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Prediction of early heat of hydration of plain and blended cements using neuro-fuzzy modelling techniques

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ABSTRACT

In this study, a new approach based on an adaptive neuro-fuzzy inference system (ANFIS) was presented for the prediction of early heat of hydration of plain and blended cements. Two different type of model is trained and tested using these data. The data used in these models are arranged in a format of five input parameters that cover the additives percentage (AP), grinding type (GT) and finesses of cements (FC) and an output parameter which is heat of hydration of cements (HHC). The results showed that neuro-fuzzy models have strong potential as a feasible tool for evaluation of the effect of additives percentage, grinding type (GT) and finesses of cements on the early heat of hydration of cements. Some conclusions concerning the impacts of features on the prediction of early heat of hydration of plain and blended cements were obtained through analysis of the ANFIS. The results are highly promising, and a comparative analysis suggests that the proposed modelling approach outperforms ANN model in terms of training performances and prediction accuracies. The results show that the proposed ANFIS model can be used in the prediction of early heat of hydration of plain and blended cements.

1. Introduction

A temperature rise in concrete caused by the hydration of cement paste is accompanied by heat evolution. This process is particularly important with respect to mass concrete where cooling can lead to cracking after a large temperature rise. Mass concrete is defined by the ACI Committee 116 (ACI Committee 116 R-85, 1989). Nowadays, not only mass concrete is no longer considered only for dam construction but it is also used for foundation and members of structures for many classes as multi-story and nuclear reactor building (Malhotra & Ramezanianpour, 1994). It is well known that using ground blast furnace slag (GBFS) and ground basaltic pumice (GBP) as cement replacement in concrete reduces the temperature rise by decreasing the amount of cement used for a unit volume. One of the earlier reports on the influence of GBFS and GBP on the heat of hydration was made by Binici, Çağatay, Tokyay, and Köse (2006).

The hydration reactions of cement compounds are exothermic. The heat of hydration studies can be used for characterizing the setting and hardening behaviour of cements, and predicting temperature rise (Mehta, 1986; Neville & Brooks, 1987). Fineness, admixtures, water/binder ratio and temperature of the materials at the time of mixing and grinding methods influence the rate of hydration (Kosmatka & Panarese, 1994). As a result, there are a lot of studies presented in the literature on the effects of different factors on heat of hydration of cements. However, there is no study in the literature regarding of accurately predict the heat of hydration of cement. Different modelling methods based on neural networks have become popular and used by many researchers for a variety of engineering applications (Yeh, 1998). The crucial approach for developing a neural network-based model for material behaviour is to train a neural network on the results of a series of experiments using that material. If the experimental results contain the related information about the material behaviour, then the trained neural network will give adequate information about materials behaviour. Such a trained neural network not only would be able to produce the experimental results, but also it would be able to estimate the results in other experiments through its generalization capability (Jung & Jamshid, 2001).

Fuzzy set theory plays a significant role in dealing with uncertainty when making decisions in different applications. Fuzzy logic and fuzzy set theory introduced by Zadeh (1965), and employed to describe human thinking and reasoning in a mathematical framework. Fuzzy-rule based modelling is a qualitative modelling scheme where the system behaviour is described using a natural language (Sugeno & Yasukawa, 1993). Fuzzy sets have attracted the growing attention and interest in modern

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information technology, production technique, decision making, pattern recognition, diagnostics, data analysis, etc. (Nauck & Kruse, 1999; Pena-Reyes & Siper,1999).

Recently, the combination of neural networks and fuzzy logic has created neuro-fuzzy systems. Neuro-fuzzy systems have potential to capture the benefits of both these fields in a single framework. Neuro-fuzzy systems remove the basic problem in fuzzy system design by using the learning capacity of artificial neural network (ANN) for automatic fuzzy if–then rule generation and parameter optimisation. As a consequence, those systems can utilize linguistic information from the human expert as well as measured data during modelling. Such applications have been used for signal processing, automatic control, information retrieval, database management, data classification and prediction (Guler & Ubeyli, 2004, 2005; Jang, 1993; Ubeyli & Guler, 2005a, 2005b).

Particular approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS), which has shown significant results in modelling non-linear functions. In ANFIS, the membership function parameters are extracted from a data set that describes the system behaviour. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion (Jang, 1992, 1993). Successful implementations of ANFIS have been reported for classification (Belal et al., 2002; Besdok, 2004; Guler & Ubeyli, 2004, 2005; Lou & Loparo, 2004; Ubeyli & Guler, 2005a, 2005b; Usher, Campbell, Vohra, & Cameron, 1999), modelling and controlling real systems (Vieira, Dias, & Mota, 2004) and data analysis (Virant-Klun & Virant, 1999).

