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Hybrid fuzzy model to predict strength and optimum compositions of natural Alumina-Silica-based geopolymers

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Abstract. This study introduces the supervised committee fuzzy model as a hybrid fuzzy model to predict compressive strength (CS) of geopolymers prepared from alumina-silica products. For this purpose, more than 50 experimental data that evaluated the effect of Al_2O_3/SiO_2, Na_2O/Al_2O_3, Na_2O/H_2O and Na/[Na+K] on (CS) of geopolymers were collected from the literature. Then, three different Fuzzy Logic (FL) models (Sugeno fuzzy logic (SFL), Mamdani fuzzy logic (MFL), and Larsen fuzzy logic (LFL)) were adopted to overcome the inherent uncertainty of geochemical parameters and to predict CS. After validating the model, it was found that the SFL model is superior to MFL and LFL models, but each of the FL models has advantages to predict CS. Therefore, to achieve the optimal performance, the supervised committee fuzzy logic (SCFL) model was developed as a hybrid method to combine the benefits of individual FL models. The SCFL employs an artificial neural network (ANN) model to re-predict the CS of three FL model predictions. The results also show significant fitting improvement in comparison with individual FL models.

Keywords: compressive strength; geopolymer; fuzzy model; Artificial Neural Network (ANN); Supervised Committee Fuzzy Logic (SCFL)

1. Introduction

Geopolyemrs, also known as alkali-activated products, are new materials with wide range of applications in different scientific and industrial fields such as medical applications, repairing and retrofitting, heat resistant coatings and adhesives, high-temperature ceramics, new binders for fire-resistant fiber composites, toxic and radioactive waste encapsulation, and cement alternatives in concrete (Duxson *et al*. 2007, Duxson *et al*. 2005, Panagiotopoulou *et al*. 2007). Geopolymers are a class of inorganic amorphous materials attained by reaction of an aluminosilicate source under strong alkaline conditions, in the presence of water soluble alkali metal silicates (Roviello *et al*. 2015). These materials are economically and environmentally more sustainable than their currently used alternatives (Ferone *et al*. 2013). The main features of geopolymers that make them more advantageous than their similar alternatives are their resistance to acid attack, fast compressive strength development, good resistance to freeze-thaw cycles, low permeability, and tendency to extremely decrease the mobility of heavy metal ions contained within the geopolymeric structure (Van Jaarsveld *et al*. 1997).

Geopolymers are being widely pondered as a sustainable replacement for traditional Portland cements to be used in green concrete due to the relatively smaller CO_2 footprint and the ability of gaining excellent compressive strength by proper mix design (Duxson *et al*. 2007, Palomo *et al*. 1999, Wang *et al*. 2005). Geopolymeric materials are usually synthesized using activating solutions based on the alkalis of sodium and potassium due to their ability to form highly concentrated aqueous solutions and consequently solvating large amounts of silicon and aluminum which are the main two significant elements for geopolymerisation. Many studies investigated the effect of alkalization on geoplymers without systematically focusing on which alkali type affects more on their mechanical properties (van Jaarsveld and van Deventer 1999, Xu and Van Deventer 2003, Xu *et al*. 200, Khater 2016).

In the past few decades, intelligent techniques such as artificial neural networks (ANN) and fuzzy logic (FL) have been used by researchers as valuable tools to generate predictive models (Nourani *et al*. 2008, Asadi *et al*. 2014, Nadiri *et al*. 2013, Nadiri *et al*. 2014, Tayfur and Nadiri *et al*. 2014, de Castilho *et al*. 2007, Ahmadi-Nedushan 2012, Cheng and Cao 2014). FL can be applied on linear and nonlinear systems and can consider more input variables without any further presumptions due to its speed, accuracy, and generality. Therefore, it can be useful in complicated structural control systems (Ö zcan *et al*. 2009). Motamedi *et al*. (2015) investigated the application of an adaptive neuro-fuzzy (ANFIS) computing technique to predict the

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unconfined compressive strength of pulverizes fuel ash cement sand (PFA) mixture. 270 samples with different contents of PFA and cement were made, cured (1, 5, 14, and 28 days), and tested. The unconfined compressive strength was investigated using ANFIS and it was concluded the ANFIS is a useful tool for predicting the strength (Motamedi *et al*. 2015). Nazari *et al*. (2015) studied compressive strength of different types of alkali-activated binders modeled using ANFIS.

