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Mechanical properties of blended cements at elevated temperatures predicted using a fuzzy logic model

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Abstract. This study aimed to develop a Rule Based Mamdani Type Fuzzy Logic (RBMFL) model to predict the flexural strengths and compressive strengths of blended cements under elevated temperatures. Clinoptilolite was used as cement substitution material in the experimental stage. Substitution ratios in the cement mortar mix designs were selected as 0% (reference), 5%, 10%, 15% and 20%. The data used in the modeling process were obtained experimentally, after mortar specimens having reached the age of 90 days and exposed to 300℃, 400℃, 500℃ temperatures for 3 hours. In the RBMFL model, temperature (C°) and substitution ratio of clinoptilolite (%) were inputs while the compressive strengths and flexural strengths of mortars were outputs. Results were compared by using some statistical methods. Statistical comparison results showed that rule based Mamdani type fuzzy logic can be an alternative approach for the evaluation of the mechanical properties of concrete under elevated temperature.

Keywords: blended cement; clinoptilolite; compressive strength; flexural strength; rule based fuzzy logic

1. Introduction

As generally known, concrete is the most widely used man made construction material in civil engineering applications such as buildings, roads, bridges, dams, power plants, flooring, and more. Compared to other building materials, concrete can be formed into a variety of shapes and sizes either at the construction site or as precast elements. While strength of concrete is commonly considered as its most valuable property, in many cases durability, impermeability and volume stability may in fact be more important. It is essential that concrete should be capable of withstanding the conditions for which it has been designed throughout the life of structure (Neville 2011).

To provide a general perspective, concretes can be broadly classified into mineral and polymer categories (Martinez-Barrera *et al.* 2011, Brostow and Hagg Lobland 2016). While concrete industry plays an important role in infrastructure development and economic growth, it faces many challenges due to environmental concerns and sustainability issues (Brostow and Hagg Lobland 2016, Mishra and Siddiqui 2014, Anik *et al.* 1996, Behera *et al.* 2014, Malhotra 2000, van Oss and Padovani 2003, Kurdowski 2014).

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Concrete production consumes much energy and a large amount of natural resources. It causes environmental, energy and economic losses as it exploits 50% of raw materials, 40% of total energy, as well as generates 50% of total wastes (Anik *et al.* 1996, Behera *et al.* 2014). Cement industry contributes to production for about 7% of all CO_2 generated in the world (Malhotra 2000). Every ton of cement production releases nearly one ton of CO_2 to atmosphere (van Oss and Padovani 2003).

In this situation we have decided to develop blended Portland cements in which clinker is partially replaced by mineral additives called supplementary cementitious materials (SCMs). There are three main types of SCMs: (a) hydraulic materials that mixed with water provide products similar to those formed in hydration of Portland cement, containing mainly calcium silicate hydrate (C-S-H) phase; (b) pozzolanic materials which in the presence of moisture react with calcium hydroxide at ordinary temperatures and form compounds with cementitious properties; (c) fillers—usually chemically inert with some beneficial effects on properties. Many studies are available in the literature about cements blended with SCMs (Kurdowski 2014, Kim *et al.* 2016).

SCMs are mainly by-products of industrial production; they include silica fume (SF), fly ash (FA), waste marble, granulated blast furnace slag (GBFS) and stone powders. Some natural minerals such as zeolite are also classified as SCMs. (Juenger and Siddique 2015, Karra *et al.* 2016).

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SCMs affect cement hydration kinetics and composition of the C-S-H phase (Juenger and Siddique 2015, Neeraj 2012, Liu *et al.* 2013). Due to pozzolanic activity and the filling effect, SCMs contribute to the strength increase of cement mortar and concrete (Neeraj 2012, Liu *et al.* 2013, Saraya 2014, Borosnyói 2016, Paris *et al.* 2016, Bilim 2011), enhance the freeze-thaw resistance (Borosnyói 2016; Paris *et al.* 2016, Bilim 2011), decrease porosity and permeability (Neeraj 2012, Borosnyói 2016, Paris *et al.* 2016, Bilim 2011) and thus improve durability of concrete (Borosnyói 2016, Paris *et al.* 2016, Bilim 2011, Lollini *et al.* 2016). Waste marble has been used to mitigate wear of concrete surfaces (Gencel *et al.* 2012), and haematite was used for the same purpose (Gencel *et al.* 2013). Fly ash was used to improve properties of pre-fabricated concrete interlocking blocks (Uygunoglu *et al.* 2012).

Certain materials properties and behavior which are difficult to determine experimentally can be deduced from computer simulations and calculations (Brostow and Hagg Lobland 2016). The approaches used include fuzzy logic (FL), artificial neural networks (ANNs), genetic algorithms (GAs), and fuzzy genetics (FG). Thus, fuzzy logic was used by Gencoglu *et al.* for the prediction of elastic modulus of steel fiber reinforced concrete (Gencoglu *et al.* 2012).

