful modeling tool for engineers and research scientists in the area of cement and concrete
- The cement data are always associated with some measurement errors, which makes the fuzzy approach more suitable than other methods is in that regard.The successful predictions of the 28-day cement mortar strength data by the fuzzy indicate that FL has the potential to predict with acceptable accuracy
- Fuzzy inference systems are powerful tools for simulating nonlinear behaviour's therefore very useful for data with high dispersion
- After successful predicted by the FL has good performance in desirable accuracy and applicability, endowing them the high potential to substitute the conventional and experimental methods in real's engineering practic

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