Soft computing techniques for evaluation of elastic modulus of ASR-affected concrete

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Abstract: Surface expansion measurements have been commonly used to evaluate alkali-silica reaction (ASR) effects on the mechanical properties of concrete, including estimating the loss of elastic modulus. However, it has been observed at any given level of ASR expansion that there is a significant variation in the estimated concrete elastic modulus. In other words, ASR expansion alone is not sufficient for providing accurate elastic modulus estimation for ASR affected concretes. This paper presents a new approach to evaluate the elastic modulus of ASR-affected concrete by utilizing different soft computing techniques, namely artificial neural network (ANN), support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS) and nonlinear regression (NLR). The proposed approaches take into account the influences of various factors observed from experimental and/or field process, consisting of mix proportion, reactive aggregate types, exposure conditions and initial strength without damage. By intelligently fusing multi-type of information, the proposed models can provide an accurate estimation of elastic modulus, which shows a significant improvement from empirical based models used in current practice. Among the four soft computing techniques, the ANN model can provide the best prediction result compared to the others, with the correlation coefficient of 0.9249.

Keywords: Alkali-silica reaction, concrete elastic modulus, soft computing.

1. Introduction

Alkali-silica reaction (ASR) is a chemical reaction between alkali hydroxides in the concrete pore solution and reactive minerals within the aggregates. The consequences are the initiation of cracks in the reactive aggregate particles, propagation of the cracks into the paste matrix, exudation of the gel from the cracks, volumetric expansion of the concrete, stress development due to expansive pressure, and changes of mechanical properties. A large number of studies have been conducted to investigate changes of strength and stiffness in relation to ASR-induced expansion [1,2]. Most of these studies agreed that the elastic modulus presents significant reduction compared to the splitting tensile strength and compressive strength. The elastic modulus has been thus commonly considered as an indicator of ASR-affected concrete deterioration [3].

To evaluate the change of elastic modulus due to ASR, many experimental investigations have been conducted. However, the results in these studies present significant variations on the measured elastic modulus at any given level of expansion [3]. In fact, both the development of ASR and the elastic modulus of ASR-affected concrete are influenced by several factors observed from experimental process, e.g. the type of reactive aggregate (rock type, reactivity and size) [4], alkali content, and exposure conditions consisting of temperature and moisture [5]. In other words, the ASR-induced expansion alone could be not sufficient in estimating modulus of elasticity of concretes affected by ASR.

Recently, artificial intelligence (AI) techniques have been widely employed in the fields of modeling concrete material and structures [6]. For instance, Pham and Hadi employed artificial neural networks (ANN) to estimate the strain and compressive strength of fiber reinforced polymer-confined concrete columns and the result shows satisfactory match between testing data and results from the ANN model [7]. Lim et al. designed a novel model based on genetic programming to evaluate the ultimate condition of FRP confined concrete [8]. Such type of models is capable of processing complicated data groups containing multiple independent variables, calculating the sensitivity degrees of input parameters and providing mathematical relationships between independent dependent variables. Accordingly, this paper aims to investigate the performances of different AI techniques in predicting the reduction of elastic modulus of ASR-affected concrete, including artificial neural networks (ANN), support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS) and nonlinear regression (NLR) methods. At first, the experimental data are collected from a large number of previous studies. Then, the capacities of four models are evaluated in terms of statistical evaluation indices of correlation coefficient, root mean square error (RMSE) and mean absolute relative error (MARE).

