Neural Prediction of the Pull-Off Adhesion of the Concrete Layers in Floors on the Basis of Nondestructive Tests

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Abstract

This paper presents the application of artificial neural networks to the identification of the pull-off adhesion of the concrete layers in floors on the basis of parameters evaluated on the structural layer surface by the nondestructive optical method and on the floor surface by the nondestructive of impulse-response and impact-echo acoustic methods. The tests were carried out on specially prepared model specimens of concrete floor. In order to vary pull-off adhesion in the specimens the surface of the base layer was prepared in four versions. The aim of the investigations was the neural prediction of the pull-off adhesion of the concrete layers in floors on the basis of nondestructive tests. This is of practical importance since in this way the condition of the surface of the tested floor is not impaired.

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Keywords: concrete floors, nondestructive tests, surface roughness, acoustic methods, artificial neural networks.

1. Introduction

Floors are usually made from concrete. Various defects and damage may occur in the particular layers of the floor and at the top layer/base layer interface. They may arise as the floor is being made and in the course of its service [1–3]. One of the serious defects, having an adverse effect on the durability of floors, is the lack of bond between the base layer and the surface layer [4–9]. This defect is usually due to the improper preparation of the base layer.

The measure of interlayer bond is the value of pull-off adhesion $f_b$ determined in practice by the seminondestructive pull-off method [10]. The method is both qualitative since it is capable of detecting a defect in the form of no adhesion at the interface between the layers, and quantitative since it enables one to determine pull-off adhesion $f_b$. According to PN-EN 12636:2001, it is required of floors that pull-off adhesion $f_b$ of the top layer to the substrate should be not lower than 0.5 MPa and that one test measurement per 3$m^2$ should be taken. In practice, the latter requirement is often not complied with. Since the damage caused by testing in the surface layer must be repaired the number of measuring points tends to be reduced.

Pull-off adhesion $f_b$ depends on, among other things, the compressive strength of the base layer concrete and the temperature of the latter [11]. The preparation of the base layer has a major bearing on pull-off adhesion $f_b$ at the interface between the concrete layers. The preparation can be described by surface roughness parameters evaluated by a nondestructive method, e.g. the optical method [12–19].

In assessing the bond between concrete layers also nondestructive methods can be helpful [20–25]. This applies mainly to the state-of-the-art, acoustic methods, i.e. the impulse-response method and impact-echo method.

It should be noted that if the correlations between pull-off adhesion $f_b$ determined by the seminondestructive pull-off method, and the parameters determined on the floor surface by the nondestructive acoustic methods (taking into account the
different ways of preparing the base layer surface, described by its surface roughness parameters) were known, it could be possible to determine pull-off adhesion \( f_b \) at any test point without impairing the condition of the tested floor.

Therefore it seems sensible to search for a new method of identifying the pull-off adhesion of the concrete layers in floors, which would draw on a database of parameters describing the roughness of the concrete base layer and parameters determined on the floor surface by means of the acoustic techniques. In order to correlate a larger number of parameters it may be necessary to employ artificial neural networks [26–28]. The latter have been increasingly, successfully used to investigate concrete or concrete structures [29–33].

However, no cases in which ANNs were used to evaluate the pull-off adhesion of concrete layers in floors on the basis on nondestructively evaluated parameters, particularly to determine pull-off adhesion \( f_b \), have been reported in the literature. This is attempted in the present study.

2. Description of investigations

Two specimens (no. 1 and 2) modelling a 2500×2500 mm concrete floor, consisting of a 25 mm thick top layer (denoted with the letter W) laid on a 125 mm thick structural layer (denoted with the letter K) were investigated. The structural layer was laid on a layer of underlayment membrane and on 100 mm high sand layer (denoted as P1).

The 25 mm thick surface layer was made of grade C20/25 concrete and quartz aggregate with a maximum grading of 2 mm. The base layer was made of grade C30/70, consistency class S2 concrete with \( w/c = 0.5 \) and crushed basalt aggregate with a maximum grading of 8 mm.

In order to vary pull-off adhesion at the interface between top layer W and base layer K the surface of the latter layer was prepared in four versions (denoted with Roman numerals from I to IV), as shown in Fig. 2. Surfaces I and II were produced on model specimen no. 1 while surfaces III and IV were produced on model specimen no. 2. Fig. 1 shows the ways of preparing the surface of the base layer, the nondestructive methods and the seminondestructive method used in the tests and the evaluated parameters.

