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Prediction of Ultimate Strength of PVC-Concrete Composite Columns Using FIS Models

Ahmed Sagban Saadoon and Nabeel Abdulrazzaq Jasim
Department of Civil Engineering, University of Basrah, Iraq.

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ABSTRACT

The main objective of the present study is to predict the ultimate strength of PVC-concrete composite columns (a new type of composite columns consisting of a PVC tube filled with concrete). The study aimed at to investigate the potential of using fuzzy inference system (FIS) to predict the strength of the composite columns. Two models, Mamdani and Sugeno FIS model, having three inputs, one output, and twenty linguistic rules were constructed. The models were trained with input and output data. Using only the input data in trained models, the ultimate strengths values of PVC-concrete composite columns were found. According to the coefficients of correlations, both models have high prediction performance. The obtained values ewre very close to the experimental results. The average values of ratios of experimental to predicted ultimate loads were 0.994 and 0.999 for the Mamdani and Sugeno FIS model, respectively. Fuzzy inference system (FIS) model has been proved to be very effective in predicting the ultimate strength of PVC-concrete composite columns without attempting any experiments in a quite short period of time with tiny error rates.

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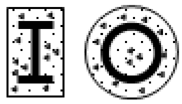
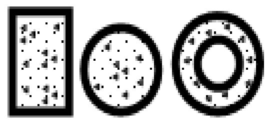
1. Introduction

A composite column is a column constructed from two or more different materials in such a way that they work together in resisting stresses and strains induced by forces or conditions external to the column. However, the term 'composite column' is normally used to indicate applications like either concrete-encased sections or concrete-filled tubes of rectangular or circular cross-section (Fig. 1). Rapid deterioration of infrastructures enhances the demand on rehabilitating and retrofitting existing concrete columns and piles in building and bridge substructures. Recently, attempts are made toward alternative columns (or piles) which make use of FRPs, recycled plastics, and other materials to replace and/or protect steel or concrete, with the intent to produce columns (or piles) that have lower maintenance costs and longer service lives than conventional columns (or piles), especially when used in marine applications and other corrosive environments.

Another alternative to the advanced composite materials tubing is the commercially available Polyvinyl Chloride (PVC) pipes. The use of PVC tubes in composite columns and piles in light construction will eliminate the reinforcing steel and the formwork. PVC is a thermoplastic material used to make long-lasting products, often with a life expectancy exceeding 60 years. This provides some main attributes that make it useful in the construction of certain structures exposed to corrosive environments. PVC pipe is a combination of plastic and vinyl materials; as such a pipe made from PVC is durable to the extreme. Fundamentally, PVC pipe is hard to damage and lasts for long periods of time without the need for replacement and having lightweight, which permits easy handling, and impermeable to gases and fluids and durable. Hence these pipes are used extensively in the construction industry.



a) **Concrete-encased**



b) **Concrete-filled**

Figure 1. Different types of composite columns

Very few authors have studied the structural behavior of PVC-concrete composite columns (columns consisting of a PVC tube filled with concrete) [1-3]. However, no work is found related to the prediction of the ultimate strength of these composite columns. Recently, fuzzy set theory has been successfully applied in many different areas of engineering including automatic control, system identification, pattern recognition, design of structures, structural modeling and many more. There have been quite a good number of applications of fuzzy logic in different fields of civil engineering [4-10].

The main objective of the present study is to predict the ultimate strength of PVC-concrete composite columns. The potential of using fuzzy inference system (FIS) to predict the ultimate strength of these columns under concentrated axial loads is investigated. Also an attempt is made to propose a design method for predicting the strength of these columns.

Tele:
E-mail address: ahmsag@gmail.com

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2. Fuzzy Inference System (FIS)

2.1. General

Term "Fuzzy" was used by Prof. Lotfi Zadeh for the first time in 1962 [11]. In 1965 [12] he published his pioneer, today still classic, papers entitled "Fuzzy set". The fuzzy sets have since spread practically to all aspects of scientific disciplines. It may be regarded both as a generalization of classical set theory and as a generalization of dual logic.

