A Fuzzy Interface System to Predict Ultimate Strength of Circular Concrete Filled Steel Tubular Columns

Kadhim Zuboon Nasser
Engineering College, University of Basrah/ Basrah
E-mail:kadhimzuboon@yahoo.com

Received on: 6 /6 / 2011 & Accepted on: 3 /11/ 2011

ABSTRACT

In this study, a model for predicting the ultimate strength of circular concrete filled steel tubular columns (CCFST) under axial loads has been developed using fuzzy inference system (FIS). The available experimental results for (129) specimens obtained from open literature were used to build the proposed model. The predicted strengths obtained from the proposed FIS model were compared with the experimental values and with unfactored design strengths predicted using the design procedure specified in the AISC 2005 and Eurocode 4 for CCFST columns. Results showed that the predicted values by the proposed FIS model were very close to the experimental values and were more accurate than the AISC 2005 and Eurocode 4 values. As a result, FIS provided an efficient alternative method in predicting the ultimate strength of CCFST columns.

Keywords: steel columns, fuzzy inference system, concrete filled steel tube.

نظام الاستدلال الضبابي لتقدير المقاومة القصوى للأعمدة المكوّنة من أنبوب حديدي ذي مقطع دائري الشكل مملوء بالخرسانة

الخلاصة

ان الهدف الرئيسي من الدراسة الحالية هو بناء نظام استدلالي ضبابي لتقدير مقاومة الأعمدة المكوّنة من أنبوب حديدي ذي مقطع دائري الشكل مملوء بالخرسانة والمعرّضة إلى أحمال ضغط مركزية. وقد استعملت النتائج المختبرية لـ (129) عيّنة (مستخلصة من بحوث سابقة) في بناء النظام المقترح. وقورنت القيم المقدّرة من هذا النظام مع القيم المختبرية ومع القيم المحسوبة في ضوء شرط التصميم في الكودين العالميين AISC 2005 و Eurocode 4. لقد أظهرت النتائج أن القيم المقدّرة من النظام الاستدلالي المقترح كانت قريبة جداً من القيم المختبرية وكانت أدقّ من القيم المحسوبة حسب مواصفات الكودين المذكورين. وبالتالي فانه من الممكن استخدام نظام الاستدلال الضبابي في تقدير مقاومة مثل هذا النوع من الأعمدة.

INTRODUCTION

Concrete-filled steel tubular structural members have a number of distinct advantages over equivalent steel, reinforced concrete, or steel-reinforced concrete members. Steel members have the advantages of high tensile strength and ductility, while concrete members have the advantages of high compressive strength and stability. Composite members combine steel and concrete, resulting in a

https://doi.org/10.30684/etj.30.3.4
2412-0758/University of Technology-Iraq, Baghdad, Iraq

member that has the beneficial qualities of both materials. The steel tube serves as a form for casting the concrete, which reduces construction cost. No other reinforcement is needed since the tube acts as longitudinal and lateral reinforcement for the concrete core. In addition, the placement of longitudinal steel at the perimeter of the section is the most efficient use of the material since it provides the highest contribution of the steel to the section moment of inertia and flexural capacity. The continuous confinement provided to the concrete core by the steel tube enhances the core's strength and ductility. The concrete core delays local buckling of the steel tube by preventing inward buckling, while the steel tube prevents the concrete from spalling.

Many research projects have been conducted since the 1960s to investigate the behaviors of CFT columns. Furlong [1] concluded from tests on 13 specimens that the stability performance of the steel tube was significantly enhanced by the concrete core. Tomii et al. [2] reported concentric loading experiments on almost 270 circular, octagonal, and square CFT columns, among which two failure modes were highlighted. They are the overall buckling for slender columns and the crushing of concrete for stub columns. Rangan and Joyce [3] investigated 9 circular CFT columns and developed a simplified method to evaluate the ultimate capacity of the CFT columns. However, the maximum discrepancy between the proposed method and the test results was as high as 60%. Schneider [4] concluded from his tests on 14 CFT stub columns that the axial loading behavior of CFT columns was significantly affected by the cross-sectional shape and the breadth-to-thickness (B/t) ratio. Han [5] provided test results of 24 rectangular CFT columns under concentric loading and commented that the strength increase of the concrete core due to the confinement of the steel tube was influenced by the cross-sectional aspect ratio, material properties and confining factor.