The model was constructed from 395 experimental data sets collected from the literature and divided into 80% and 20% for training and testing phases, respectively. Absolute fraction of variance, absolute percentage error and root mean square error of both training and testing phases showed relatively high accuracy of the proposed ANFIS model. In another study, Bondar (2014) investigated the effect of Alumina-Silica-based products on compressive strength of geopolymers. For this purpose, more than 50 pieces of data were collected from literature. The ANN method was applied to simulate this process. In another similar study, Bohlooli *et al*. (2012) predicted the compressive strength of geopolyemrs made from seeded fly ash and rice husk bark ash by employing adaptive FL. The model, training and testing were built using experimental results of 120 specimens. Based on the training and testing results, it was concluded that the adaptive FL model has a strong potential for predicting the compressive strength of the geopolymer specimens.

The main reason of high capability of the FL method for prediction of the geochemical parameters stems from their inherent uncertainty. FL model is one of the modern and powerful techniques for the analysis of parameters which is not clear-cut and inherently certain (Nadiri *et al*. 2013). Different FL models including Sugeno fuzzy logic (SFL), Mamdani fuzzy logic (MFL) and Larsen fuzzy logic (LFL) models as well as other Artificial Intelligent (AI) models have their own abilities and advantages (Pulido Calvo *et al*. 2009; Gutiérrez Estrada *et al*. 2013, Nadiri *et al*. 2015, Nadiri *et al*. 2017a, b, c). Therefore, combination of multiple FL models developed through a committee machine FL (CFL) method can be extremely useful to estimate geological and engineering parameters (Kadkhodaie-Ilkhchi and Amini 2009). In the CFL method, the predictions are made by linearly combining the outputs of individual FL models through a set of weights. There are two methods to determine the CFL weights (Labani *et al*. 2010, Chen and Lin 2006); simple averaging using equal weights and weighted averaging using optimized weights.

In this study, the abilities of different FL models were evaluated to predict the compressive strength and optimum compositions of natural Alumina-Silica-based geopolymers. The study employs total of 52 data sets including Al_2O_3/SiO_2, Na_2O/Al_2O_3, Na_2O/H_2O and Na/[Na+K], and their compressive strength that were collected by Bondar (2014) and were trained and tested using three FL approaches including Sugeno, Mamdani and Larsen fuzzy logic models. Ultimately, the study introduces a hybrid fuzzy model called supervised committee fuzzy logic (SCFL) to reap the advantages of three FL models and to simulate this process. In contrast to the CFL, the SCFL model replaces linear combination with an ANN as a nonlinear combiner. In the SCFL model, the ANN receives individual FL model predictions as input and derives a new prediction. The advantage of the SCFL model is the nonlinear combination of FL models under supervision. The obtained results were compared with literature to evaluate the accuracy of the proposed methodology for predicting the compressive strength of the geopolymer specimens (Bonder 2014).

2. Methodology

2.1 Fuzzy Logic (FL)

The FL was first introduced by Zadeh in 1965 and is able to handle problems associated with inherent uncertainty. Therefore, fuzzy sets are more suitable to describe inherently imprecise problems such as geochemistry parameters. Each fuzzy set is represented by a membership function (MF) including partial membership ranging between 0 and 1. The MF has ambiguous boundaries and gradual transitions between the defined sets which render their amenably to overcome the inherent uncertainty (Chen and Lin 2006, Grande *et al*. 2010, Nadiri *et al*. 2013).

Different shapes of membership functions, such as Gaussian, triangular, trapezoidal, sigmoid, etc., can be used in FL models. An FL model consists of three main parts: 1) fuzzification, 2) inference engine (fuzzy rule based), and 3) defuzzification. In fuzzification step, the four crisp inputs change to fuzzy sets for constructing the inference engine. The inference engine consists of rules. Each rule, in turn, is formed from output single output derived from multiple input. When the antecedents of fuzzy rules include more than one rule, fuzzy operators are used to connect them. The most commonly used fuzzy operators are “AND” which supports min (minimum) and prod (product), “OR” (maximum) and “NOT”. The consequences of a fuzzy rule assign the entire fuzzy set to the output through the process, which is called implication. The input to implication process is a single number given by the antecedent, and the output is a fuzzy set. Since decisions are based on testing all of the rules in an FL model, the rules must be combined via aggregation processes in order to make a decision. The process of transforming the aggregation result into a crisp output is termed defuzzification. The most commonly used defuzzification methods are centroid, bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum, and smallest of maximum.