Arslan and Durmuş used also fuzzy logic approach for estimating bond behaviour of lightweight concrete (Arslan and Durmuş 2014) / Garzón-Roca *et al.* used fuzzy logic with artificial neural networks to estimate compressive strength of masonry made of clay bricks and cement mortar (Garzón-Roca *et al.* 2013). Akkurt *et al.* developed a fuzzy logic model for the prediction of cement compressive strength (Akkurt *et al.* 2004). Pani and Mohanta used different approaches including fuzzy inference for online monitoring of cement fineness (Pani and Mohanta 2014).

Topçu *et al.* predicted the strength development of cements produced with different pozzolans (Topçu *et al.* 2008).

The aim of this study is to develop a Rule Based Mamdani Type Fuzzy Logic (RBMFL) model to predict the flexural strengths and compressive strengths of blended cements under elevated temperatures.

2. Fuzzy logic in MATLAB

Two types of Fuzzy Inference Systems (FISs) are available that can be implemented in the MATLAB's FIS toolbox. These are Mamdani-type and Sugeno-type FISs. Mamdani's method is the most commonly used FL and it expects the output Membership Functions (MFs) to be fuzzy sets (Omid 2011). Mamdani's method was one of the first control systems built using fuzzy set theory. It was proposed in 1975 by Mamdani and Assilian as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators (Mamdani and Assilian 1975). Mamdani's effort was based on Lotfi Zadeh's works on fuzzy algorithms for complex systems and decision processes. The main difference between Mamdani and Sugeno algorithms is that the Sugeno output membership functions are either linear or constant. For this reason, the Sugeno system is a more compact and computationally efficient representation than the Mamdani system. The Sugeno system allows the use of adaptive techniques for constructing fuzzy models. The Mamdani method is widely accepted for capturing expert knowledge. It allows one to describe the expertise in a more intuitive and human-like manner. Due to the interpretable and intuitive nature of the rule base, Mamdani type FIS is widely used for decision support applications in particular (Kaur and Kaur 2012).

In MATLAB environment, we may use the graphical user interface (GUI) to build, edit, and view Mamdani type FIS. There are five primary GUI tools for building, editing, and observing Mamdani type FIS in the FL Toolbox: the Fuzzy Inference System or FIS Editor, the Membership Function Editor, the Rule Editor, the Rule Viewer, and the Surface Viewer. Fuzzy Inference System (FIS) Editor displays general information about a fuzzy inference system; Membership Function Editor lets us to display and edit the membership functions associated with the input and output variables of the FIS; Rule Editor lets us to view and edit fuzzy rules using one of three formats; Rule Viewer lets us to view detailed behaviour of a FIS to help diagnose the behaviour of specific rules or study the effect of changing input variables; Surface Viewer generates a 3-D surface from two input variables and the output of an FIS (MATLAB Fuzzy Logic Toolbox™ 2012).

3. Experimental: Materials and methods

In this study, CEM I 42.5 R type cement produced by OYAK Bolu Cement Factory was used as the binder. Natural zeolite in clinoptilolite form used by us was obtained from the Gördes Mining Company, Gördes region, Turkey. Physical and mechanical properties of cement are given in Table 1 and chemical compositions of cement and clinoptilolite are given in Table 2. Our zeolite contains a high concentration of the clinoptilolite phase but very low quartz and opal cristobalite (opal CT) content; see Fig. 1. The XRD diagram in Fig. 1 was provided by Gördes Mining Company. The mortar mixtures were prepared with 450 g of cement, 1350 g of CEN standard sand, and 225 mL of water and mixed in accordance with the Turkish standard TS EN 196-1. Clinoptilolite was used at 0%, 5%, 10%, 15% and 20% replacement by weight for cement—while sand and water quantities were kept constant.

For the mixture preparation, the mortars were placed in 40×40×160 mm prismatic molds. After removal from the molds at 24 h of age, mortar specimens were immersed in water saturated with lime at 20°C until the time of testing. After 90 days curing period, each specimen was exposed to 300°C, 400°C, and 500°C temperatures for 3 h in a furnace. After those 3-hour-exposures at the specified temperatures, the hot mortar specimens were cooled in ambient conditions. Upon reaching the room temperature, flexural strengths were determined, taking the averages of three test results while the compressive strengths were determined by taking the averages of six test results.