The main objective of these tests was to determine the different parameters that influence the structural behavior of this type of 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 (among them: Fa-Liang [6], Akkurt et al. [7], Demir [8], Nataraja et al. [9], Unal et al. [10], Topcu and Saridemir [11], and Ozcan et al. [12]).

The main objective of the present study is to predict the ultimate strength of circular concrete fill steel tube columns. The potential of using fuzzy inference system (FIS) to predict the ultimate strength of these columns under concentrated axial loads is investigated.

FUZZY SETS AND LOGIC

Zadeh [13] introduced the concept of fuzzy logic instead of two-valued Aristotelian logic (1 or 0, exist or not exist) in dealing with logical statements. Fuzzy approach considers cases where linguistic uncertainties play some role in the control mechanism of the phenomena concerned. Herein, uncertainties do not mean random, probabilistic and stochastic variations, all of which are based on the numerical data.

Zadeh has motivated his work on fuzzy logic with the observation that the key elements in human thinking are not numbers but levels of fuzzy sets. Further he saw each linguistic word in a natural language as a summarized description of a fuzzy subset at a universe of discourse representing the meaning of this word. In consequence, he introduced linguistic variables as variables whose values are sentences in a natural or artificial language.

The fuzzy logic definition in the following sequel is tailored to the application of ultimate strength of CCFST column modelling which in many ways is very similar to the established use of fuzzy logic in the control of dynamic systems, also known as "fuzzy logic control". In both contexts, fuzzy propositions, i.e. IFTHEN statements are used to characterise the state of a system and the truth value of the proposition is a measure of how well the description matches the state of the system. Fuzzy logic has been developing since then and is now being used especially in Japan for automatic control for commercial products such as washing machines, cameras and robotics. Many textbooks provide basic information on the concepts and operational fuzzy algorithms [14–16]. The key idea in the fuzzy logic is the allowance of partial belonging of any object to different subsets of the universal set instead of belonging to a single set completely. Partial belonging to a set can be described numerically by a membership function which assumes values between 0 and 1 inclusive. For instance, Fig. 1 shows typical membership functions for small, medium and large class sizes in a universe, U. Hence, these verbal assignments are the fuzzy subsets of the universal set. In this figure, set values less than 2 are definitely "small"; those between 4 and 6 are certainly "medium" and values larger than 8 are definitely "large". However, intermediate values such as 2.2 partially belong to the subsets "small" and " medium". In fuzzy terminology 2.2 has a membership value of 0.9 in "small" and 0.1 in "medium" but 0.0 in "large" subsets. The literature is rich with references concerning the ways to assign membership values or functions to fuzzy variables. Among these ways are intuition, inference, rank ordering, angular fuzzy sets, neural networks, genetic algorithms, inductive reasoning, etc. [17]. Intuition involves contextual and semantic knowledge about an issue; it can also involve linguistic truth values about this knowledge [18]. Even if the measurements are carefully carried out as crisp quantities they can be fuzzified. Furthermore, if the form of uncertainty happens to arise because of imprecision, ambiguity or vagueness, then the variable is fuzzy and can be represented by a membership function. Unlike the usual constraint where, say, the variable in Fig. 1 must not exceed 2, a fuzzy constraint takes the form as saying that the same variable should preferably be less than 2 and certainly should not exceed 4. This is tantamount in fuzzy sets terms that values less than 2 have membership of 1 but values greater than 4 have membership of 0 and values between 2 and 4 would have membership between 1 and 0. In order to simplify the calculations, usually the membership function is adopted as linear in practical applications. The objective then can be formulated as maximizing the minimum membership value, which has the effect of balancing the degree to which the objective is attained with degrees to which the constraints have to be relaxed from their optimal values.

Fuzzy rule base

In the present study, fuzzy logic is used for the estimation of the ultimate strength of circular concrete filled steel tubular columns (CCFST) under axial compression loads. For control purposes, fuzzy sets can be used to set up rules of the following forms:

R: IF the value of variable X_1 is "large" and variable X_2 is "medium" THEN the result *Y* is "small" ….(1)

This statement resembles human thinking more closely than any explicit mathematical rules. Therefore, FLS can be used for modeling the behavior of a human expert. Besides, it is also very effective in relating a set of outputs to a set of inputs without specifying a mathematical model, and here a ''fuzzy inference procedure'' becomes dominant. In the modeling of human expert thinking, the input variables are first specified by fuzzy subsets such as ''large'' and then fuzzy rules similar to Eq. (1) are developed on the basis of the experts' knowledge and experience. In the fuzzy inference method, sets of corresponding input and output measurements are provided to the FLS, and it learns how to transform a set of inputs to the corresponding set of outputs through a Fuzzy Associative Map. The fuzzy logic approach does not provide a rigorous way for developing or combining fuzzy rules, which can be achieved through many ways. The method adopted in this paper is outlined below.