2. Data collection

Due to the extensive differences in the testing procedure, where many factors influence the development of ASR and elastic modulus, it is difficult to compare and evaluate the reduction of elastic modulus due to ASR by considering only the expansion. The existing empirical models, however, consider only the expansion level for all the testing condition, which may lead to the huge variation of prediction results at the given level of expansion. This phenomenon can be observed from Figure 1. Actually, in addition to the expansion, other factors that affect to the mechanism of ASR and concrete properties should be considered. It is well known that the proportion of different ingredients such as cement (C), water, fine and coarse aggregates (FRAC and CRAC) are the key factor in design and determination of concrete modulus of elasticity. Reactive aggregate is the source of reactive non-crystalline silica for the alkali silica reaction in concrete. However, the utilization of reactive aggregate for investigation of mechanical properties of ASR-affected concrete subjected to expansion measurements did not follow the same testing standard. Therefore, the maximum measured expansion (MAXEXP), obtained from the expansion measurement from same set of data to represent the difference in reactivity of the utilized reactive aggregate, is included as an input variable. Moreover, Alkali in concrete is the other reactant for ASR together with the reactive non-crystalline silica from reactive aggregate. In this study, the proportion of sodium oxide equivalent as an input (ALKALI) is total alkali content of concrete mixes, which is from both cement and adding amount to mixing water. Besides the reactive aggregate and alkali content, exposure condition, herein including temperature and moisture, creates environment for initiating and developing of the alkali silica chemical reaction as well as for curing concrete. Nevertheless, the relative humidity remains at very high levels and therefore it is not selected as variable for exposure condition. The other factor, temperature (T), is considered as an input for the model development. In current practice, the elastic modulus is commonly estimated through compressive strength (CS) due to their strong relationship, which should be selected as the input factor. To sum up, the inputs of the models in this study should include mix proportion, proportion of reactive sand and coarse aggregate, exposure condition, proportion of sodium oxide equivalent, initial compressive strength at the undamaged condition, and maximum measured expansion. On the other hand, the output of the developed models is elastic modulus degradation. Here, a new parameter that normalizing damaged elastic modulus to the undamaged elastic modulus is adopted to demonstrate the elastic modulus change in this study, which is expressed by the following formula:

$$\beta_{Ec} = \frac{E_c}{E_{co}} \tag{1}$$

To develop the soft computing-based predictive models with high accuracy, a large number of data samples are required for the training purpose. Hence, this study collected the data set from 11 studies with 38 concrete mixes, consisting of 169 testing groups of elastic modulus at different levels of the ASR-induced expansion [9]. The ranges of input and output variables are shown in Table 1.

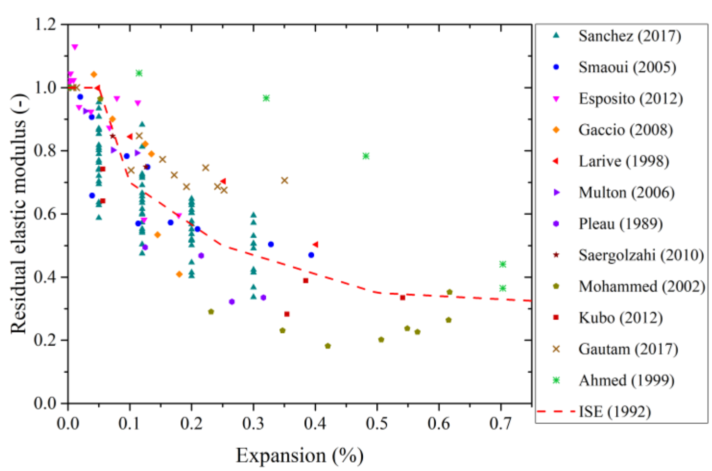


Figure 1. Variations of prediction results from previous studies.

Table 1. Ranges of model variables.

Type	Model variables	Symbol	Range [min, max]
Input	Cement content (kg/m^3)	C	[300, 424]
	Fine reactive aggregate/cement ratio	FRAC	[0, 2.85]
	Coarse reactive aggregate/cement ratio	CRAC	[0, 3.42]
	Exposure temperature (^{o}C)	T	[38, 50]
	Proportion of sodium oxide equivalent (%)	ALKALI	[1.17, 2.87]
	Initial compressive strength at “non-expansive” condition (MPa)	CS	[18.2, 58.5]
	Maximum measured expansion (%)	MAXEXP	[0.072, 0.916]
	Measured expansion (%)	EXP	[0.001, 0.916]
Output	Normalized elastic modulus	β_{Ec}	[0.163, 1.130]

3. Methodology

3.1 Artificial neural network

Artificial neural network (ANN) is a computational system which simulates the human biological neural system with the ability of reasonably learning and tackling the practical problems. Generally, the ANN is made up of a set of inter-connected artificial elements via a layer-by-layer configuration and employs the transfer function to transform the information between arbitrary two layers. Through the network training, the ANN is able to adaptively change its configuration according to internal and external information, and the trained ANN is used to characterize the complicated relationship between the input and output. In a standard ANN model, there are three types of network layer: input layer, hidden layer, and output layer. The schematic layout of an artificial neural network developed in this study is illustrated in Figure 2. The neurons at different layers are connected with each other via the connection weight, the value of which is optimized through an objective function of the network during a learning process. The signals are sent from the input neurons to the hidden neurons, then processed by linear calculation with weights and bias, before passed through a transfer function to obtain signals for the output layer. The tangent sigmoid functions, which is one of the most commonly used transfer function, is employed in hidden layer to develop the networks in this study. One of the most important tasks in developing ANN is the learning process. In this study, Levenberg-Marquardt is selected to train the model. About the model configure, except for the input and out layers with confirmed variables, a hidden layer with 8 hidden neurons is considered.