The fuzzy inference system (FIS), also known as fuzzy rule-based systems or fuzzy models, is the process of formulating the mapping from a given input to an output using fuzzy logic. The dynamic behavior of an FIS is characterized by a set of linguistic description rules based on expert knowledge. This expert knowledge is usually of the form:

IF - a set of antecedent conditions is satisfied.

THEN - a set of consequences can be inferred.

2.2. Basic design of FIS

In order to solve a problem which is based on uncertain or fuzzy observations or correlations, it is necessary to describe, map, and process the influencing factors in fuzzy terms and to provide the result of this processing in a useable form. These requirements result in the following basic elements of a FIS [13]:

1- Knowledge base (definition of the linguistic variables, terms and rules).

2- Processing of the input variables (fuzzification).

3- Inference engine (analysis).

4- Processing results (defuzzification)

The (scalar) inputs are transformed into memberships of fuzzy sets by fuzzification functions. This information, together with the declared rules, is given to the inference engine; the result again being a set of memberships of fuzzy sets (terms for the output variables). The last step is to transform these membership values into the required scalar output variables by defuzzification. The following sections will discuss in detail each of these individual steps.

The knowledge base defines the relationships between the input and output parameters of a system. The most commonly used representation of the input-output relationships is Mamdani type fuzzy models. In this type of fuzzy models, linguistic propositions are used both in antecedent and consequent parts of the If-Then rules. Another type of representing the input-output relationships is Sugeno fuzzy models in which the antecedent part of the rules is composed of linguistic propositions, but the consequent parts is defined by either a constant number (zero order) or linear equations (first order). A Mamdani model and a zero-order Sugeno model of a multi-input-single-output system may be represented by a set of linear subsystems (rules) shown in Eq. (1) and Eq. (2), respectively, as:

$$R_i{:}\,\boldsymbol{IF}\ x_1\ is\ A_{i1}\ \boldsymbol{AND}\ \ldots x_m\ is\ A_{im}\ \boldsymbol{THEN}\ y_i\ is\ B_i, \qquad (1)$$

$$R_i{:}\,\boldsymbol{IF}\ x_1\ is\ A_{i1}\ \boldsymbol{AND}\ \ldots x_m\ is\ A_{im}\ \boldsymbol{THEN}\ y_i = C_i, \qquad (2)$$

where R_i represents the i^{th} rule ($i=1,\ldots.,n$), n is the total number of rules, x_j ($j=1,\ldots.,m$) are the input variables, A_{ij} is an input fuzzy set defined in the input space U_j, y_i is the output variable, B_i is an output fuzzy set defined in the output space V_i, and C_i is the consequent constant. Thus, every rule is a local fuzzy relationship that maps a part of the multidimensional input space U into a certain part of the output space V. The inference mechanism of Mamdani type, as shown in Fig. (2*a*), consists of three connectives: the aggregation of antecedents in each rule (AND connectives), implication (i.e., IF-THEN connectives), and accumulation (or aggregation) of the rules (ALSO connectives). The operators performing the connectives distinguish the type of fuzzy inferencing. The AND and ALSO connectives are chosen from a family of *t-norm* (e.g., minimum and product operators) and *t-conorm* operators (e.g., maximum and sum operators), respectively. The implication (IF-THEN connective) also uses *t-norm* operators, but not necessarily identical to the ones used for the AND connectives.

The inference mechanism of Sugeno models (Fig. (2*b*)) is more straightforward than the more common Mamdani's type because the outputs of individual subsystems are crisp numbers. An algebraic product operator is usually selected to perform the *t-norm* to simplify the computations. The result of implication of each rule is a weight factor that indicates the rule degree of firing (*dof*), w_i. The aggregation of the rules is simply adding the weighted result of the output of the individual rules.