First the input and output variables are divided into a number of subsets with simple triangular fuzzy membership functions. Generally, there are n^m fuzzy rules where *n* and *m* are the numbers of subsets and input variables, respectively.
In the case, say, of two inputs *X1* and *X2* with *m* subsets each, the rule base takes the form of an output Y_k (k=1,2,…,m^2). If there are two input variables as X_1 with "very small" and "small" fuzzy subsets and X_2 say, "medium" and "large" subsets then there will be four rules as:

R_1: IFX_1 is very small and X_2 is medium
THEN Y_1

R_2: IFX_1 is very small and X_2 is large
THEN Y_2

R_3: IFX_1 is small and X_2 is medium
THEN Y_3

R_4: IFX_1 is small and X_2 is large
THEN Y_4

For each triggered rule the membership degrees for both X_1 and X_2 are computed and these are multiplied to give the weight W_k to be assigned to the corresponding output Y_k. Hence, the weighted average of the outputs from four rules gives a single output, y, as

$$y = \frac{\sum_{k=1}^{4} W_k Y_k}{\sum_{k=1}^{4} W_k} \qquad \ldots(2)$$

Thus once the rule base is set up, values of the output can be computed from Eq. (2) for any combination of input variables fuzzy subsets. A common method in deciding about the fuzzy rule base is to use sample data and derive the necessary rule base by the fuzzy inference procedure. This involves computing the weight of each rule triggered, accumulating weights and outputs for each rule and finally computing the weighted output for each rule. and, finally, computing the weighted output for each rule [19].

FIS MODEL DEVELOPMENT FOR ULTIMATE STRENGTH PREDICTION

The FIS is used to predict the ultimate strength of CCFTS columns under axial compression loads. The FIS model is implemented using Fuzzy Logic Toolbox in MATLAB program version 7 (R14). This program implements the FIS model. In this section, the results of using this FIS model is presented and discussed to examine the ability of this model to predict the ultimate strength of CCFTS columns.

Preparation of data

The experimental results of (129) test CCFST columns that are used to build the proposed FIS model are obtained from a database developed by Kim [20]. The data used to build the model should be divided into two subsets: training data and validating or testing data. The testing data contains approximately 20% from total database. The total number of (129) test columns were utilized. The training data contained (103) samples and the testing data comprised of (26) samples. FIS interpolate data very well. Therefore, patterns chosen for training set must cover upper and lower boundaries and a sufficient number of samples representing particular features over the entire training domain [14].

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 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. Therefore, after a thorough study on the collected experimental data, five major variables are adopted to model the ultimate strength of CCFTS columns. The five major input variables are listed in Table (1) as follows:

1- fy= Yield stress of steel tube (MPa).

2- f'_c = cylinder compressive strength of concrete (MPa),

3- L / D= column slenderness ratio.

4- t = wall thickness of a steel tube (mm),
5- D = diameter of a steel tube (mm).and
The ultimate axial load P (kN) will be determined

Membership functions

According to the collected data, and using the scatter method for partitioning, five linguistic terms to describe the input variables fy, f'_c, L/D, t, and D were chosen, for the model, while 103 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 constants (equal in value to the correspond actual (experimental) output membership function. Based on this concept of the data classification, membership functions were determined for all input variables , as shown in Figs. (2 - 6).

Rule definition

Since there are just 103 training data, then a rule base of 103 rules would be performed. Hence, 103 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).

Model construction

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 CCFTS columns.

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 model validation, which resulted in a total of 26 testing data for the FIS model. The FIS model predicted and target (actual) ultimate strength are used for model validation. Table (2) presents the actual and predicted ultimate load capacity of the FIS models for testing data.

As seen from this table, the values obtained for the FIS model are very close to the experimental results. The average values of ratios of actual to predicted ultimate loads are 1.019 for the model. These results demonstrate that the FIS can be successfully applied to establish accurate and reliable prediction model.

