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NEURAL NETWORK APPLICATION OVERVIEW IN PREDICTION OF PROPERTIES OF CEMENT-BASED MORTAR AND CONCRETE

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ABSTRACT

Neural networks have recently been broadly used in civil engineering applications due to their versatile capability as a simulator for the complex behavior of many problems (Adeli 2001). Compressive strength of cement mortar is mainly affected by water/cement ratio and aggregate/cement ratio. Recently, high performance concrete has been actively studied, however it is more difficult to predict the properties of high performance concrete. The neural networks (NN) have been considered as a method to solve very complex problems by using interconnected computing elements. This paper summarizes feasibility studies of neural network application for investigating complex non-linear interactions between various variables in complex concrete performance. It can be concluded from the investigation that the application of NNs in the field of concrete material can be more user-friendly and more precise model, and helps prevent some problems like corrosion, workability loss, strength loss, creep, and shrinkage, which are related to durability and safety of concrete.

Keywords: neural network; property; overview; slum flow; compressive strength.

1. INTRODUCTION

Most of the mathematical models have been employed to study various problems in the field of civil engineering including mathematical rules and expressions (Adeli 2001). Using mathematical models to take and express experiences from experimental data are very accurate, scientific, and applicable recognized methods (Adeli 2001). However, if the problem consists of many independent parameters, regression methods cannot be employed due to lack of accuracy and more assumptions in regression form (Adeli 2001). Consequently, new modelling techniques like artificial neural networks (NNs) are able to estimate non-linear and complex relations due to trial and error process (Adeli 2001).

The NN approach has been used to solve various problems in civil engineering due to their exclusive features such as non-linearity, generalization, and adaptively (Adeli 2001). Adeli (1989) published the first journal paper regarding the applications of NNs in the field of civil engineering (Adeli 1989). Afterwards, a huge number of papers have

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been published in various applications of NNs in civil engineering. The potential applications of NNs in structural engineering was established by showing NNs' application to three problems as follows: first, a simple beam load location problem considering pattern recognition; second, analysis of a simply supported plate; and third, selecting a cross-section of reinforced-concrete beams including typical design determinations (Vanluchene 1990). Another challenging problem is an automation of design of large systems in civil engineering due to the highly nonlinear constraints (Adeli 1994). Adeli (1995) presented a NN for optimal design of structures with the aid of the penalty function method (Adeli 1995). Some researchers used NNs to identify the structural dynamics systems (Masri 1993; Chen 1995).

One of the main applications of NNs in civil engineering is their application in structural material characterization and modelling. NNs were applied to predict the strength and slump of ready-mix concrete and high strength concrete with added chemical admixtures and mineral additives (Dias 2011). In another study, the application of two types of NNs, so called back propagation and cascade correlation, to predict the compressive strength of a light weight concrete mixtures at various ages was outlined (Alshihri 2009). In accordance with the results, it was found that the cascade correlation NN model performed better compared to back propagation network (Alshihri 2009). Oztas (2006) offered a 4-layered NN model that accurately predicted not only slump but also compressive strength of high strength concrete after 28 days (Oztas 2006).

In this review paper, applications of NNs in predicting some properties including compressive strength and flow ability of concretes are reviewed to help researchers in the field of concrete to solve various complex problems related to properties of cement-based mortar and concrete.

2. TYPES OF ARTIFICIAL NEURAL NETWORKS

2.1 SINGLE LAYER FEED FORWARD NETWORK

An NN that the input layer connects to an output layer of neurons is called "single layer feed forward network" (Awodele 2009; Bangal 2009). In this type of NN, 'single layer' referred to as the output layer.

2.2 MULTILAYER FEED FORWARD NETWORK

This type of NNs includes one or more hidden layers, whose nodes are called "hidden neurons" (Awodele 2009; Bangal 2009). The interaction between the external input and network output is the function of hidden neurons (Awodele 2009; Bangal 2009). The input signal of the second layer (1st hidden layer) is supplied by the source nodes in input layers (Awodele 2009; Bangal 2009). The output signals of first hidden layer are applied as inputs for the second hidden layers, and so forth (Awodele 2009; Bangal 2009). Typically in feed-forward networks, activation is fed forward from input to output via hidden layers (Awodele 2009). Also, static input-output mappings are implemented (Bangal 2009).