3. FIS Model Development for Ultimate Strength Prediction

The FIS is used to predict the ultimate strength of PVC-concrete composite columns under axial compression loads. The FIS model is implemented using Fuzzy Logic Toolbox in MATLAB program version 7 (R14). This program implements two different FIS models, Mamdani and Sugeno model. In this section, the results of using these two FIS models are presented and discussed to examine the ability of these models to predict the ultimate strength of PVC-concrete composite columns.

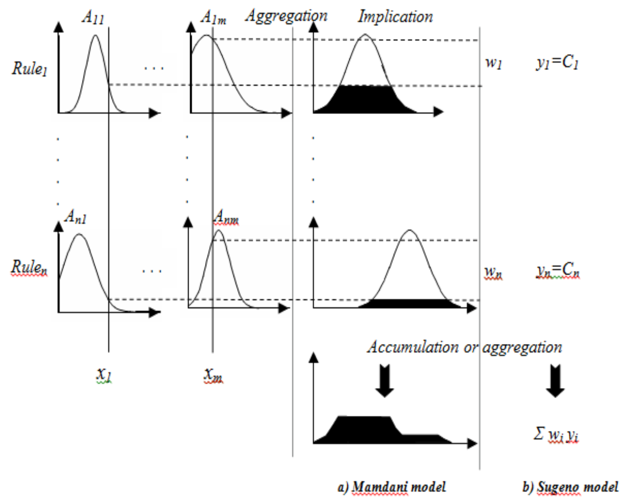

Figure 2. Fuzzy reasoning models

3.1. Preparation of data

In general, a good training data set should include comprehensive information about the characteristics of the materials behavior. In this study, the used experimental data are obtained from available literature and the complete list of these data is given in Table (1). Among the collected data, 20 experimental data were sampled randomly and used for the training data (constructing rules) and the remaining six data for the testing data of the two FIS models, as shown in Table (1).

3.2. Input and output variables

Generally, the input and output variables are usually determined by the nature of problem. As discussed previously, rules are influential in selecting the number of variables and membership functions to be modeled with fuzzy

Table 1. Actual (experimental) data for PVC-concrete composite columns

Column No.	Cylinder compressive strength (f'_c) (MPa)	Tube diameter (D) (mm)	Tube thickness (t) (mm)	Length (L) (mm)	Slenderness ratio (L/r)	Ultimate compressive load (P) (kN)	Reference
1*	20.6	114.3	6.35	203.2	7.7	315.1	Kurt [1]
2	20.6	114.3	6.35	457.2	17.5	309.3	
3	36	106	3	270	11.0	318.0	Marzouck and Sennah [2]
4*	36	106	3	416	17.0	311.0	
5	36	106	3	562	22.0	291.0	
6	36	106	3	758	30.0	287.0	
7	24	110	3.2	220	8.0	278.7	Saadoon [3]
8*	24	110	3.2	400	14.5	272.3	
9	24	110	3.2	600	21.8	265.6	
10	24	110	3.2	800	29.1	254.3	
11	24	110	3.2	1000	36.4	240.1	
12*	24	110	5.3	220	8.0	331.6	
13	24	110	5.3	400	14.5	327.0	
14	24	110	5.3	600	21.8	322.3	
15	24	110	5.3	800	29.1	316.3	
16	24	110	5.3	1000	36.4	300.7	
17	40	110	3.2	220	8.0	369.2	
18	40	110	3.2	400	14.5	360.8	
19	40	110	3.2	600	21.8	350.3	
20*	40	110	3.2	800	29.1	338.6	
21	40	110	3.2	1000	36.4	328.9	
22	40	110	5.3	220	8.0	438.0	
23	40	110	5.3	400	14.5	428.6	
24*	40	110	5.3	600	21.8	420.7	
25	40	110	5.3	800	29.1	408.1	
26	40	110	5.3	1000	36.4	391.2	

* Testing data, and the remaining are training data.

logic model and complexity increases, in terms of the number of rules to be defined, as each new input variable is added. According to the few number of the collected experimental data, a limited number of rules can be performed. Therefore, the input variables and their membership functions must be minimized as much as possible. Hence, in this study, initial screening is carried out on the candidate parameters to eliminate any unnecessary input parameter. The simultaneous use of PVC tube diameter/wall thickness ratio and the corresponding diameter and wall thickness values as input parameters is unnecessary. Therefore, after a thorough study on the collected experimental data, three major variables are adopted to model the ultimate strength of PVC-concrete composite columns. The three major input variables are listed in Table (2) as follows:

1- f'_c = cylinder compressive strength of concrete (MPa),
2- D/t = diameter to wall thickness of a PVC tube, and
3- L/r = column slenderness ratio.