2.2 Fuzzy clustering

The most important task of fuzzy modeling is to identify a model structure which is composed of the optimal number of rules and cluster of the data. To perform structure identification, many studies used different clustering methods (Chiu 1994). The goal of fuzzy clustering is to find natural data groupings within a large dataset and consequently revealing patterns to represent one specific part of system behavior (Li *et al*. 2000). The most applicable clustering methods are fuzzy C-means (FCM) and subtractive clustering (SC) (Chiu 1994, Chen and Wang 1999, Li *et al*. 2000).

The FCM method categorizes data points that populate multidimensional spaces into a specific number of clusters. The FCM clustering starts with an initial iteration for the cluster centers which intends to mark the mean location of each cluster. Moreover, the FCM assigns a membership grade to every data point for each cluster.

By iteratively updating the cluster centers and the membership grades for each data point, the FCM iteratively leads the cluster centers to the correct location within a data set. During this iteration, an objective function is minimized and shows the distance from any given data point to a cluster center weighted by the membership grade of the data point. The FCM output is a list of cluster centers and several membership grades for each data point. Therefore, the MFL fuzzy rules are extracted from the FCM. In this fashion, the model matrices of data pass through the FCM algorithm and the cluster centers are calculated. In the FCM algorithm, the number of clusters is defined by the user. Selecting the optimum number of clusters can be accomplished by measuring the performance of the model during systematically changing the number of the clusters from 1 to the number of the model data points.

The SC method was introduced by Li *et al*. (2000) The important parameter in subtractive clustering, which controls the number of clusters and the fuzzy if-then rules is the cluster radius (Chen and Wang 1999). Decreasing the cluster radius will increase the number of clusters and results in smaller clusters. This will create more rules and would complicate the system behavior and may lead to a low performance of the model. In contrary, a large cluster radius produces large clusters in the data and results in few rules (Chiu 1994), which may not be sufficient to cover the entire domain. Finding the optimal cluster radius can be accomplished by systematically varying cluster radius value from 0 to 1 until minimal root mean squared error (RMSE) is met.

2.3 Fuzzy model

Based on the type of output membership function and fuzzy operators, FL may be constructed by the methods proposed by Mamdani, Sugeno, and Larsen (Mamdani and Asilian 1975, Mamdani 1976, Larsen 1980, Sugeno 1985). In the MFL method, the output membership functions are fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification (Mamdani 1976, Mamdani 1977, Nadiri, 2015). The SC method was adapted to the SFL model construction and has been improved as an efficient and useful way to cluster the data and determine the number of membership functions and rules in recent studies (Nadiri *et al*. 2013, Tayfur *et al*. 2014).

For compressive strength estimation, a fuzzy if-then rule i can be expressed as:

Rule i: If (SiO_2/Al_2O_3 belongs to $MF^i_{SiO_2}/Al_2O_3$) and
(Na_2O/Al_2O_3 belongs to $MF^i_{Na_2O}/Al_2O_3$) and
(Na/[Na+K] belongs to $MF^i_{Na/[Na+K]}$) and
(H_2O/Na_2O belongs to $\mathrm{MF}^i_{H_2O/Na_2O}$),
then (CS belongs to MF^i_{CS}) (1)

where CS (compressive strength) is the output, MF^i_{CS} is the corresponding membership function of the output of rule i, $MF^i_{SiO_2}/Al_2O_3$ is the membership function of the i^{th} cluster of input SiO_2/Al_2O_3, $MF^i_{Na_2O}/Al_2O_3$ is the membership function of the i^{th} cluster of input Na_2O/Al_2O_3, and so on. The operator among the input membership function is "AND" (minimize) operator and the outputs from the rules are aggregated via "OR" (maximize) operator. The most popular defuzzification method-centroid calculation-was employed to produce the crisp output. The LFL method is similar to the MFL method. The major difference between the two methods is that the LFL uses the product operator for the fuzzy implication which scales the output fuzzy set. In contrast to the MFL method, the SFL method uses linear or constant output membership functions (Sugeno 1985). For CS prediction in this study, a fuzzy if-then rule i can be expressed as