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 model and the corresponding target for training and testing data respectively. From Figs. (9) and (10), R^2 = 0.979, 0.981 for training and testing data of the model, respectively. These values indicate an excellent agreement between the predicted and the actual values for the model.

COMPARISON WITH DESIGN STRENGTH

The predicted strengths, of the CCFST columns in Table (2), obtained from the proposed FIS model are compared with unfactored design strengths predicted using the design procedure specified in the American Institute of Steel Construction (AISC) [21] and the Eurocode 4 [22] for CCFST columns as calculated by Kim [20]. The predicted strengths of the proposed FIS model P(fuzzy) are compared with the design strengths calculated using AISC specifications P(AISC) and the design strengths calculated using Eurocode 4 specifications P(Euro) as shown in Table (3). The value of P(exp)/P(fuzzy), P(exp)/P(AISC), and P(exp)/P(Euro) ratio with the corresponding average are shown in this table. It can be seen, from table (3) , the average ratio of actual to predicted load is 1.019 for the FIS, 1.278 for AISC, and 1.113 for Eurocode 4. There for the design strength calculated using AISC and Eurocode 4 specifications are generally conservative.

In Fig. (11), the predicted strengths P(fuzzy) and the design strengths P(AISC) and P(Euro) are plotted against the experimental strengths. As shown in this figure, the coefficient of correlation R^2 = 0.981, 0.895 and 0.916 for FIS, AISC, and Eurocode 4, respectively. These values clearly show that the proposed FIS performs much better than the AISC and Eurocode 4 methods and that FIS provided an efficient alternative method in predicting the ultimate strength of CCFST columns.

CONCLUSIONS

In this study, the fuzzy interface system was used for the prediction the ultimate strength of CCFST columns subjected to axial loads. It has been shown that the fuzzy inference system (FIS) can effectively be used to predict the ultimate strengths of CCFST columns subjected to axial loads. It has also been shown that the FIS designed predicted the outputs with acceptable accuracy. It should be noted that once the FIS was trained, the time required to output results for a given set of inputs was instantaneous. This indicates the potential of the fuzzy interface system for solving time-consuming problems. Furthermore, the FIS directly use the experimental results in training, there is no need to make any assumptions on material parameters particularly in problems that have more than one existing calculation method, or the one based on only empirical approximations. This model was trained with input and output data. Using only the input data in trained model the ultimate strengths of CCFST columns were found. The ultimate strength values predicted were very close to the experimental results. The predicted strengths obtained from the proposed FIS model were compared with current design provision for CCFST columns (AISC and Eurocode 4). The average ratio of actual to predicted loads was 1.019 for the FIS, 1.278 for AISC, and 1.113 for Eurocode 4. It was noticed that the design strengths calculated using AISC and Eurocode 4 specifications are generally conservative and that the proposed FIS model can predict more accurate results than AISC and Eurocode 4 specifications.

As a result, ultimate strength of CCFST columns can be predicted in the proposed FIS model in a quite short period of time with tiny error rates. The conclusions have demonstrated that the FIS provided an efficient alternative method in predicting the ultimate strength of CCFST columns.

REFRENCES

[1] **Furlong, BW**, "Strength of steel-encased concrete beam columns", Journal of Structural Division 1967;93(5):113–24.

[2] **Tomii, M, Yoshimura, K**, and **Morishita, Y.** " Experimental studies on concrete filled steel tubular stub columns under concentric loading", In: Proceedings of the international colloquium on stability of structures under static and dynamic loads. 1977.

[3] **Rangan, BV.,** and **Joyce M.** "Strength of eccentrically loaded slender steel tubular columns filled with high-strength concrete", ACI Structural Journal 1992;89(6):676–81.

[4] **Schneider, SP**. "Axially loaded concrete-filled steel tubes", ASCE Journal of Structural Engineering 1998;124(10):1125–38.

[5] **Han, LH**. "Tests on stub columns of concrete-filled RHS sections", Journal of Constructional Steel Research 2002;58(3):353–72.

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

[7] **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.

[8] **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.

[9] **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.

[10] **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.

[11] **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.

[12] **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.

[13] **Zadeh**, **L.A.**, "Fuzzy sets", Journal of Information and Control, 8, 1965, pp. 338-353.

[14]- **Klir GJ**,and **Fogel TA**. "Fuzzy sets", uncertainty and information. New York (NY): Prentice Hall, 1988.