The output includes one output variable represents the ultimate axial load P (kN).

Table 2. Range of input parameters

Parameters	Range
Concrete cylinder compressive strength (f'_c) (MPa)	20.6 - 40.0
Diameter to tube thickness ratio (D/t)	18.0 - 35.33
Column slenderness ratio (L/r)	7.7 - 36.4

3.3. Membership functions

According to the collected data, and using the scatter method for partitioning, three linguistic terms to describe the input variables f'_c, D/t, and L/r were chosen, for both the Mamdani and Sugeno models, while twenty two linguistic terms for the Mamdani model and twenty constants (equal in value to the correspond actual experimental output of the training data) for the Sugeno model were chosen to describe the output variable P.

To account for the non-linearity, each input variable is modeled using a Gaussian type membership function. While the output variable is modeled using a triangular (linear) type membership function. Based on this concept of the data classification, membership functions were determined for all input variables and output variable, as shown in Figs. (3 - 6).

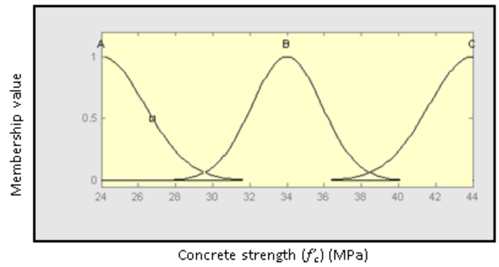

Figure 3.Membership functions for concrete strength (f'_c)

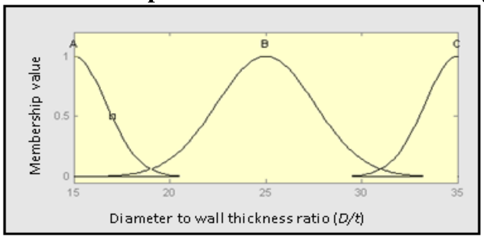

Figure 4. Membership functions for diameter to wall thickness ratio (D/t)

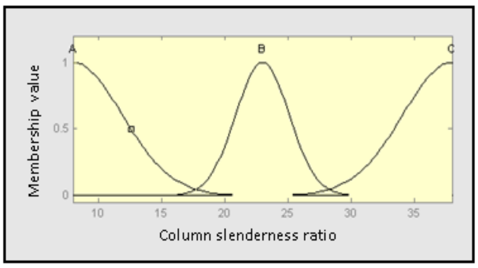

Figure 5. Membership functions for column slenderness ratio (L/r)

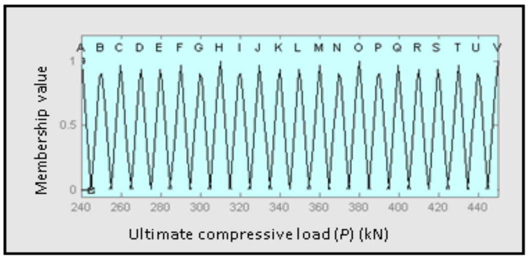

Figure 6. Membership functions for ultimate compressive load (*P*) (for Mamdani model)

3.4. Rule definition

Since there are just 20 training data, then a rule base of 20 rules would be performed. Hence, 20 fuzzy rules were constructed with appropriate relations between input and output. Figure (7) shows a sample of the rule base, while the rule viewer is shown in Fig. (8).