Rule i: If (If (SiO_2/Al_2O_3belongs to $MF^i_{SiO_2}/Al_2O_3$) and
(Na_2O/Al_2O_3 belongs to $MF^i_{Na_2O}/Al_2O_3$) and (Na/[Na+K]
belongs to $MF^i_{Na/[Na+K]}$) and (H_2O/Na_2O belongs to
$\mathrm{MF}^i_{H_2O/Na_2O}$), then ($CS_i$=

$$m_i\, {}^{SiO_2}\!/\!{}_{Al_2O_3} + n_i\, {}^{Na_2O}\!/\!{}_{Al_2O_3} + p_i Na/[Na+K] + q_i H_2O/Na_2O + c_i) \tag{2}$$

where m_i, n_i, p_i, q_i, and c_i are the coefficients. The final output is the weighted average of all outputs (aggregation) as follows

$$Out_j = \frac{\sum_i w_{ij} Out_{ij}}{\sum_i w_{ij}} \tag{3}$$

where w_{ij} is the firing strength of rule i and output j, which is obtained via the "AND" (minimize) operator.

2.4 SCFL model

The committee machine approach combines FL model results to obtain advantages of all FL models producing the final output. Previous works recommend two methods for construction of committee machine model (Kadkhodaie-Ilkhchi and Amini 2009, Labani *et al*. 2010, Chen and Lin 2006); simple averaging and weighted averaging. In this study, a SCFL model is introduced that employs an ANN model as a supervised combiner of FL models to replace simple averaging or weighted averaging. The SCFL model consists of three FL models shown in Fig. 1 and includes two major steps. In the first step, CS is estimated using the FL models including MFL, LFL, and SFL. In the second step, a supervised ANN is constructed as a nonlinear and supervised combiner for each output variable. The most widely used neural network method is the multi-layer

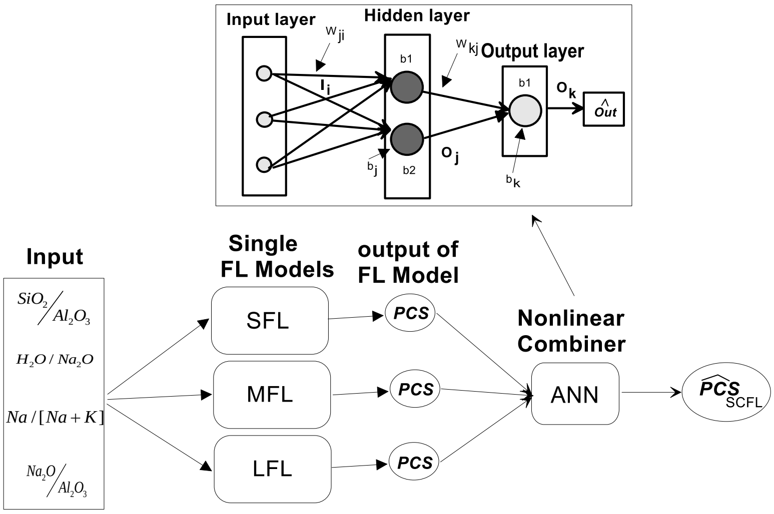

Fig. 1 Schematic of SCFL model structure

perceptron (MLP) (Nourani *et al*. 2008, ASCE 2000a, Chitsazan *et al*. 2015) which consists of one input layer, multiple hidden layers, and one output layer. This study considers one hidden layer. There are three neurons in the input layer corresponding to the input data, Out_{MFL}, Out_{LFL}, Out_{SFL} two neurons in the hidden layer, and one neuron in the output layer. The normalized input signal propagates through the network in a forward direction via connections between neurons. Incoming signals are linearly combined and converted to outgoing signals. The signal conversion is done by assigning activation functions.

The mathematical expression of the SCFL model is

$$Out_i^{Fl} = FL_i\left({SiO_2}/{Al_2O_3} + {Na_2O}/{Al_2O_3} + \frac{Na}{[Na+K]} + H_2O/Na_2O\right) \tag{4}$$

$$O_j = f_1\left(b_j + \sum_i w_{ji}\ out_i^{FL}\right) \tag{5}$$

$$O_k = Out_{SCFL} = f_2\left(b_k + \sum_j w_{kj}\ O_j\right) \tag{6}$$

Where out_i^{FL} is the output of each FL model which has been used as i^{th} input, f_1 and f_2 are activation functions for the hidden layer and output layer, respectively. O_j is the j^{th} output of nodes in hidden layer, W_{ji} and W_{kj} are weights that control the strength of connections between the two layers, and the biases b_j and b_k are used to adjust the mean value for hidden layer and output layer, respectively. The activation function for the hidden layer is typically a continuous and bounded nonlinear transfer function such as sigmoid and log-sigmoid functions. The activation function for the output layer is usually a linear function, hyperbolic tangent sigmoid (Tansig) for f_1 and linear (Purelin) for f_2. The output O_k of the SCFL model is $\hat{K}_{SCFL}$. In the ANN training step, a supervised learning algorithm is needed to estimate the weights W_{ji} and W_{kj} and biases. Several previous research studies have found Levenberg-Marquardt (LM) algorithm to be superior to other training algorithms