In this study, a new approach based on ANFIS was presented for the prediction of early heat of hydration of plain and blended cements. Also some conclusions were drawn regarding the superiority of the ANFIS over the ANN and impacts of features on the prediction of early heat of hydration of plain and blended cements.

2. Materials and methods

2.1. Mixture proportions

Clinker, GBFS and GBP were obtained from Adana Cement Factory, Iskenderun Iron and Steel Factory, and Osmaniye, respectively. The cement specimens were prepared one of the grinding method of interground and separate grinding of each constituent and then by intimate blending. Besides the clinker and mineral admixtures, all specimens contained 5% gypsum by the weight of the clinker. A 20 kg capacity laboratory ball mill was used for the grinding. Three groups of specimens were prepared. The first group specimens prepared by Blaine values of 2800 ± 30 cm^2/g and 4800 ± 30 cm^2/g were selected as the control specimens and no additives were used in this group. The second group of specimens was prepared using separate grinding with the same Blaine values and three different ratios of additives, 10%, 20% and 30% of clinker. The last group of specimen was prepared by intergrinding with the same Blaine values and three different ratios of additives, 10%, 20% and 30% by weight of clinker. The notations and the compositions of the cements specimens were given in Table 1. In this table, A1 and A2 show the control specimens with two different Blaine values. For the rest of the specimens, a notation in the form of B_i, C_i and D_i, E_i were used. The chemical compositions of the materials obtained from the previous study (Binici, 2002).

Table 1
Notations and compositions of the cements prepared

Sample code	Clinker + gypsum (%)	GBFS (%)	GBP (%)	Blaine fineness (cm^2/g)
A1	100	–	–	2800
A2	100	–	–	4800
Separate grinding				
B1	90	5	5	2800
B2	80	10	10	2800
B3	70	15	15	2800
C1	90	5	5	4800
C2	80	10	10	4800
C3	70	15	15	4800
Intergrinding				
D1	90	5	5	2800
D2	80	10	10	2800
D3	70	15	15	2800
E1	90	5	5	4800
E2	80	10	10	4800
E3	70	15	15	4800

2.2. Test procedure

Test procedure is done as in the previous study (Binici et al., 2006). The heat of hydration and its rate were determined at 25 °C by using a Tonical Isothermal Conduction calorimeter. Cement sample (4.2 g) was placed into the test chamber and 2.1 g of distilled water was put into the small container positioned above the cement sample. After reaching the thermal balance, the water was injected into the test chamber through a hollow needle by means of a piston ensuring an intimate mixing with cement under pressure. Completion of the each test took 24 h.

2.3. Artificial neural network (ANN)

ANNs are computing and information processing systems consists of large numbers of simple and highly interconnected processing elements that can emulate human brain's characteristics such as adaptation to new conditions and generalizing from previous examples to solve new problems. A typical neural network made up of three layers such as input, hidden and output layers. Number of hidden layer can be one or more. There are weighted connection and communication between layers. The input layer neurons receive information from the outside environment and transmit them to the neurons of the hidden layer without performing any calculation. The hidden layer neurons then process the incoming information and extract useful features to reconstruct the mapping from the input space. Lastly, the output layer neurons produce the network prediction as a result. Neurons in input have pure linear activation function but some non-linear activation functions such as logarithmic and tangent sigmoid functions are used in the neurons of hidden and output layers. ANNs may propose a potentially superior method with compared to the conventional estimation methods (Chaudhuri & Bhattacharya, 2000; Fausett, 1994; Luo & Unbehaben, 1998). Feedforward neural networks are a basic type of ANNs capable of approximating broad classes of functions. A significant class of feedforward neural networks is multilayer perceptron neural networks (MLPNNs). The MLPNNs have features such as the ability to learn and generalize, smaller training set requirements, fast operation, and ease of implementation and as a result, they are the frequently used neural network architectures (Subasi, 2005; Subasi & Erçelebi, 2005).

2.4. Modelling of Adaptive neuro-fuzzy inference system (ANFIS) as an Estimator

Jang is introduced the adaptive network-based fuzzy inference system (ANFIS) in 1993 (Jang, 1993). ANFIS is a model that maps inputs through input membership functions (MFs) and associated parameters, and then through output MFs to outputs. Human expertise can design the initial membership functions and rules