[15]- **Kosko B.** "Neural networks and fuzzy systems. " Englewood Cliffs (NJ): Prentice Hall, 1992.

[16]- **Zadeh, L**., and **Kacprzyk J**, "editors. Fuzzy logic for the management of uncertainty". 1992.

[17]- **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.

[18]- **Mustafa Sarıdemir** " Predicting the compressive strength of mortars containing metakaolin by artificial neural networks and fuzzy logic " Advances in Engineering Software 40 (2009) 920–927
[19]- **Kirschfink**, **H.**, and **Lieven**, **K.**, "Basic tools for fuzzy modeling", Liebigstrasse 20, D-52070, Aachen, Germany, 2000.
[20] **Kim, D.K**., 2005, "A Database for Composite Columns", M.Sc thesis, School of Civil and Environmental Engineering, Georgia Institute of Technology.
[21] AISC, 2005, "Specification for Structural Steel Buildings", American Institute of Steel Construction, Chicago, IL.
[22] Eurocode 4, 1994, DD ENV 1994-1-1, "Design of Composite Steel and Concrete Structures, Part 1.1: General Rules and Rules for Buildings (with U.K National Application Document)", British Standards Institution, London.

Table (1) Range of input parameters

Parameter	Range
Yield stress of steel tube (*fy)* (MPa).	**221 - 634**
Concrete cylinder compressive strength (f'_c) (MPa)	**17.9 – 100**
column slenderness ratio (*L/D*)	**1.8 – 45.5**
wall thickness of a aluminum tube (*t*) (mm)	**1.4 – 6.7**
diameter of a steel tube (*D*) (mm)	**76 -218**

Table (2) Actual (experimental) and predicted values for testing data

Column designation	f_y (MPa)	f'_c (MPa)	*L/D* (mm)	*t* (mm)	*D* (mm)	*P(exp)* (kN)	*P(Fuzzy)* (kN)	*P(exp)/ P(Fuzzy)*
4	605	31.2	2.0	3.1	102	1067.6	1110.0	0.962
14	415	23.1	2.0	3.1	153	1201.0	1200.0	1.001
2a	317	36.5	1.8	2.6	169	1307.8	1320.0	0.991
7a	261	32.9	1.8	5.0	169	1966.1	1980.0	0.993
–	414	29.0	8.0	3.2	114	756.2	712.0	1.062
–	331	25.9	6.0	1.5	152	721.5	691.0	1.044
4	317	33.6	11.7	2.6	169	689.5	704.0	0.979
1	605	34.1	14.9	3.1	102	818.5	801.0	1.022
11	415	20.9	11.0	3.1	153	938.6	881.0	1.065
1	400	40.1	19.4	5.8	89	614.7	616.0	0.998
6	483	41.4	20.8	1.4	83	224.6	245.0	0.917
8	483	40.9	13.5	1.4	83	355.9	331.0	1.075
5	301	31.4	4.3	6.4	218	2745.0	2660.0	1.032
10.1	281	29.6	20.2	3.7	96	362.5	389.0	0.932
11.3	281	33.6	15.5	3.7	95	495.1	499.0	0.992
13.1	281	33.6	5.3	3.7	95	637.4	599.0	1.064
SC154-	410	26.5	38.5	4.5	108	342.5	361.0	0.949

SC149-2	410	39.0	37.3	4.5	108	320.3	361.0	0.887
SC130-3	410	39.0	32.5	4.5	108	440.4	361.0	1.220
C12-0	353	31.9	12.0	4.1	165	1373.2	1490.0	0.922
C4	343	93.6	2.6	4.0	115	1307.3	1240.0	1.054
C9	365	57.6	2.6	5.0	115	1412.3	1260.0	1.121
C14	343	98.9	2.6	3.8	115	1358.5	1270.0	1.070
S-1	340	20.1	3.0	2.6	120	639.7	636.0	1.006
KLM200	280	54.2	3.0	2.3	76	438.6	392.0	1.119
KLM200	365	46.7	3.0	2.3	114	669.5	651.0	1.028
							Average	1.019

Table (3) Comparison between actual (experimental) and predicted values for testing data