Table 1 Train data (Data from Subaer and van Riessen 2007, Duxson *et al*. 2007, Bondar 2014)

Al_2O_3/SiO_2	$Na_2O/Al2O_3$	Na_2O/H_2O	$Na/[Na+K]$	*CS* (MPa)
10	1	0.8	4	2.3
10	1	1	4	2.74
10	1	0.6	2.5	6.6
10	1	1	2	8.23
11	0	1	2.3	8.94
10	1	0.8	2	12.09
11	0.75	1	2.3	12.62
11	0.5	1	2.3	13.81
11	1	1	2.3	15.79
17.5	1	1.14	3.8	25.03
11	1	1.2	4.4	26.62
20	1	1.04	3.55	27
15	1	1	4	30.02
10	1	0.8	2.5	30.56
12	1	0.95	3.9	32.57
11.42	1	0.7	3.05	33.43
11	1	1	4	33.86
10	1	1	2.5	34.19
11	1	1.1	4.2	36.57
14	1	0.75	3.5	37.93
11	1	1	3.5	38.44
11	1	1	2.8	38.93
12	1	1.04	3.63	39.05
9.3	1	1	3.5	40.55
11	0	1	2.8	46.07
11	0.25	1	2.8	47.16
11	0.75	1	2.8	48.71
11	0.5	1	2.8	49.71
10	1	0.81	3	52.36
11	1	1	3.3	57.91
10	1	0.6	4	59.11
10	1	0.98	3.5	60.22
11	0.5	1	4.3	60.73
11	0	1	3.3	65.9
11	1	1	4.3	66.83
11	0.75	1	4.3	71.02
10	1	0.805	3.5	74.09
11	0.25	1	3.3	74.41
11	0.25	1	4.3	75.66
10.3	1	1.57	4.5	24.95

Table 2 Test data (Data from Subaer and van Riessen 2007, Duxson *et al*. 2007, Bondar, 2014)

Al_2O_3/SiO_2	$Na_2O/Al2O_3$	Na_2O/H_2O	*Na*/[*Na+K*]	*CS* (MPa)
11	0.75	1	3.3	77.68
11	0	1	3.8	83.22
11	0.25	1	3.8	78.78
11	1	1	3.8	81.6
10	1	0.6	2	4.3
11	0.25	1	2.3	9.11
13.1	1	1.16	4.01	31.98
10.58	1	0.85	3.275	38.83
10	1	0.6	3	46.28
10	1	0.595	3.5	57.26
11	0	1	4.3	65.31
11	0.5	1	3.3	74.33

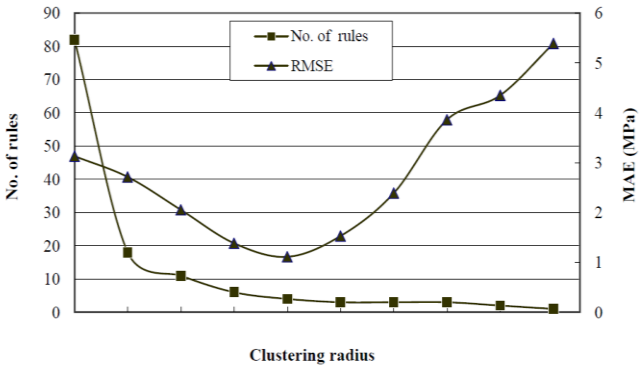

Fig. 2 Average MAE of train and test steps versus the number of rules based on the clustering radius for SFL model

such as the conjugate gradient (CG), Bayesian regularization (BR) and gradient descent with momentum (GDX) algorithms (Tayfur *et al*. 2014). In the ANN training step, the LM algorithm was adopted as a learning algorithm to estimate the weights W_{ji}, W_{kj} and biases.