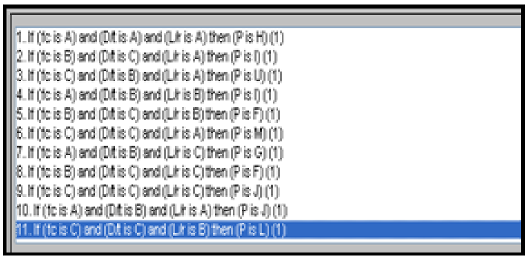

Figure 7. A segment of the rules frame (for Mamdani model)

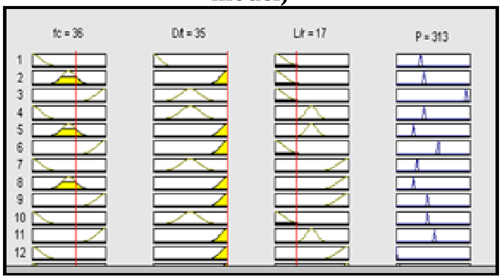

Figure 8. Inference module (the rules viewer)

3.5. Model construction

In the Mamdani model, the variables were combined into rules using the concept of '**AND**'. The fuzzy operator 'minimum' was applied as the '**AND**' function to combine the variables. No weightings were applied, which means no rule was emphasized as more important in respect to estimating the ultimate strength. Implication was performed with the minimum function, and accumulation (or aggregation) was performed with the maximum function. The centroid, or centre of gravity, method was applied as a means of defuzzification of the output membership functions to determine a crisp set. Based on this structure, a Mamdani FIS model for ultimate strength prediction was constructed for PVC-concrete composite columns. Alternate functions for the FIS were investigated through sensitivity analysis in the next section.

In the Sugeno model, the variables were combined into rules using the concept of '**AND**'. The fuzzy operator 'product' was applied as the '**AND**' function to combine the variables. No weightings were applied. Implication of each rule was calculated using weighted average defuzzification method. Based on this structure, a Sugeno FIS model for ultimate strength prediction was constructed for PVC-concrete composite columns. Alternate functions for the FIS were investigated through sensitivity analysis in the next section.

3.6. Sensitivity analysis

A sensitivity analysis was performed for the fuzzy logic operator AND, and for the methods of implication, accumulation (or aggregation), and defuzzification. The results of changing a single operator or method while the rest of the model was held constant were compared with the actual results. In the present study, two norms were used to control the performance of the prediction capacity of the predictive models developed in the study. These norms are the root mean square error (RMSE) and mean percentage error (MAPE) between models' results and experimental results and they are given, respectively, as:

$$RSME=\sqrt{[(1/n)\sum(P_a\text{-}P_p)^2]}, \quad (3)$$

$$MAPE = (1/n)[(\sum\left|P_a\text{-}P_p\right|/\sum P_a)\times 100], \quad (4)$$

where P_a and P_p are the actual and predicted values, respectively. If RMSE and MAPE are 0 then the model will be excellent.

Based on the sensitivity analysis, for the Mamdani model a modification on the prototype model configuration was developed using product for the AND operator, product for the implication, maximum for the aggregation, and the centroid for the defuzzification method. For the Sugeno model, the prototype model configuration was adopted using product for the AND operator and the weighted average for the defuzzification method.

3.7. FIS model validation

Model validation must be carried out using the input-output data that are not used for training (i.e., testing data) to evaluate the efficiency of the FIS models in predicting ultimate strength. The testing data are combined in the models validation, which resulted in a total of 6 testing data for the FIS models. The FIS models predicted and target (actual) ultimate strength are used for models validation. Table (3) presents the actual and predicted ultimate load capacity of the FIS models for testing data.