Column designation	*P(exp)* (kN)	*P(Fuzzy)* (kN)	*P(AISC)* (kN)	*P(Euro)* (kN)	*P(exp)/ P(Fuzzy)*	*P(exp)/ P(AISC)*	*P(exp)/ P(Euro)*
4	1067.6	1110.0	785.0	1100.6	0.962	1.360	0.970
14	1201.0	1200.0	976.4	1364.8	1.001	1.230	0.880
2a	1307.8	1320.0	1167.7	1486.1	0.991	1.120	0.880
7a	1966.1	1980.0	1285.0	1739.9	0.993	1.530	1.130
--	756.2	712.0	675.2	706.7	1.062	1.120	1.070
--	721.5	691.0	655.9	721.5	1.044	1.100	1.000
4	689.5	704.0	985.0	1044.7	0.979	0.700	0.660
1	818.5	801.0	634.5	660.1	1.022	1.290	1.240
11	938.6	881.0	861.1	893.9	1.065	1.090	1.050
1	614.7	616.0	579.9	602.6	0.998	1.060	1.020
6	224.6	245.0	238.9	249.6	0.917	0.940	0.900
8	355.9	331.0	304.2	326.5	1.075	1.170	1.090
5	2745.0	2660.0	2250.0	2745.0	1.032	1.220	1.000
9.1	362.5	389.0	366.2	381.6	0.932	0.990	0.950
10.3	495.1	499.0	419.6	442.1	0.992	1.180	1.120
12.2	637.4	599.0	486.6	574.2	1.064	1.310	1.110
SC154-1	342.5	361.0	187.2	196.8	0.949	1.830	1.740
SC149-2	320.3	361.0	209.3	220.9	0.887	1.530	1.450
SC130-3	440.4	361.0	273.5	280.5	1.220	1.610	1.570
C12-0	1373.2	1490.0	885.9	980.9	0.922	1.550	1.400
C4	1307.3	1240.0	947.3	1107.9	1.054	1.380	1.180
C9	1412.3	1260.0	825.9	1069.9	1.121	1.710	1.320
C14	1358.5	1270.0	970.4	1122.7	1.070	1.400	1.210
S-1	639.7	636.0	394.9	528.7	1.006	1.620	1.210
KLM2002	438.6	392.0	353.7	434.3	1.119	1.240	1.010
KLM2002	669.5	651.0	712.2	869.5	1.028	0.940	0.770
				Average	1.019	1.278	1.113

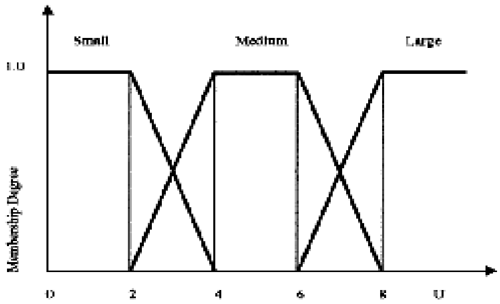
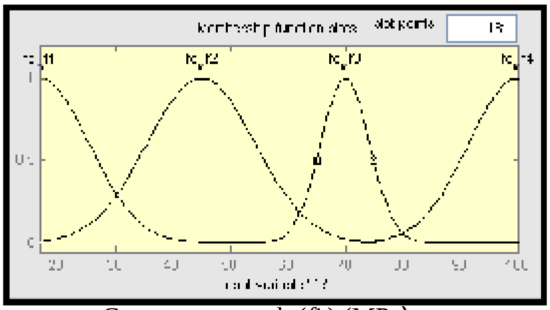
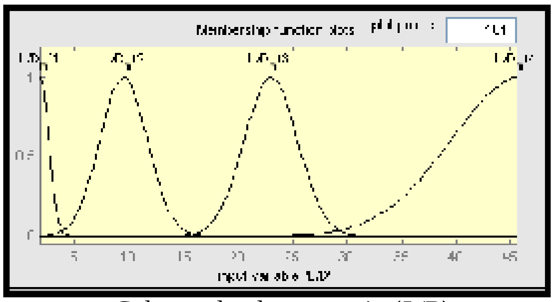


Figure (1) Fuzzy subsets.