2.5 Data analysis

In this study, the natural Alumina-Silica-based products were used to develop three FL models for predicting strength and optimum compositions of geopolymers. 52 data sets were employed from previous works (Duxson *et al*. 2007; Subear and Van Riessen 2007; Bondar 2014); including, Al_2O_3/SiO_2, Na_2O/Al_2O_3, Na_2O/H_2O and Na/[Na+K] and their corresponding CS. These were divided into two parts to form the three FL models; the 40 and 12 data sets for training and testing steps, respectively, which are both statistically the same (Table 1 and Table 2).

3. Results and discussion

3.1 FL models

The SC method was adopted for construction of the SFL model. The clustering radius of 0.6 was obtained based on the minimum Mean Absolute Errors (MAE) through the

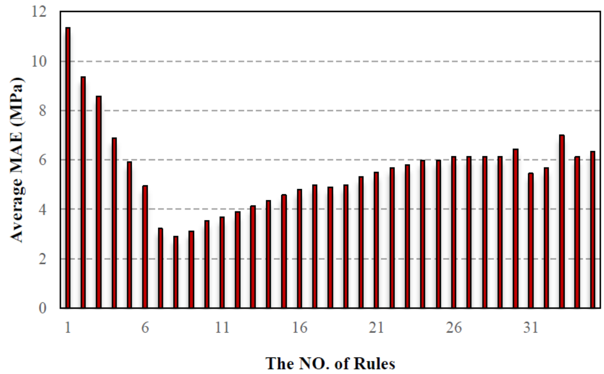

Fig. 3 Average MAE of train and test steps versus the number of rules for MFL model

Table 3 Comparison of single FL and SCFL model efficiencies

Criteria	Step	SFL	MFL	LFL	SCFL
MAE (MPa)	Train	2.41	2.47	2.91	1.89
	Test	2.76	3.32	3.77	2.10
R^2	Train	0.84	0.77	0.81	0.95
	Test	0.86	0.71	0.76	0.96

trial and error method (Fig. 2). The input and output clusters were generated using Gaussian and linear membership functions, respectively. The number of if-then rules was the same as the input and output data clusters that were categorized in five clusters. Table 3 shows the efficiency of SFL model to predict the compressive strength based on two criteria including MAE and R^2. The average of MAE of SFL model is 2.58 (MPa) in both training and test steps. Therefore, the obtained criteria values (Table 3 and Fig. 4) of the SFL model are confirmed to have the high capability of the model to predict compressive strength values.

For the MFL and the LFL models, an FCM clustering method was used for extraction of clusters and fuzzy if-then rules. Searching for the optimal clustering number was done by performing the clustering process several times and gradually increasing the clustering number from 1 to 35 (with interval of 1). Thus, 35 fuzzy models with different numbers of if-then rules were established. The lowest average MAE values (2.9 MPa) of the fuzzy models indicated that optimal cluster number is 8 (Fig. 3). In other words, the FL model was adopted with 8 fuzzy clusters for each of the 5 input data and 1 output data. The MFs of input and output parameters are shown in Tables 3. The R^2, MAE of MFL, SFL, and LFL models are shown in Table 3 and Fig. 4. The results show high performance of different FL models than ANN (Bondar 2014) and regression (Bondar *et al*. 2012) models to predict compressive strength

According to the results of three fuzzy models presented in Table 3, all models are applicable to predict compressive strength values, while each FL model has different and diverse abilities and advantages. In other words, each FL model has high efficiency for a specific type of data. Therefore, taking the advantages of these individual FL models, multi-models such as SCFL can now be considered to obtain minimum error for predicting compressive strength values.