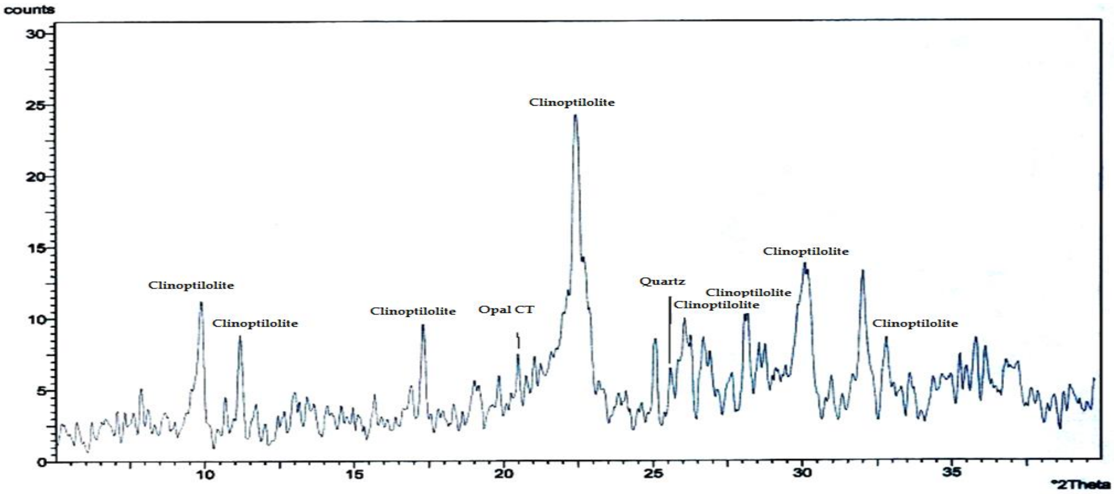


Fig. 1 XRD analysis of zeolite

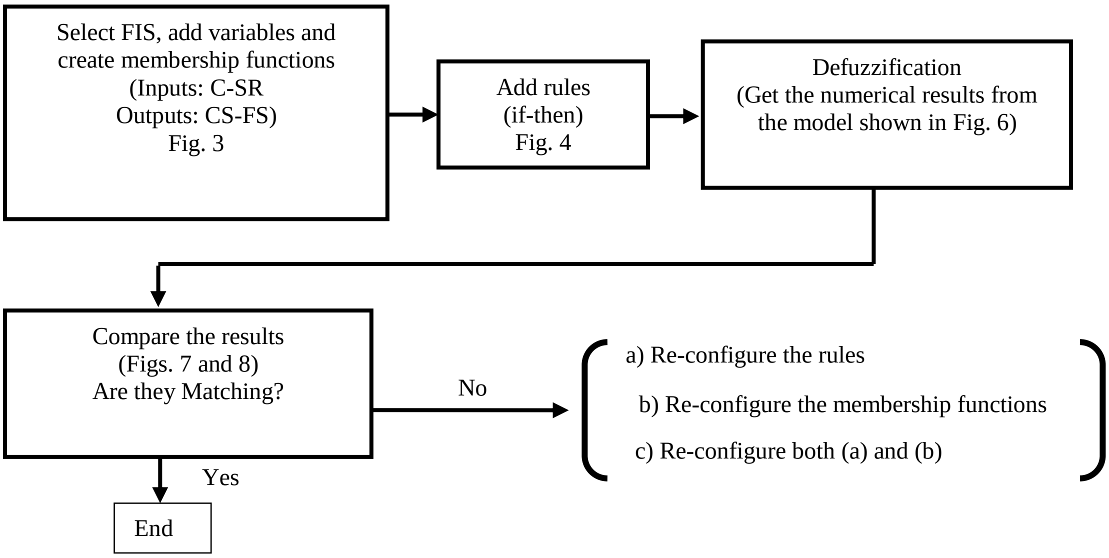


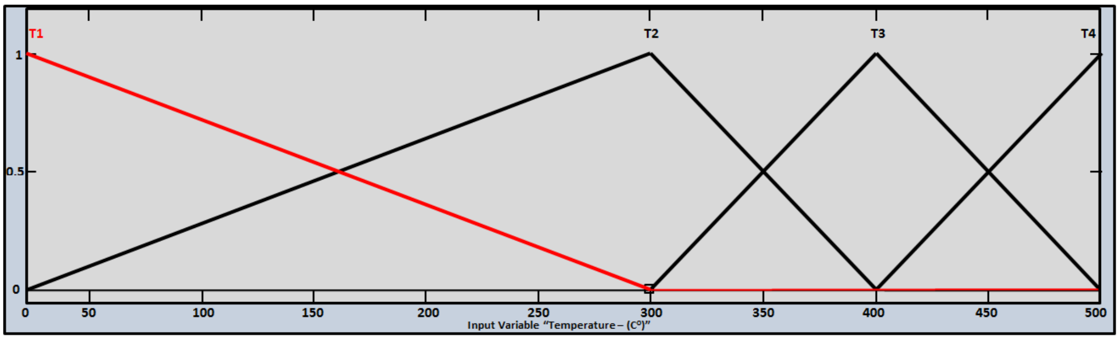
Fig. 2 Flow diagram for this research

Table 1 Physical and mechanical properties of cement

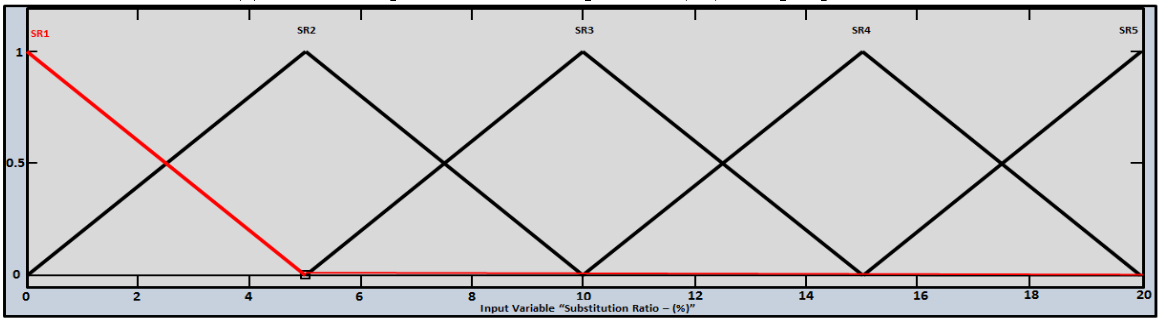
Physical properties of cement	
Initial setting time (min)	140
Final setting time (min)	160
Volume expansion (mm)	1
Specific gravity	3.18
Specific surface (Blaine cm2/g)	4663
Mechanical properties of cement	
Compressive strength (MPa)	
7 days	45
28 days	55
90 days	62