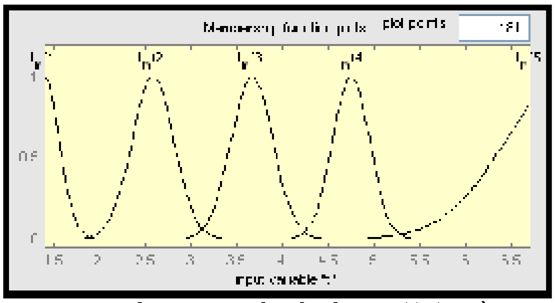
Concrete strength (f'_c) (MPa)

Figure (2) Membership functions for concrete strength ($f'c$)



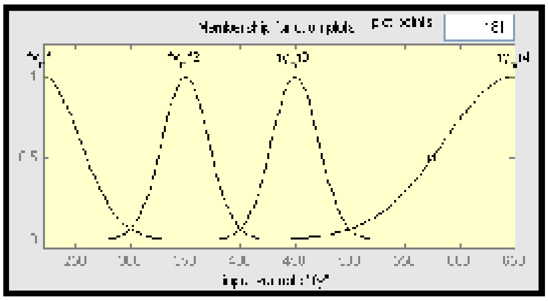
Column slenderness ratio (*L/D*)

Figure (3) Membership functions for Column slenderness ratio (*L/D*)



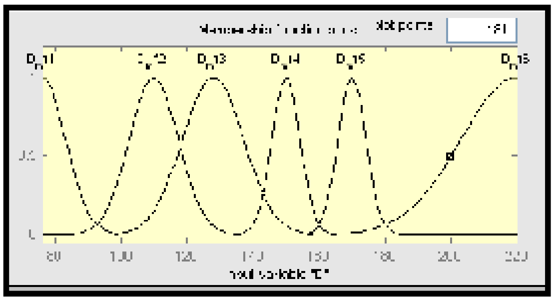
Aluminum tube thickness (*t*) (mm)

Figure (4) Membership functions for steel tube thickness (*t*)



Yield stress of steel tube (*fy)* (MPa)

Figure (5) Membership functions for yield stress of steel tube (*fy)* (MPa)



Column diameter (*D*) (mm)

Figure (6) Membership functions for column diameter (*D*)

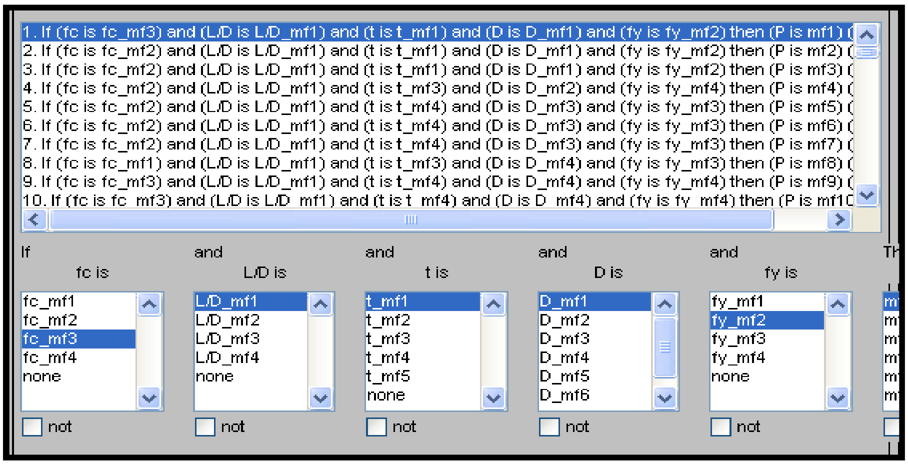


Figure (7) a segment of the rules frame for FIS model

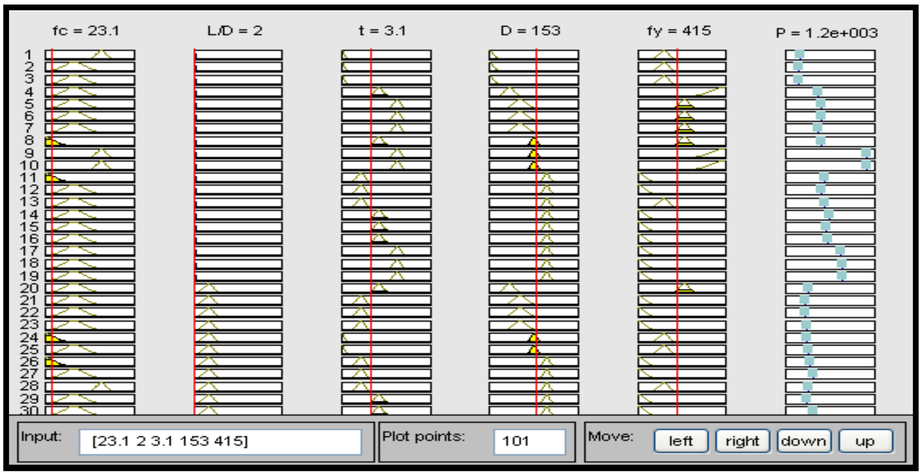


Figure (8) Inference module (the rules viewer)