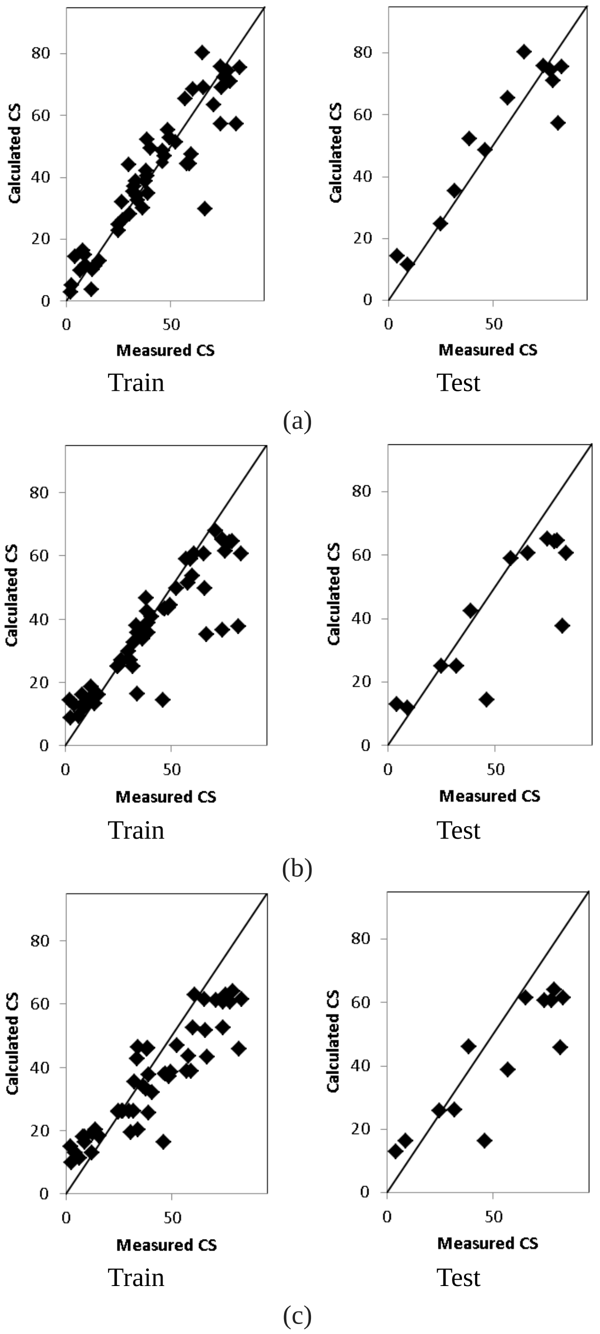

Fig. 4 Measured and calculated CS (Mpa) in test and training steps (a) SFL, (b) MFL, (c) LFL