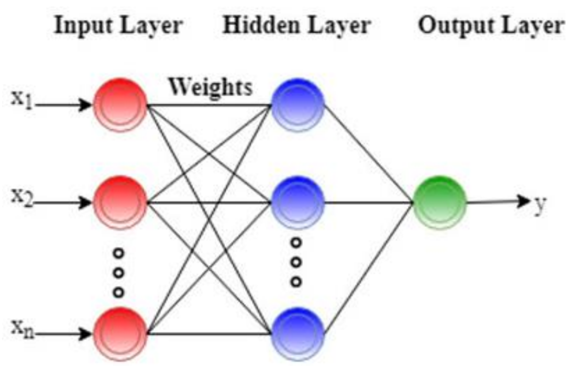


Figure 2. Configuration of ANN model [10].

3.2 Support vector machine

Support vector machine (SVM) is regarded as a powerful method to deal with the classification and regression problems, which is based on the structural risk minimization principle [11-13]. So far, SVM has been successfully applied to the field of nonlinear system modelling. The main idea of SVM is illustrated as: Suppose there is a given training set S=[(xi, yi), i=1,2,…,l], where xi and yi denote the input vector and the output (target) value, respectively; l is the total number of the data pattern. The objective of SVM is to design a regression model to perfectly portray the nonlinear relationship between input and output variables, and forecast the output result according to the new input samples. The expression of SVM function can be described by:

$$f(x) = w\phi(x) + b$$
$$\phi : R^n \rightarrow F, w \in F \tag{2}$$

where $\phi(x)$ is a nonlinear function in the high-dimensional characteristic space; w and b denote coefficients. To obtain w and b, two positive slack variables ξ_i and ξ_i^* are introduced so that the problem is transformed to the following optimization problem:

$$\begin{aligned} \min \ & \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ s.t. \ \ & y_i - w\phi(x_i) - b \le \varepsilon + \xi_i \\ & w\phi(x_i) + b - y_i \le \varepsilon + \xi_i^*, \ \xi^{(*)} \ge 0 \end{aligned} \tag{3}$$

Eventually, the optimal nonlinear regression function (hyper-plane) can be obtained by utilizing above minimization function:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)k(x_i, x) + b \tag{4}$$

where k(xi,x) denotes the kernel function, which plays an important role in building the optimal hyper-plane. The conventional kernel functions include linear function, polynomial function, radial basis function and sigmoid function. Different kernel functions have different parameters, which correlate the configuration of the feature space as well as the solution complexity. In this study, the radial basis function (RBF) is used to perfect performance of nonlinear prediction. The configuration of a typical SVM model is shown in Figure 3.

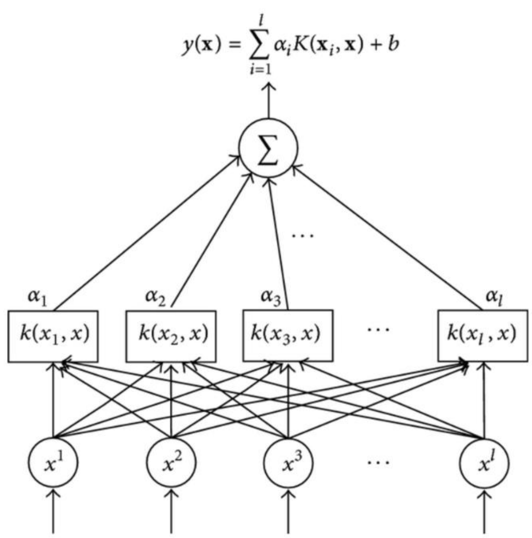


Figure 3. Configuration of SVM model [14].

3.3 Adaptive neuro-fuzzy inference system

The adaptive neuro-fuzzy inference system (ANFIS) has great capacity in dealing with the imprecision and uncertainty of nonlinear systems and is frequently implemented to build the fuzzy IF-THEN rules of logical inference through its powerful and effective data mining techniques. Data mining techniques are used to extract the main features inside the data sets and self-configure their interactive relations. The Sugeno fuzzy model is used to establish IF-THEN rules. Regarding the learning procedure and parameter adjustment, a feedforward neural network coupled with a supervised learning algorithm is implemented, which effectively and appropriately adjusts all parameters of the fuzzy inference system so that the model can possess the self-learning and generalization capacity.