2.3 RECURRENT NETWORK

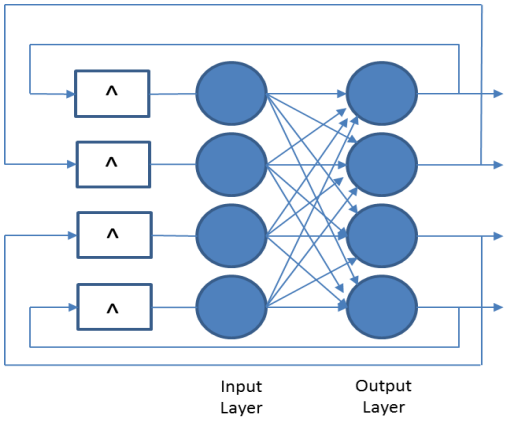

Fig. 1 recurrent network (Bangal 2009)

As illustrated in Fig. 1, recurrent network has not only one or more hidden layers but also at least one feedback loop (Bangal 2009). The nonlinear dynamic behaviour can be caused by involving delay elements in the feedback loops. These types of networks have been prevented to be used in practical applications due to their theoretical and practical difficulties (Bangal 2009).

3. TRAINING OF ARTIFICIAL NEURAL NETWORKS

At the initial point, the initial weights are randomly chosen, and then, the training or learning process will be (Bangal 2009).There are two main approaches to train a network; supervised and unsupervised.

3.1 SUPERVISED TRAINING

In this type of training, both the inputs and outputs are given. The inputs are processed and the resulting outputs are compared to the given outputs. The network can be controlled when errors are propagated back through the system, which causes the system to adjust the weights (Bangal 2009).This process repeatedly occurs as the weights are adjusted (Bangal 2009).The set of data that enables the training process is called “training set” (Bangal 2009). The weights can be fixed after the system has been correctly trained (Bangal 2009).

3.2 UNSUPERVISED OR ADAPTIVE TRAINING

The other type is the unsupervised training (Bangal 2009). In this type, the networks are provided with inputs but not the outputs. This system is referred to as self-organization since it will decide the features to be used to group the input data (Bangal 2009). However, the unsupervised learning has not been well understood so far (Bangal 2009).

4. TRANSFER FUNCTIONS

Transfer functions of a NN have to be differential and continuous so that it is feasible to correct error (Bangal 2009). For computing the local gradient, derivative of the transfer functions is needed (Bangal 2009). One of the most common forms of transfer functions used in building a NN is sigmoid function, which is like an S-shaped graph (Bangal 2009). Its derivative is always positive and it shows an elegant balance between linear and nonlinear behaviors (Bangal 2009).

5. THE BACK-PROPAGATION ALGORITHM

The back-propagation (BP) algorithm is the most commonly used training method for feed forward networks, which is powerful but time-consuming in terms of computational requirements for training (Bangal 2009). In order to train a network by using BP, three steps are needed as follow: First, feed-forward of the input training pattern; second, BP of the associated error; and third, adjustment of weights (Awodele 2009). During training process, the computed activation of each output unit is compared with its target value to determine the error related to the pattern with that unit (Awodele 2009). The optimization technique known as gradient descent is the fundamental mathematics used in this algorithm (Awodele 2009).

6. MATERIALS AND MIX DESIGN

Concrete is a highly complex material, and a precise prediction of the compressive strength of concrete is very difficult. Concrete generally consists of cement, sand, water, and gravel. Concrete strength development is not only determined by the water-to-cement ratio, but also affected by the content of other concrete ingredients (Ouchi 1999). Recently, high performance concrete (HPC) has been actively studied to improve the performance using mineral admixture and additive admixture. In the high performance concrete, it is more difficult to predict the performance of concrete. Thus, NNs are a method to solve very complex problems by using interconnected computing elements. NNs effectively can predict the performance of concrete. Especially, both self-compacting concrete (SCC) and HPC are highly complex materials where NNs can be used to predict the performance of the SCC and HPC (Yeh 1998).

7. COMPRESSIVE STRENGTH

Compressive strength of concrete is generally measured after curing of 28 days and considered as one of the most important mechanical properties. It is clear that the compressive strength is affected by the proportions of the basic combinations such as cement content, water/cement, fine aggregate/ powder and coarse aggregate/powder (Prasad 2009). Prediction of the strength of concrete are usually based on the linear and nonlinear regression methods (Zain 2009; Tsivilis 1995).

The strength model based on the NNs is known to be more precise than the one based on regression analysis (Yeh 1998). The strength model can be used to investigate the effect of age or water-to-binder ratio on strength (Yeh 1998). In the literature, several regression, NNs and adaptive network-based fuzzy inference

systems (ANFIS) models were tested to predict the 28-days compressive strength of no-slump concrete by considering concrete ingredients as input variables (Sobhani 2010). It was found from their study that the NNs' models were effective in estimating the compressive strength of lightweight concrete (Alshahiri 2009).