Table 2 Chemical composition of cement and clinoptilolite

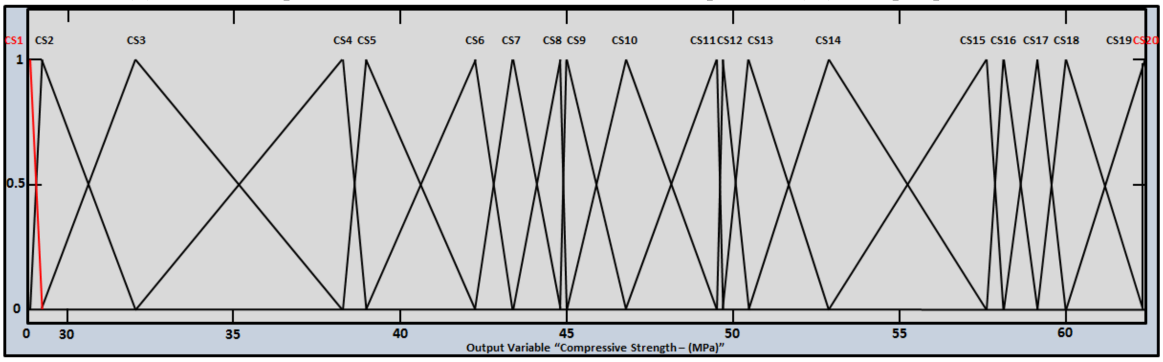
Chemical composition (%)	Cement	Clinoptilolite
SiO_2	18.9	67.1
Al_2O_3	5.3	11.8
Fe_2O_3	4.1	1.5
CaO	64.7	2.2
MgO	1.3	1.2
SO_3	2.9	-
Na_2O	0.2	0.4
K_2O	0.5	3.4
Loss of ignition	3.8	12.5
Insoluble residue	0.6	
Free CaO	1.52	



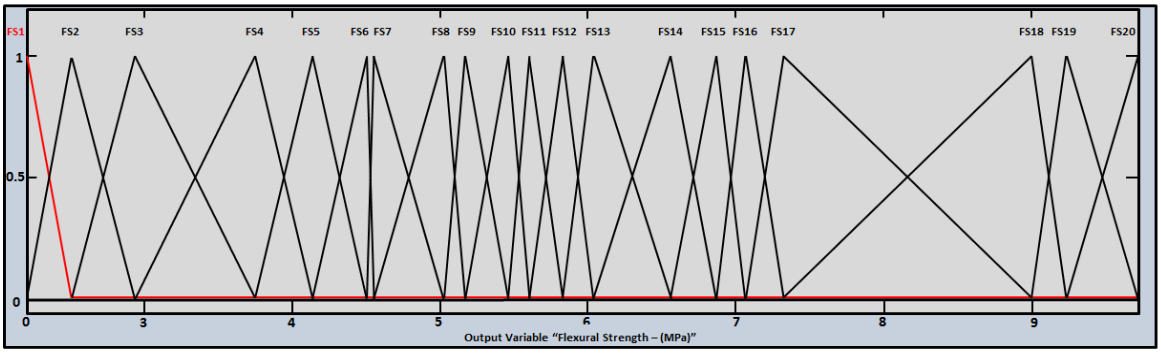
(a) Membership functions of temperature (C^o) as input parameter



(b) Membership functions of substitution ratio of clinoptilolite (%) as input parameter



(c) Membership functions of compressive strength (MPa) as output parameter



(d) Membership functions of flexural strength (MPa) as output parameter

Fig. 3 Membership functions of inputs and outputs of the model

4. Details of developed rule based MAMDANI FIS model and results

In this study, a Rule Based Mamdani Type Fuzzy Logic (RBMFL) model for prediction of flexural strengths and compressive strengths of cement mortars containing clinoptilolite as a substitution material was developed. Substitution ratios in the cement mortar mix designs were selected as 0% (reference), 5%, 10%, 15% and 20%. A flow diagram is displayed in Fig. 2.