![Fig. 1. Breakdown of: methods of preparing base layer surface (nondestructive methods and seminondestructive method) with parameters evaluated on base layer surface and on floor surface.](image-url)
The investigations were carried out in the previously marked grid points by means of an optical camera with a resolution of 1028×768 pixels, mounted on a guide (Fig. 3a). The acquired data were transmitted to a software installed on a laptop. The camera was equipped with a laser diode illuminator. The camera, with its lens by default fixed at an angle of 53°, was manually shifted. The investigations consisted in scanning 50×50 mm surface profiles at every 0.1 mm. The scanning time of the test area in each test grid point did not exceed 2 seconds. As a result of the scanning a 3D image of the concrete surface within the test area was obtained. The data were processed by the software and the roughness parameters of the concrete surface were obtained.

The surface of the top layer was investigated by nondestructive acoustic methods: the impulse response method and the impact-echo method.

The impulse response tests were carried out using a system consisting of a calibrated hammer for exciting an elastic wave (by striking the hammer against the surface of the tested material), a geophone and a software for recording and processing the data. A schematic of the rig for impulse-response testing is shown in Fig. 3b. Impact-echo tests were carried out using equipment consisting of a set of balls with different diameters (used to generate an elastic wave by striking them against the surface of the tested material), a receiving head (probe) and a software for recording and processing the data. A schematic of the rig for impact-echo testing is shown in Fig. 4a. The tests were carried out in accordance with the recommendations given in [34].

A schematic of the rig for testing by the seminondestructive pull-off method is shown in Fig. 4b. The tests were performed in the same points in which the nondestructive tests had been carried out.
3. Test results

Table 1 shows sample parameter values obtained experimentally by the nondestructive methods (the optical and the acoustic) and the seminondestructive method for model specimens no. 1 and 2 for the surfaces I-IV. The full data can be found in [35]. Then the sets of results obtained from the principal tests, amounting to 472, were subjected to statistical analyses which reduced the database to 460 sets of results. The latter constituted input variables for a neural network.

Table 1. Sample parameter values obtained by nondestructive (optical and acoustic) methods and seminondestructive method for model specimens no. 1 and 2, for surfaces I-IV

| Number of test point | Name of test method and parameter symbol | Impulse-response method | Impact-echo method | Pull-off method |
|----------------------|-----------------------------------------|------------------------|--------------------|----------------|
|                      | Optical method                          | Impulse-response method | Impulse-echo method | Pull-off method |
|                      | $S_a$, $S_q$, $S_s$, $S_v$, $S_p$, $K_d$, $N_m$, $M_p$, $v$, $f_t$, $f_s$ | mm, Mm, mm, mm, mm, mm, mm, mm, mm, mm, mm, mm, mm | MHz, MHz, MHz, MHz, MHz, MHz, MHz, MHz, MHz, MHz, MHz, MHz, MHz | MPa, MPa, MPa, MPa, MPa, MPa, MPa, MPa, MPa, MPa, MPa, MPa, MPa |
| I/A8                 | 0.276, 0.393, –0.772, 8.138, 0.033, 0.617, 0.044, 2.056, 1.194, 0.069, 51.294, 1.417, 0.410, 8.500, 1.020 | | | |
| I/A9                 | 0.375, 0.507, –0.900, 5.301, 0.053, 0.633, 0.060, 2.257, 1.022, 0.039, 43.399, 1.312, 0.505, 8.500, 1.070 | | | |
| I/A10                | 0.262, 0.344, –0.453, 4.000, 0.069, 0.685, 0.032, 1.575, 0.695, 0.069, 70.227, 1.258, 0.547, 8.000, 1.100 | | | |
| ...                  | ...                                     | ...                    | ...                | ...            |
| II/B14               | 0.025, 0.222, –0.454, 4.045, 0.003, 0.768, 0.012, 1.262, 0.677, 0.080, 65.684, 2.569, 1.391, 5.500, 0.640 | | | |
| II/B15               | 0.171, 0.212, –0.675, 3.919, 0.001, 0.764, 0.018, 1.080, 0.637, 0.087, 86.766, 2.628, 2.449, 5.000, 0.610 | | | |
| II/B16               | 0.165, 0.156, –0.644, 4.091, 0.010, 0.752, 0.017, 0.977, 0.520, 0.085, 257.087, 0.783, 2.751, 5.000, 0.610 | | | |
| ...                  | ...                                     | ...                    | ...                | ...            |
| III/D7               | 0.935, 0.811, –0.187, 4.154, 0.004, 0.740, 0.028, 4.877, 3.835, 0.010, 135.950, 1.281, 0.449, 3.500, 0.410 | | | |
| III/D8               | 0.643, 0.646, 0.005, 3.708, 0.003, 0.756, 0.026, 3.715, 3.667, 0.030, 238.160, 1.115, 0.644, 4.000, 0.420 | | | |
| III/D9               | 0.691, 0.807, 0.197, 3.263, 0.002, 0.772, 0.025, 2.554, 3.499, 0.028, 238.182, 2.075, 0.293, 4.000, 0.460 | | | |
| ...                  | ...                                     | ...                    | ...                | ...            |
| IV/G6                | 0.492, 0.630, –0.156, 3.630, 0.002, 0.744, 0.041, 2.582, 2.436, 0.050, 67.180, 0.735, 0.298, 7.000, 0.690 | | | |
| IV/G7                | 0.557, 0.706, –0.074, 3.283, 0.001, 0.736, 0.057, 2.541, 2.666, 0.036, 75.897, 0.922, 0.399, 7.000, 0.590 | | | |
| IV/G8                | 0.533, 0.678, –0.125, 3.337, 0.001, 0.750, 0.042, 2.661, 2.453, 0.020, 70.928, 0.829, 0.392, 6.500, 0.610 | | | |