Fig. 3 gives the structure of ANFIS, which is regarded as a five-layer neural network. The first layer consists of n membership functions, where the fuzzy decision rule is realized in each function. Each input degree can be obtained in the range of [0, 1] in the fuzzification layer. The second layer is rule layer. The output of this layer is the outcome of related degrees from the first layer. The third layer is the normalization layer, which is used to compute the ratio of each ith rule's firing strength to the sum of all rules' firing strength. The fourth layer is the defuzzification layer, where each node computes the contribution of ith rules towards the whole output. The last layer is to summarize all the outputs. Generally, the ANFIS is based on a first order Takagi-Sugeno-Kang (TSK) architecture that is generally composed of r rules of the form, given as follows:

Rule i: IF x is A_i and $\hat{x}$ is B_i and f is C_i, THEN $z_i=p_ix+q_i\hat{x}+s_if+d_i$

where A_i, B_i and C_i denote the fuzzy sets; x, $\hat{x}$ and f denote the input variables; z_i denotes the output variable; m_i denote the output parameters of fuzzy system.

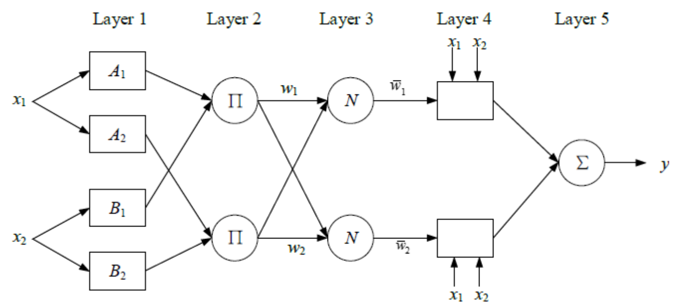


Figure 4. Configuration of ANFIS model.

3.4 Nonlinear regression

To characterize nonlinear relationship between elastic modulus reduction and the influential factors, the nonlinear exponential polynomial function is used to set up the regression model as the following expression:

$$\beta_{Ec} = \exp\left(a_0 + \sum_{i=1}^{8} a_i \times \frac{x_i}{Mean(x_i)}\right) \tag{5}$$

where a_0, a_1, …, a_5 are coefficients of the regression equation to be identified. In the expression, the coefficients are normalized to the mean value of the respective variable data. Therefore, the impact of each influential factor on the output could be evaluated based on the sign and magnitude of these coefficients.

4. Results and discussions

The algorithms of soft computing methods are implemented using Matlab v.2018a. Before the models are trained, all the input parameters are normalized to eliminate the errors caused by the parameter ranges. For the data division for the purpose of training and testing, around 70% of data is used as the training samples and the rest is used as the testing samples. To assess the performance of four soft computing models for the prediction of the elastic modulus reduction, the correlation coefficient, root mean square error (RMSE) and mean absolute relative error (MARE) between real results and model predictions are computed with the following expressions:

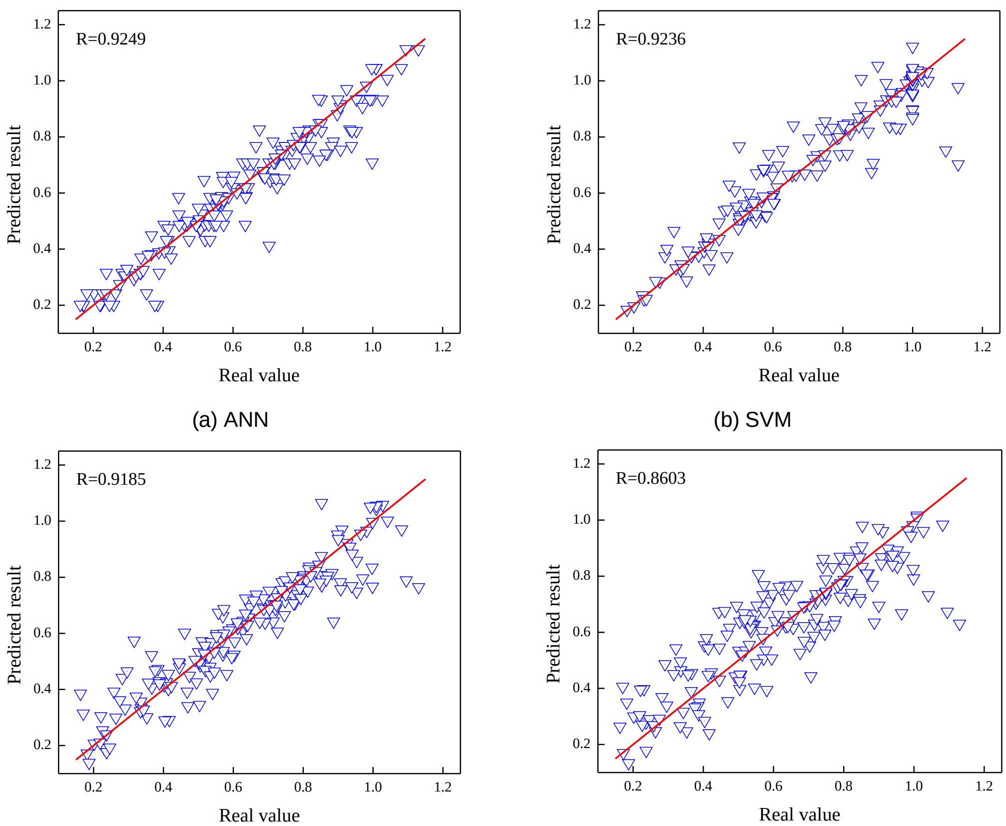
$$R = \frac{p\sum_{i=1}^{p} t_i \cdot o_i - (\sum_{i=1}^{p} t_i)(\sum_{i=1}^{p} o_i)}{\sqrt{p\sum_{i=1}^{p} t_i^2 - (\sum_{i=1}^{p} t_i)^2}\sqrt{p\sum_{i=1}^{p} o_i^2 - (\sum_{i=1}^{p} o_i)^2}} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{p}\sum_{i=1}^{p}(t_i - o_i)^2} \quad (7)$$

$$MARE = \frac{100}{p}\sum_{i=1}^{p}\frac{|t_i - o_i|}{o_i} \quad (8)$$

where p denotes the sample number; o_i and t_i denote the ith measured and predicted results.

The analysis results are shown in Figure 5 and Table 2. It is clearly noted that most data points evenly scatter near the fitted line y=x for three models. The closer the distances between the points and the regression line are, the more accurate the model is. According to the evaluation results, it is clearly seen that ANN and SVM models outperforms ANFIS and NLR models, the R values of which are 0.9185 and 0.8603, respectively. The RMSE and MARE values of ANN model are 0.1472 and 6.1936 while the corresponding values of SVM models are 0.1501 and 6.8239. Apparently, among four models, the ANN model has the best prediction accuracy of elastic modulus reduction of ASR-affected concrete, which can be considered as a promising tool for elastic modulus evaluation in practice.



(a) ANN (b) SVM

(c) ANFIS (d) NLR

Figure 5. Model evaluation results

Table 2. Evaluation index values of soft computing models.

Model	Evaluation index		
	R	RMSE	MARE
ANN	0.9249	0.1472	6.1936
SVM	0.9236	0.1501	6.8239
ANFIS	0.9185	0.1763	9.0467
NLR	0.8603	0.2132	13.7434

5. Conclusions

ASR in concrete is regarded as one of the major factors causing degradations of mechanical properties of concrete. According to previous studies, ASR induced reduction in elastic modulus is the most significant compared to tensile and compressive strength. Many empirical models have been proposed to evaluate mechanical properties degradation based on the expansion level. However, the experimental results from the literature present significant variations in the measured elastic modulus at any given level of expansion; these empirical models thus could not produce an accurate estimation of the reduction level. In fact, both the development of ASR and the elastic modulus of ASR-affected concrete are influenced by several factors. Therefore, to consider all the influence factors and develop more accurate models to predict the elastic modulus of ASR-affected concrete, soft computing techniques are utilized in this study and four predictive models, including ANN, SVM, ANFIS and NLR. The experimental data from existing literatures were employed to adjust optimal model parameters via the training procedures. Finally, the model performances were evaluated and compared using the statistical indices. The results show that ANN model has the best performance in predicting the elastic modulus reduction of concrete due to ASR. The relevant values of RMSE, R and MARE are 0.1472, 0.9249 and 6.1936, respectively. The outcome of this research can provide the theoretical guidance for the engineers to evaluate the mechanical property of ASR-affected concrete structures in the field.

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