The developed model has two inputs and two outputs. Inputs were temperature (C°) and substitution ratio of clinoptilolite (%) while outputs are compressive strength and flexural strength of mortars. In the model development

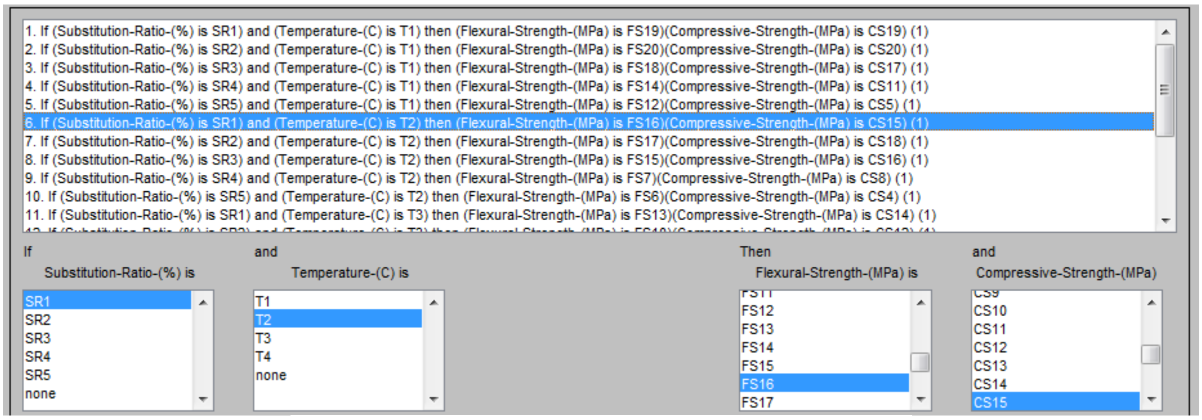
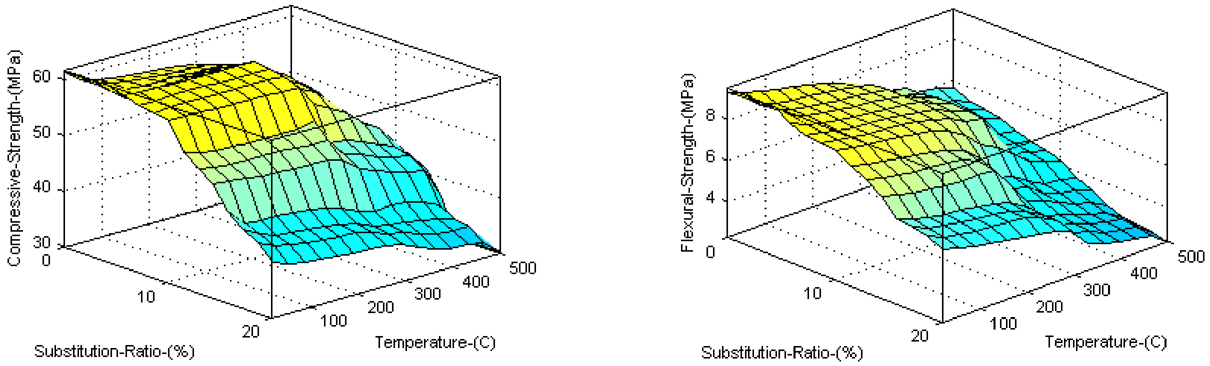


Fig. 4 Fuzzy rules screen of the developed RBMFL model



(a) Changes in compressive strength

(b) Changes in flexural strength

Fig. 5 Inputs and outputs relations according to the developed RBMFL model

the membership functions for temperature (C°), substitution ratio of clinoptilolite (%), compressive strength (MPa) and flexural strength (MPa) were used as 4-5-20 and 20 respectively (Figs. 3(a)-3(d)).

RBMFL uses fuzzy rules which are formed by users. The rules play a key role between input and output relationships in obtaining crisp output. After determining membership functions, 20 rules were formed to explain relationship between inputs and outputs. Summary of the rules is provided in Fig. 4. Output values variation as a function of inputs in the RBMFL model according to the defined rules are given in Figs. 5(a) and 5(b). To obtain crisp output values of compressive and flexural strength, defuzzification was performed using a centroid of area (COA) method. This method is also known as center of gravity or center of area defuzzification and is very accurate. It can be represented by Eq. (1) in which x* is the defuzzified output, μi(x) is the aggregated membership function, and x is the output variable

$$x* = \frac{\int \mu_i(x)x\,dx}{\int \mu_i(x)dx} \tag{1}$$

At the end of the modeling process, the crisp results of the model are seen on the defuzzification screen (Fig. 6). To evaluate RBMFL model predictability, the values obtained from the model and experimental were divided into 4 groups according to the applied temperature. Results of each group were evaluated for both compressive strength and flexural strength. Predictability of the developed RBMFL model was evaluated by considering three statistical parameters. These statistical parameters are coefficient of determination (R^2) in Eq. (2), Root Mean Squared Error (RMSE) in Eq. (3) and the Mean Absolute Error (MAE) defined by Eq. (4)

$$R^2 = 1 - \left\{\left[\sum_{i=1}^{n}(Y_{i(m)} - Y_{i(p)})^2\right] \Big/ \left[\sum_{i=1}^{n}(Y_{i(m)} - Y_{i(mean)})^2\right]\right\} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{i(m)} - Y_{i(p)})^2} \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Y_{i(m)} - Y_{i(p)}| \tag{4}$$

Histogram diagrams were created to see the relationships between the RBMFL model and the experimental results. The diagrams for the compressive strength are shown in Fig. 7, for the flexural strength in Fig. 8.