As seen from this table, the values obtained for both FIS models are very close to the experimental results. The average values of ratios of actual to predicted ultimate loads are 0.994 and 0.999 for the Mamdani and Sugeno model,

Table 3. Actual and predicted ultimate load capacity for testing columns

Column No.	Cylinder compressive strength (f'_c) (MPa)	Diameter to tube thickness (D/t)	Slenderness ratio (L/r)	Actual ultimate compressive load (P_a) (kN)	Predicted ultimate compressive load (P_p) (kN)			
					Mamdani model		Sugeno model	
					P_p	P_a/P_p	P_p	P_a/P_p
1	20.6	18	7.7	315.1	313	1.007	312	1.010
4	36	35.33	11	311	314	0.990	313	0.994
8	24	34.38	14.5	272.3	280	0.973	279	0.976
12	24	20.75	8	331.6	330	1.005	327	1.014
20	40	34.38	29.1	338.6	333	1.017	332	1.020
24	40	20.75	21.8	420.7	432	0.974	430	0.978

respectively. These results demonstrate that the FIS can be successfully applied to establish accurate and reliable prediction models.

The performance of a FIS model can be measured to some extent by the errors on the training and testing sets, but it is often useful to investigate the model response in more detail. One option is to perform a regression analysis between the model response and the corresponding targets. Figures (9) and (10) show the results of the regression analysis between the output of the Mamdani model and the corresponding target for training and testing data respectively, while Figs. (11) and (12) show the results for the Sugeno model for training and testing data respectively. From Figs. (9) and (10), R^2 = 0.9924, 0.9858 for training and testing data of Mamdani model, respectively, while from Figs. (11) and (12), R^2 = 0.9931, 0.9851 for training and testing data of Sugeno model, respectively. These values indicate an excellent agreement between the predicted and the actual values for both the Mamdani and Sugeno models.

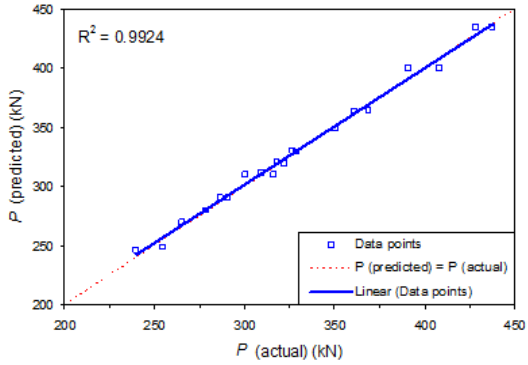

Figure 9. Regression analysis between predicted and actual values for training data of Mamdani model

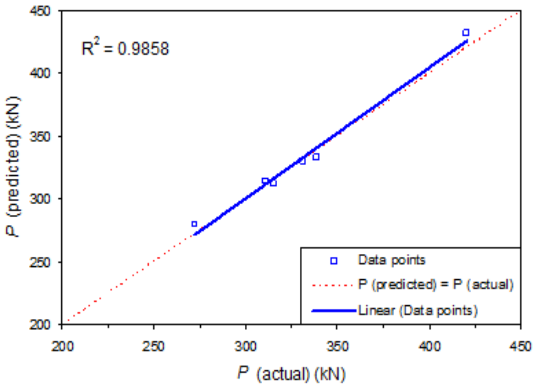

Figure 10. Regression analysis between predicted and actual values for testing data of Mamdani model

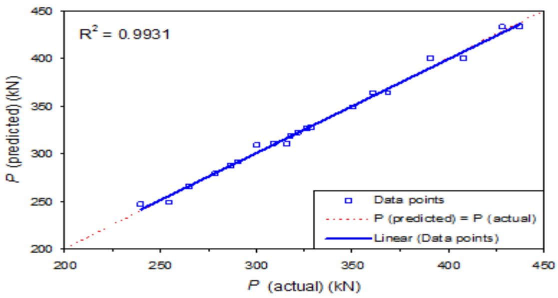

Figure 11. Regression analysis between predicted and actual values for training data of Sugeno model

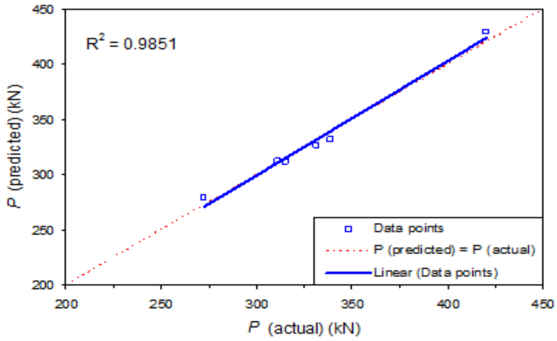

Figure 12. Regression analysis between predicted and actual values for testing data of Sugeno model