Moreover, Sebastia (2003) developed a NN based method to predict the unconfined compressive strength of FA-cement mixtures (Sebastia 2003). In another study, single and multiple NNs for predicting the concrete strength were used (Lee 2003). Guang (2000) proposed a multi-layer feed forward NN to predict 28-days compressive strength of concrete (Guang 2000). In addition, NNs and fuzzy logic (FL) models for predicting the 7, 28 and 90 days compressive strength of concrete with the high-lime and low-lime FA were obtained (Saridemir 2008). The prediction of mechanical properties of recycled aggregate concretes with silica fume using NN and FL were studied (Topcu 2008). Sarıdemir (2009) used ANN to predict the compressive strength of concrete containing silica fume and metakaolin (Saridemir 2009).

8. FLOWABILITY

Chien (2010) introduced a back-propagated network (BPN) and applied it to predict the slump flow of high-performance concrete (HPC). The behavior of HPC is difficult to model, in particular slump flow. Slump flow is related to a function of the content of all concrete constituents, including cement, water, fly ash, blast furnace slag, superplasticizer, and fine and coarse aggregate (Chien 2010). BPN is a widely used method that elucidates the complex relationships among nonlinear systems (Chien 2010). The results showed that BPN could predict the slump flow of HPC with acceptable estimating errors (Chien 2010). In another research, the coefficient of determination (R2) for compressive strength and slump flow of SCC were 0.92 and 0.82, respectively (Prasad 2009). All of the statistical values showed that the proposed NNs' model was suitable and it predicted the compressive strength very accurately compared to the experimental values (Prasad 2009).

9. HOW TO INCREASE THE PREDICTIBILITY OF CONCRETE PROPERTIES

In the literature (Lee 2003), two major techniques were employed to improve the accuracy of prediction of concrete strength development. One is to use parameter condensation technique in determining input neurons; the other one is to apply the weighting factor of input neurons for more prediction accuracy (Lee 2003).

In accordance with the simulation model for durability using trained neural networks, the optimum cement content of HPC in terms of durability was found to be in the range of 450-500 kg/m^3 (Parichatprecha 2009). The results also showed that the durability of concrete in terms of chloride resistance could be remarkably improved by using at least 20% fly ash to substitute for cement (Parichatprecha 2009). In addition, it was concluded that silica fume was more effective in reducing the chloride ions penetrability than fly ash. This study illustrated that ANNs could be used to predict chloride ions permeability according to a wide range of mix proportion parameters of HPC (Parichatprecha 2009).

9. APPLICATION OF NNS IN PREDICTION OF COMPRESSIVE STRENGTH OF ALKALI-ACTIVATED MORTAR

In the literature, NNs were applied to predict compressive strength of alkali-activated mortar (Lee 2014). A series of experimental works were conducted to evaluate the compressive strength of AA mortars and the test results were compared with the model in which the Levenberg-Marquardt back propagation algorithm in the MATLAB NN toolbox was utilized (Lee 2014). The input variables were activator/binder ratio, mixing-ratio of fly ash-to-slag, aggregate/binder ratio, and alkali-modulus of alkali-activator (SiO_2/Na_2O) (Lee 2014). The results of experimental works were shown to be in a good agreement with the predicted results by neural network.

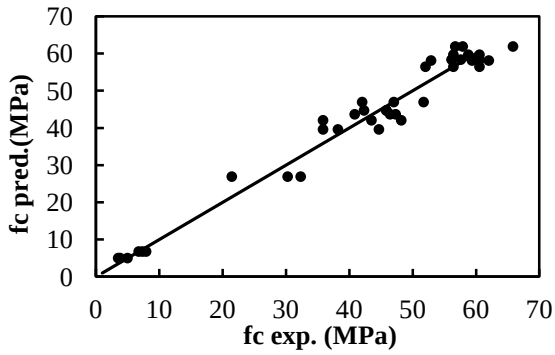

Fig. 2 Comparison of predictions and experimental results (Lee 2014)

10. CONCLUSIONS

This paper summerized feasibility studies of neural network application for investigating non-linear interactions between diverse parameters in complex concrete performance. It can be concluded that the application of NNs in concrete field is more user-friendly and more precise model (Gupta 2014). It can also help the concrete industry to prevent some problems like corrosion, workability loss, strength loss, creep, and shrinkage, which happen regarding durability and safety of concrete (Gupta 2014). This computational intelligent method would be beneficial to ready-mix operators and concrete mix designers in civil engineering.

10. ACKNOWLEDGEMENTS

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