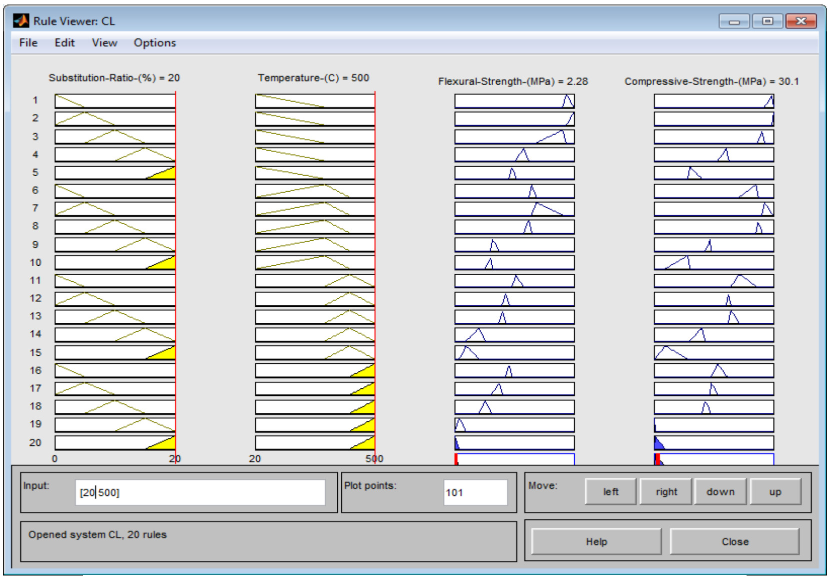
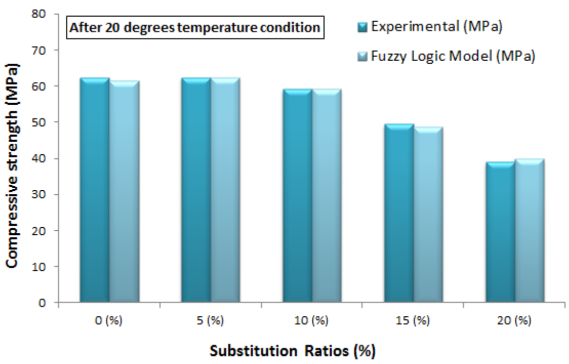
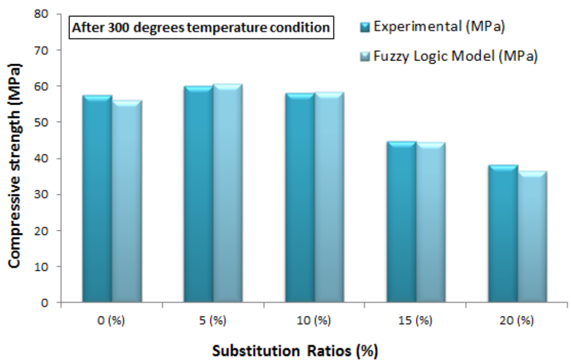


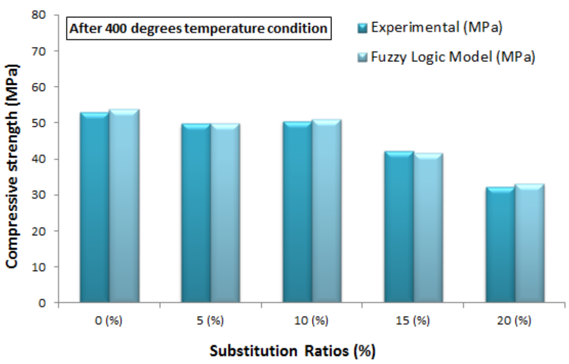
Fig. 6 Defuzzification screen of the developed RBMFL model



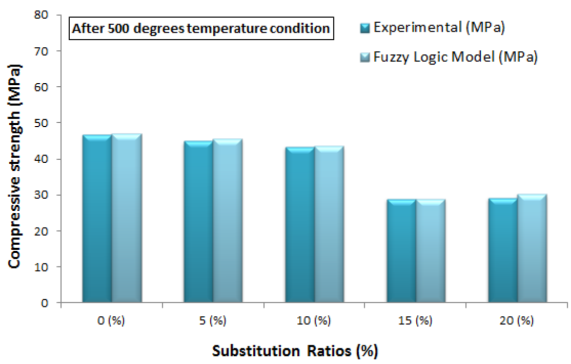
(a) After 20 degrees temperature condition



(b) After 300 degrees temperature condition



(c) After 400 degrees temperature condition



(d) After 500 degrees temperature condition

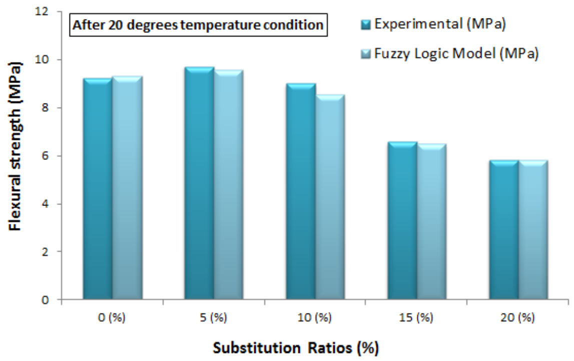
Fig. 7 Comparison of experimental and predicted values of the compressive strength results

The statistical values of R^2, RMSE and MAE, including all the data sets for compressive strength (CS) results are given in Table 2. The statistical values of R^2, RMSE and MAE, including all the data sets for flexural strength results were given in Table 3.

