Construction and Building Materials 78 (2015) 386–396

Contents lists available at ScienceDirect

Construction and Building Materials

journal homepage: www.elsevier.com/locate/conbuildmat

Principal Component Analysis combined with a Self Organization Feature Map to determine the pull-off adhesion between concrete layers

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HIGHLIGHTS

- New proposition of determination of the pull-off adhesion between concrete layers was presented.
- Principal Component Analysis and Self Organization Feature Map have been used in analysis.
- Genetic Algorithm was used to optimize the weights.
- Higher correlation than using conventional approach was observed.
- Presented analysis is applicable to the same grade of concrete with similar characteristics.

ARTICLE INFO

Article history:
Received 1 July 2014
Received in revised form 16 December 2014
Accepted 4 January 2015
Available online 17 January 2015

Keywords:
Concrete layers
Pull-off adhesion
Principal Component Analysis
Self Organizing Feature Map
Genetic Algorithm

ABSTRACT

This study attempted to use Principal Component Analysis (PCA) combined with a Self Organization Feature Map (SOFM) to determine the pull-off adhesion between concrete layers. Also Genetic Algorithm (GA) was used to optimize the weights. Finally a constant model was selected among all of the PCA_SOFM combinatory models. To evaluate the precision of this model, it was compared to Multilayer Perceptron (MLP) model as well as Feed Forward (FF) model. The results indicated that the PCA_SOFM model had more ability, precision and flexibility in forecasting the pull-off adhesion between concrete layers parameter than the two mentioned models.

1. Introduction

The long term service of the concrete multilayer structures is determined largely by the interlayer bond between the layers: top layer and the base layer [1–5]. The normalized measure of this bond is the value of pull-off adhesion f_b of the top layer to the base layer, experimentally determined by the pull-off method [6]. This method has significant disadvantages like: the effectiveness depends on the number of measuring points, the tested surface is damaged in each of the measuring points and each damage must be repaired after the test.

In the last few years researchers tried to assess the pull-off adhesion of the top concrete layer to the base in concrete multilayer structures by using nondestructive testing (NDT) methods [7–8]. Authors of the works [9–12] indicates that the most suitable parameters for this purpose are average mobility N_{av} and stiffness K_d. In [23] an attempt was made to determine the correlations between the parameters obtained by impulse response (IR) acoustic method and pull-off adhesion f_b. Nevertheless, the obtained low values of determination coefficient R^2 indicated that it was not proper method.

Applications of 3D roughness parameters has been very popular in the last few years in numerous engineering applications [13–18]. There have been few cases in which 3D parameters, such as the arithmetical mean height *Sa*, the root mean square height *Sq* or the surface bearing index *Sbi* were used to describe the morphology of concrete surfaces [19–22]. However there have been no documented cases of their use to evaluate the pull-off adhesion of concrete layers.

A positive attempt of the integrated use of the IR method and the impact-echo (*I–E*) method in testing the bond between layers in floors was concisely described in [24], where it has been

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http://dx.doi.org/10.1016/j.conbuildmat.2015.01.034
0950-0618/

developed a zero-one methodology for assessing the bond. It is proper to note that this methodology has no possibility of identifying pull-off adhesion values. That is why the prediction of the value of the pull-off adhesion has been performed in papers [26–27] on the basis of parameters determined by NDT methods such the 3D optical laser scanner and the IR and the *I–E* methods in combination with artificial neural networks (ANN). However, it should be noted that the parameter determined by the *I–E* method significantly depends on the layers thickness and it cannot be universally applied to multilayer concrete elements with different thickness.

It is proper to note that in recent years the applications of ANN were used commonly years for solving optimization problems in many civil engineering applications [28–32]. Subsequently in practice, multilayer concrete elements have top layers of different thickness, a method of identifying pull-adhesion by means of the ANN – but on the basis of parameters independent of top layer thickness – has been proposed in [25,33] with relatively high values of linear correlation coefficient *R*: amounting to 0.8175, 0.8225 and 0.8401 for respectively training, testing and experimental verification of radial basis function (RBF) neural network and 0.8847, 0.8492 and 0.8989 for the training, testing and experimental verification of multilayer backpropagation ANN with the QUASI-NEWTON training algorithm (MLP-QN).

In all of the articles above, the artificial intelligence systems with supervisory training, as well as a limited number of inputs have been used. But in this paper, in order to increase the precision of the model and to reduce the number of inputs, the Principal Component Analysis (PCA) is used. The Self Organization Feature Map (SOFM) is used as a new model with competitive learning method for training and specifying the pull-off adhesion of concrete layers. The advantage of this method is that it can adjust a large amount of input data onto a two-dimensional structure with higher correlation than using conventional ANN approach.