Fig. 4. Schematic of (a) rig for impact-echo testing and (b) rig for pull-off testing
4. Statistical analyses of test results

Statistical analyses were carried out in order to select input variables from the experimentally determined parameters, which would be suitable for the input layer of an artificial neural network.

Therefore a test of goodness of fit with the normal distribution was done in 472 test points for all the parameters obtained by the nondestructive methods and the seminondestructive method. The Shapiro-Wilk test, in which results are ordered into a nondecreasing sequence and subsequently test statistics are built, was used for this purpose. According to [36], if probability level \( W \) of these test statistics falls below the fixed test significance level \( W_n(\alpha) \), the hypothesis about the fit with the normal distribution is rejected.

In testing practice it happens that one or more results markedly differ from the rest. A doubt arises whether the given result should be taken into account in an analysis of the distribution or whether it should be rejected. For this purpose Chauvenet’s criterion for eliminating uncertain results is used here.

The Shapiro-Wilk test results for the particular elements after the application of Chauvenet’s criterion are presented in Table 2.

On the basis of the statistical analyses involving the Shapiro-Wilk test the parameters determined in 460 test points were used in further analysis. Thanks to the application of Chauvenet’s criterion twelve uncertain results were eliminated.

It appears from Table 2 that for assumed significance level \( \alpha = 0.01 \) one should reject the hypothesis about the good fit of parameters \( S_{sk}, S_{ku}, S_{bi}, S_{ci}, S_{vi}, S_{v}, S_{p}, K_d, N_{av}, M_p/N \) and \( v \) with the normal distribution. Thus it seems highly probable that the most useful experimentally determined parameters to serve as the input variables for the nondestructive identification of the pull-off adhesion of the concrete layers in floors by means of artificial neural networks are parameters: \( S_a, S_q, K_d, N_{av} \) and \( f_T \).

The most suitable output variable seems to be parameter \( f_b \).

Table 2. Shapiro-Wilk test results

| Parameter name | \( W \) | \( \alpha \) | \( W_n(\alpha) \) |
|----------------|-------|---------|---------------|
| \( S_a \)      | 0.957 | 0.01    | 0.956         |
| \( S_q \)      | 0.958 | 0.01    | 0.956         |
| \( S_{sk} \)   | 0.983 | 0.01    | 0.956         |
| \( S_{ku} \)   | 0.877 | 0.01    | 0.956         |
| \( S_{bi} \)   | 0.630 | 0.01    | 0.956         |
| \( S_{ci} \)   | 0.550 | 0.01    | 0.956         |
| \( S_{vi} \)   | 0.913 | 0.01    | 0.956         |
| \( S_v \)      | 0.912 | 0.01    | 0.956         |
| \( S_p \)      | 0.881 | 0.01    | 0.956         |
| \( K_d \)      | 0.839 | 0.01    | 0.956         |
| \( N_{av} \)   | 0.617 | 0.01    | 0.956         |
| \( M_p/N \)    | 0.721 | 0.01    | 0.956         |
| \( v \)        | 0.751 | 0.01    | 0.956         |
| \( f_T \)      | 0.964 | 0.01    | 0.956         |
| \( f_b \)      | 0.957 | 0.01    | 0.956         |