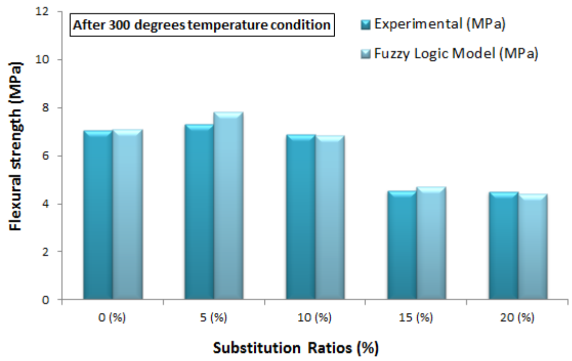
Fig. 7 and Table 2 show virtually perfect agreement of predicted values of the compressive strength with the experimental ones. The same applies to the flexural strength values in Fig. 8 and the statistical analysis of these values in Table 3. As a final stage of discussion, Fig. 9 for compressive strength and Figure 10 for flexural strength were created as matching figures to demonstrate clearly the relationship between RBMFL model results and experimental results. As seen in figures, there is a very good overlap between the results of RBMFL model and experimental.

Table 2 Statistical results of CS prediction using RBMFL model

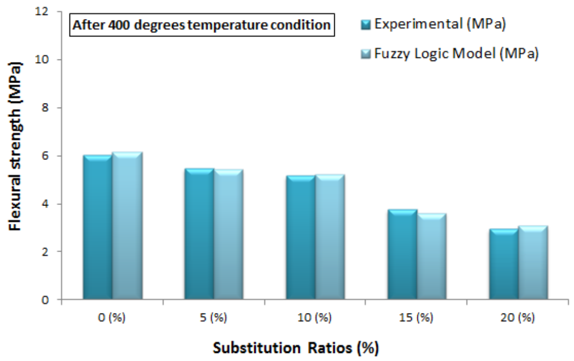
Data group	R^2	RMSE	MAE
After 20 degrees CS	0.994	0.67	0.53
After 300 degrees CS	0.983	1.11	0.901
After 400 degrees CS	0.991	0.73	0.66
After 500 degrees CS	0.996	0.47	0.36



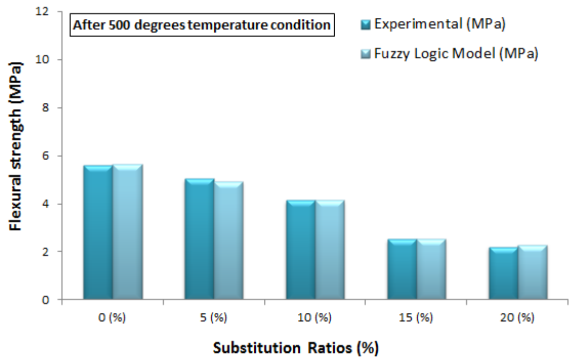
(a) After 20 degrees temperature condition



(b) After 300 degrees temperature condition



(c) After 400 degrees temperature condition



(d) After 500 degrees temperature condition

Fig. 8 Comparison of experimental and predicted values of the flexural strength results

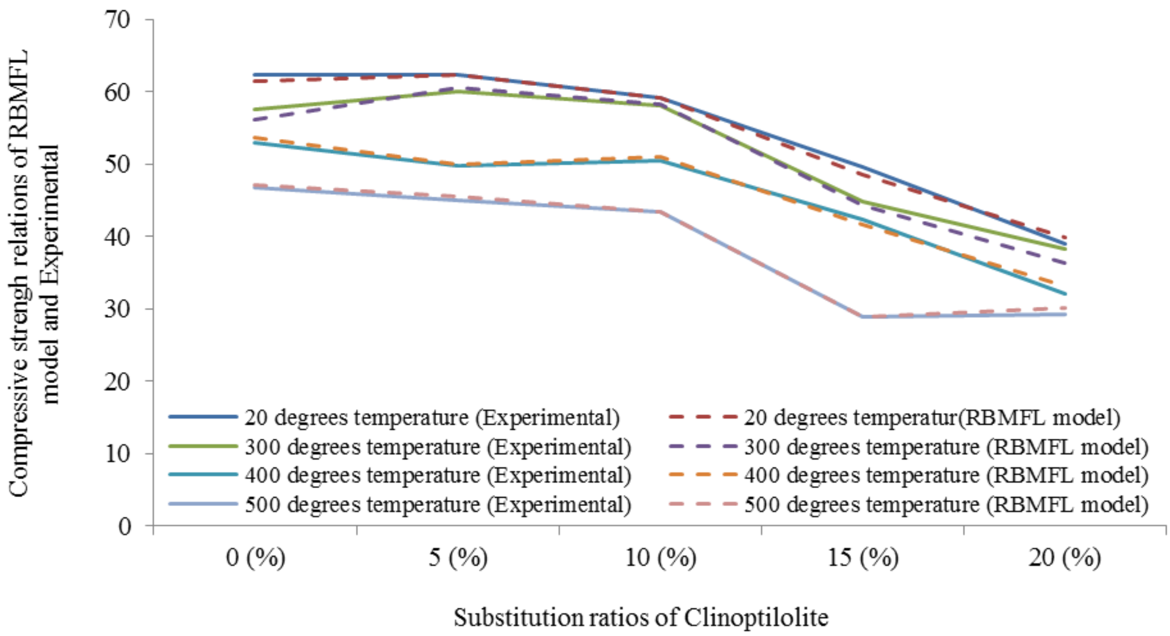


Fig. 9 Matching figure of the results of experimental and RBMFL model for compressive strength