2. Introduction of Self-Organization Feature Maps, Genetic Algorithm and Principal Component Analysis

2.1. Self-Organization Feature Maps (SOFM)

SOFM has been developed based on specific features of human brain's cells organized in variant areas of senses presented by arranged computational maps [34–36]. In this method the processor units are placed in the nodes of the network, positioned in a competitive learning process and then disciplined such that for the input features a significant coordinate is created on the network [34–36]. Thus a SOFM forms a topographic map from input patterns, in which the locations of the units are corresponding the inherent characteristics of the input patterns and in every learning stage the units compete with each other for being activated. At the end of a competing process one unit wins whose weights are modified differently compared to the other units' weights which is called the unsupervised learning [36]. SOFM are divided mainly to few types such as MaxNet Network, Mexican Hat Network, Hamming Network and Kohonen Network [34]. In late 70s, Kohonen described the important conclusion that the purpose of the learning rule should be creating a vector set, w_i, which forms the equiprobable presentations of a constant probability density function of ρ. This means that the w_i vectors must change themselves so that each input vector *X* forms by the probability density function of ρ as mentioned in [34] by formula (1):

$$p(\underline{X}) = \frac{1}{m} \tag{1}$$

The Kohonen layer is an array of one-, two-, or more-dimensional neurons, a sample of which is shown in Fig. 1.

Each unit computes it's the distance of the input vector *X* from its weight as described according to [34] by the Eq. (2):

$$I_i = D(\underline{X}, \underline{w_i}) \tag{2}$$

where *D* is the distance measure function. Although any common functions of distance measuring can be used, such as spherical arc distance shown by Eq. (3) as described in [34–36]:

$$D(\underline{u}, \underline{v}) = 1 - \cos\theta \tag{3}$$

To calculate the angle between u and $\theta = v$ or the Euclidean distance, $D(u,v) = |u - v|$ can be used. By this calculation the units want to know whether they have the closest weight vector to the x. this is the very competitive part in these kinds of networks. The unit with the closest weight to the input vector, will win this stage of the competition for which the related Z_i is set to 1 and other Z_i will set to zero. Then to update the weights the Kohonen Rule is used by using the Eq. (4) according to [36]:

$$\underline{w_i}^{\text{new}} = \underline{w_i}^{\text{old}} + \alpha(\underline{X} - \underline{w_i}^{\text{old}})Z_i \quad 0 < \alpha \leqslant 1 \tag{4}$$

The rule of Eq. (4) is the same as the rule of Eq. (4) as described in [34–36]:

$$\underline{w}_i^{\text{new}} = \begin{cases} (1-\alpha)\underline{w}_i^{\text{old}} + \alpha\underline{x} & \text{for winner} \\ \underline{w}_i^{\text{old}} & \text{other unites} \end{cases} \tag{5}$$

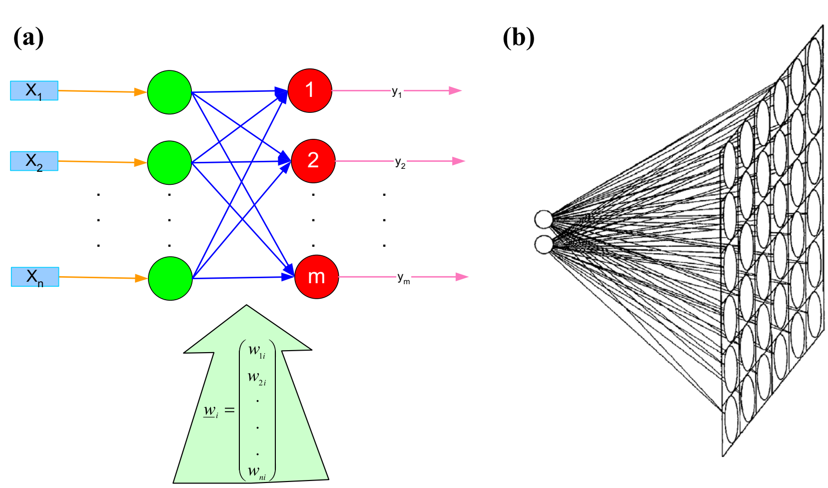

Fig. 1. The structural model of: (a) one-dimensional Kohonen network [36], (b) two-dimensional Kohonen network [37].