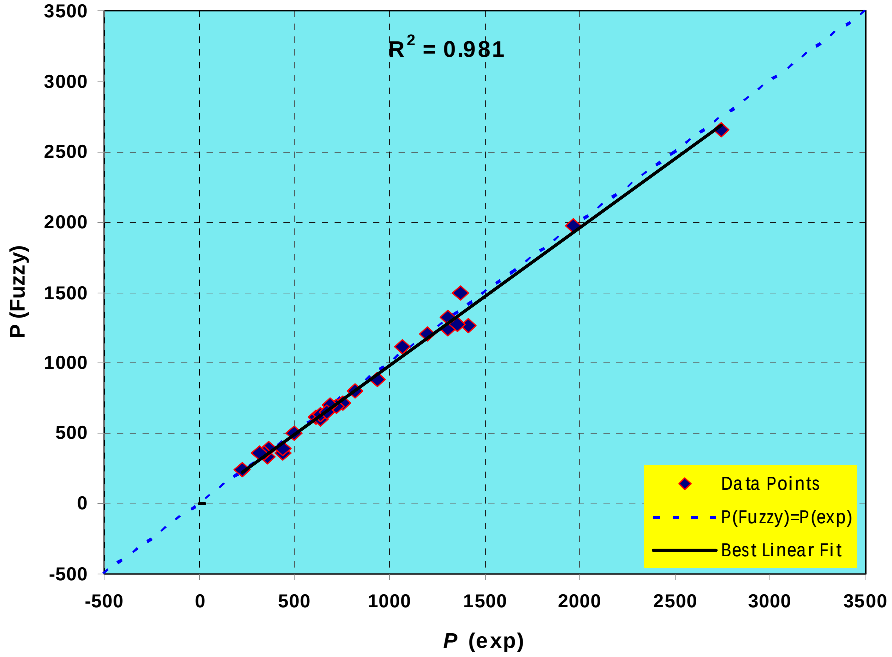


Figure (9) Regression analysis between predicted and actual values for testing data

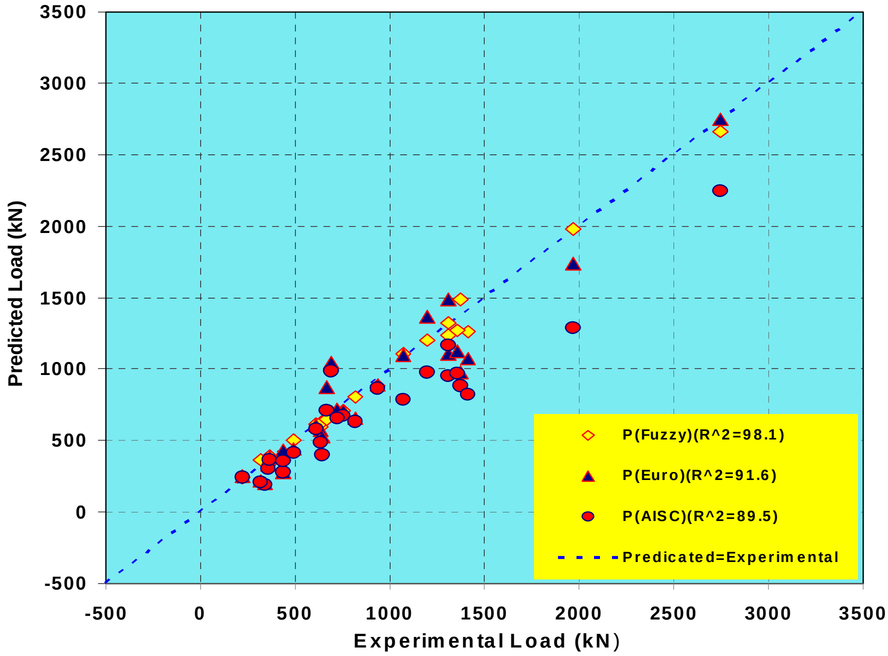


Figure (10) Regression analysis between predicted and actual values