Table 3 Statistical results of FS prediction using RBMFL model

Data group	R^2	RMSE	MAE
After 20 degrees FS	0.979	0.23	0.15
After 300 degrees FS	0.966	0.23	0.16
After 400 degrees FS	0.992	0.10	0.09
After 500 degrees FS	0.998	0.06	0.05

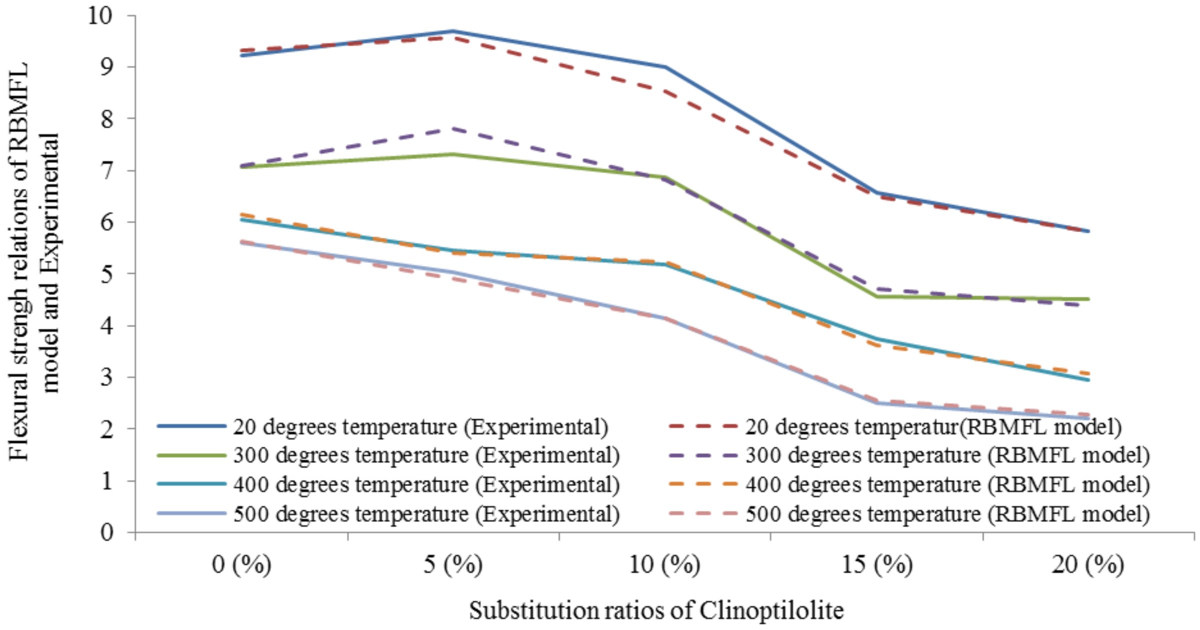


Fig. 10 Matching figure of the results of experimental and RBMFL model for flexural strength

5. Conclusions

In this paper, a RBMFL model using the FL Toolbox in MATLAB was developed to estimate the compressive strengths and flexural strengths of clinoptilolite substituted mortars under elevated temperature. The results obtained from the developed model compared with the experimental results using statistical parameters. According to the findings following conclusions can be written;

• When the results compared using the coefficient of determination (R2) values for CS prediction, the values were found 0.994 for 20 degrees temperature condition, 0.983 for 300 degrees temperature condition, 0.991 for 400 degrees temperature condition and 0.996 for 500 degrees temperature condition. If the same statistical parameter is evaluated for FS, the R2 values were found as 0.979, 0.966, 0.992 and 0.998 for 20, 300, 400 and 500 degrees respectively.

• MAE results were found 0.53, 0.91, 0.66, 0.36 for CS prediction and 0.15, 0.16, 0.09, 0.05 for FS prediction under 20, 300,400 and 500 degrees temperature conditions respectively. When the MAE was evaluated to verify the accuracy of prediction method, it is clearly seen that RBMFL model gives very accurate results with very little percentage errors were found.

• As well known, the RMSE represents the sample standard deviation of the differences between predicted values and observed values. The RMSE values found in this research (from 0.47 to 1.11 for CS and from 0.06 to 0.23 for FS) support the other statistical results by its little results.

It is clearly seen from this work that the mechanical properties of mortars such as compressive strength and flexural strength can be estimated using developed models of RBMFL without performing any more experiments. Rule based Mamdani type fuzzy logic can be an alternative approach for the evaluation of the mechanical properties of concrete under elevated temperature.

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