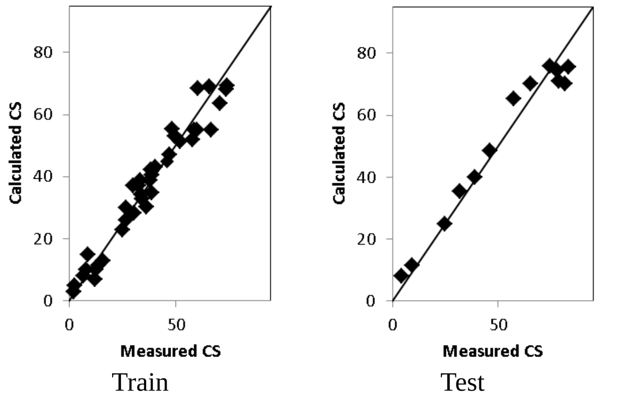

Fig. 5 Comparison of the measured and calculated CS (MPa) values by SCFL

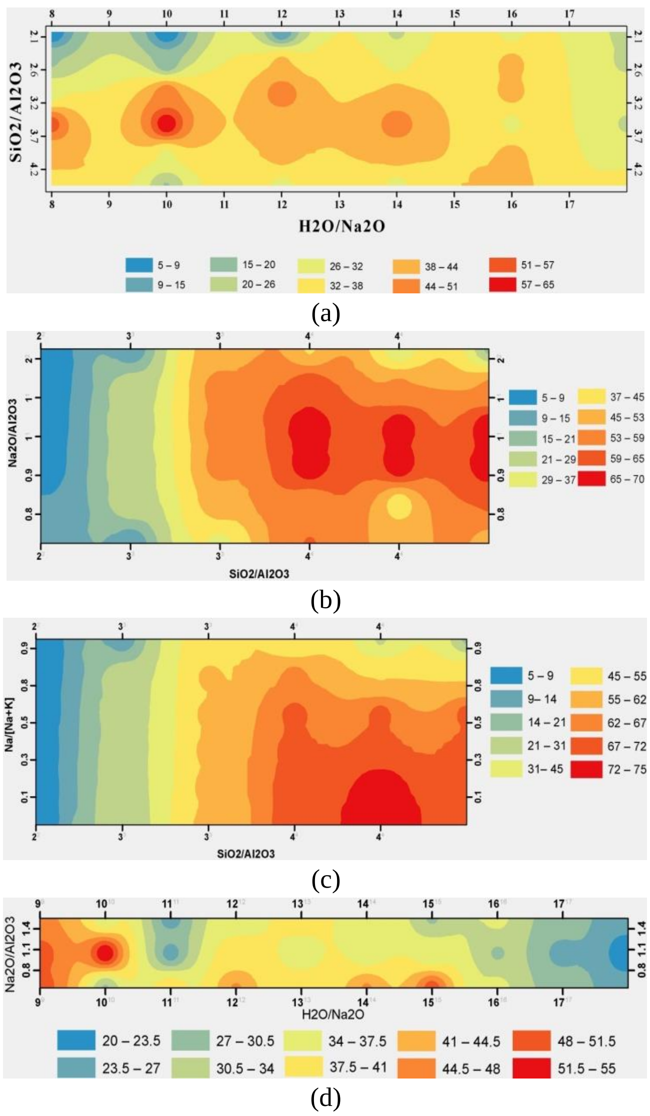

Fig. 6 A contour map of effect of geopolymers on CS (MPa), (a) SiO_2/Al_2O_3, vs. H_2O/Na_2O, (b) SiO_2/Al_2O_3 vs. Na_2O/Al_2O_3, (c) $Na/[Na+K]$ vs. SiO_2/Al_2O_3 and, (d) Na_2O/Al_2O_3 vs. H_2O/Na_2O

3.2 CFL model

The SCFL model was constructed to predict the overall CS values by integrating the results of predicted data from SFL, MFL, and LFL. For constructing the SCFL model shown in Fig. 1, a simple ANN method was adopted to re-estimate each parameter obtained by SFL, MFL, and LFL in the training step (40 data sets). The MLP-LM structure based on Eqs. (5) and (6) was employed in the ANN model to be used in the SCFL. These ANN models have three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The transfer functions for the hidden layer and output layer were Tansig and Purelin, respectively. The LM algorithm was used to optimize 8 weights and 3 biases in the ANN. The training epoch was 21. After training, the SCFL model was tested with the 12 data sets. The results of these ANN models are shown in Table 3 and Fig. 5.

Comparing the results for SCFL predictions with single FL models, SCFL outperforms individual FL models with much smaller fitting errors. These results support the importance of a nonlinear combination of FL models and the effectiveness of using the SCFL for predicting the CS values.

3.3 Effect of Alumina-Silica-based products on compressive strength

Fig. 6 shows effects of variation of the Alumina-Silica-based products on compressive strength of samples and represent the optimum ranges of Al_2O_3/SiO_2, Na_2O/Al_2O_3, Na_2O/H_2O and Na/[Na+K].

Based on Fig. 6(a), it can be seen the optimum range of SiO_2/Al_2O_3 is about 2.8 to 3.8 that is approved by previous research (Duxon *et al*. 2005, Bondar 2014). Increasing the concentration of amplify the compressive due to low solubility and gel formation. In contrast to rarely distributed voids in high SiO_2/Al_2O_3 ratios (>3.8), the low SiO_2/Al_2O_3 ratio (<2.8) create course voids which result in lower compressive strength. Also, Fig. 3(b) shows optimum values of Na_2O/Al_2O_3 ratios which is 0.85 to 1.1. This range approved by theoretical principles of geopolymer formation mechanisms (Duxon *et al*. 2005). Fig. 6(c) indicates in high value of SiO_2/Al_2O_3 (>3) and low value of Na/[Na+K] (<0.8), the highest values of compressive strength were obtained. Fig. 6(d) shows the optimum value of H_2O/Na_2O is between 9.7 to 10.5. All these optimum ranges are in line with existing literatures (Duxon *et al*. 2005, Duxson *et al*. 2007, Bondar 2014).

4. Conclusions

In this research three different FL models (MFL, SFL, and LFL) were adopted to predict the compressive strength value of geopolymers prepared from alumina-silica products. The results show that all these FL models are able to predict the compressive strength and it shows the capability of FL model to deal with uncertainty of compressive strength and geopolymers parameters. The results of this study demonstrate that selecting of the best FL model may not enforceable and reasonably in complex system modeling. Therefore, to improve the obtained results of the FL models, the presented SCFL method was employed by combining it with nonlinear model output through a committee machine discipline. The nonlinear combination of the FL models is vital for simulating the effects of geopolymers on CS value as a complex system. The SCFL shows about 10% better performance than existing models and more than 25% outperforms a single FL model. Since most of these systems are complex with complicated processes, the SCFL model can be applied to other similar systems. It remains for future research to conduct the uncertainty analysis using SCFL.

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