4. Conclusions

In order to predict the ultimate compressive strength of PVC-concrete composite columns without attempting any experiments, fuzzy inference system (FIS) was used. Two models, Mamdani and Sugeno FIS model, having three inputs, one output, and twenty linguistic rules were constructed. The models were trained with input and output data. Using only the input data in trained models, the ultimate strengths values of PVC-concrete composite columns were found. According to the coefficients of correlations, both models have high prediction performance. The obtained values are very close to the experimental results. The average values of ratios of experimental to predicted ultimate loads are 0.994 and 0.999 for the Mamdani and Sugeno FIS model, respectively. As a result, ultimate strength of PVC-concrete composite columns can be predicted by the constructed FIS models without attempting any experiments in a quite short period of time with tiny error rates. The obtained results have shown that FIS is practicable method for predicting the ultimate strength of PVC-concrete composite columns.

References

[1] **Kurt**, **C.E.**, "Concrete filled structural plastic columns", Journal of the Structural Division, Proceedings of the American Society of Civil Engineers, Vol. 104, No. ST1, January, 1978, pp. 55-63.

[2] **Marzouck**, **M.**, and **Sennah**, **K.**, "Concrete-filled PVC tubes as compression members", Proceedings of the International Challenges of Concrete Construction Congress, Scotland, U.K., Vol. 4, 2002, pp. 31-37.

[3] **Saadoon**, **A.S.**, "Experimental and theoretical investigation of PVC-concrete composite columns", Ph.D. thesis, University of Basrah, 2010.

[4] **Fa-Liang**, **G.**, "A new way of predicting cement strength - fuzzy logic", Cement and Concrete Research, 27, 6, 1997, pp. 883–888.

[5] **Akkurt**, **S.**, **Tayfurb**, **G.**, and **Can**, **S.**, "Fuzzy logic model for the prediction of cement compressive strength", Cement and Concrete Research, 34, 2004, pp. 1429–1433.

[6] **Demir**, **F.**, "A new way of prediction elastic modulus of normal and high strength concrete-fuzzy logic", Cement and Concrete Research, 35, 2005, pp. 1531– 1538.

[7] **Nataraja**, **M.C.**, **Jayaram**, **M.A.**, and **Ravikumar**, **C.N.**, "Prediction of early strength of concrete: a fuzzy inference system model", International Journal of Physical Sciences, Vol. 1, 2, 2006, pp. 047-056.

[8] **Unala**, **O.**, **Demir**, **F.**, and **Uygunoglua**, **T.**, "Fuzzy logic approach to predict stress–strain curves of steel fiber-reinforced concretes in compression", Building and Environment, 42, 2007, pp. 3589–3595.

[9] **Topcu**, **I.B.**, and **Saridemir**, **M.**, "Prediction of rubberized concrete properties using artificial neural network and fuzzy logic", Construction and Building Materials, 22, 2008, pp. 532–540.
[10] **Ozcan**, **F.**, **Atis**, **C.D.**, **Karahan**, **O.**, **Uncuoglu**, **U.**, and **Tanyildizi**, **H.**, "Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete", Advances in Engineering Software, 40, 2009, pp. 856–863.
[11] **Zadeh**, **L.A.**, "From circuit to system theory", Roc. of Institute of Ratio Eng., Vol. 50, 1962, pp. 856-865.
[12] **Zadeh**, **L.A.**, "Fuzzy sets", Journal of Information and Control, 8, 1965, pp. 338-353.
[13] **Kirschfink**, **H.**, and **Lieven**, **K.**, "Basic tools for fuzzy modeling", Liebigstrasse 20, D-52070, Aachen, Germany, 2000.