In order to confirm these suppositions the correlations between the particular parameters obtained by the nondestructive methods and the parameter determined by the seminondestructive pull-off method were checked out. Spearman’s rank correlation coefficient was used for this purpose.

The results of the calculations of Spearman’s rank correlation coefficient for the correlations between the particular parameters and the output variable (pull-off adhesion \( f_b \)) are shown in Table 3.

According to the table 3, Spearman’s rank correlation coefficient \( \rho \) ranges from –1 to –0.4 and from 0.4 to 1 for respectively parameters \( S_p \) and \( S_q \) obtained by the optical method and parameters \( K_{d}, N_{av} \) and \( f_T \) obtained by the nondestructive acoustic methods. The coefficient assumes the highest value of 0.925 for parameter \( f_T \), which may indicate that the latter is of the greatest importance in the selection of input variables for the artificial neural network. A positive value of Spearman’s rank correlation coefficient means that parameter \( f_T \) increases with output variable \( f_b \). The correlation coefficient is also high (amounting to –0.711) for parameter \( N_{av} \) despite the lack of agreement between the hypothesis distribution and the normal distribution. A negative value of Spearman’s rank correlation coefficient in this case indicates that \( N_{av} \) decreases with increasing output variable \( f_b \). The correlation coefficient amounts to 0.416 for parameter \( K_{d} \) to –0.447 for parameter \( S_p \) and to –0.446 for parameter \( S_q \). This is indicative of the usefulness of the above parameters as input variables for building an artificial neural network.
The calculated values of Spearman’s rank correlation coefficient \( \rho \) confirm the usefulness of parameters \( S_a, S_q, N_{av}, K_d \) and \( f_T \) as input parameters for an artificial neural network.

| Parameter name | \( f_b \) |
|----------------|-----------|
| \( S_a \)      | -0.447    |
| \( S_q \)      | -0.446    |
| \( S_{sk} \)   | -0.116    |
| \( S_{kq} \)   | -0.052    |
| \( S_d \)      | 0.204     |
| \( S_{ti} \)   | -0.077    |
| \( S_{ni} \)   | 0.176     |
| \( S_{bi} \)   | -0.037    |
| \( S_{ci} \)   | -0.077    |
| \( S_{vi} \)   | 0.176     |
| \( S_{pi} \)   | -0.067    |
| \( K_d \)      | 0.416     |
| \( N_{av} \)   | -0.711    |
| \( M_p/N \)    | -0.395    |
| \( v \)        | 0.333     |
| \( f_T \)      | 0.925     |

5. Numerical analyses by means of artificial neural networks

A unidirectional multilayer artificial neural network with three different training algorithms was used for numerical analyses. The combinations of the network with a training algorithm are specified below:

- a unidirectional multilayer error back propagation network with the steepest gradient descent algorithm – network A,
- a unidirectional multilayer error back propagation network with a conjugate gradient algorithm – network B,
- a unidirectional multilayer error back propagation network with a QUASI-NEWTON algorithm – network C.

On the basis of the statistical analyses the following parameters (determined by the three nondestructive methods) were chosen as useful for the nondestructive identification of the pull-off adhesion of the concrete layers in floors by means of the artificial neural network:

- the average arithmetical mean height of the tested surface from the reference surface \( (S_a) \) and the root mean square height from the reference surface \( (S_q) \), determined by the nondestructive optical method;
- stiffness \( K_d \), an average mobility \( N_{av} \), determined by the nondestructive impulse-response method;
- the frequency of ultrasonic wave reflection from the bottom \( (f_T) \), determined by the nondestructive impact-echo method.

The parameters were randomly divided into training data, testing data and data for experimental verification of the neural network. From among the 450 sets of results, 322 sets were adopted for training the ANN, 69 for testing the ANN and 69 for the experimental verification of the ANN.

Fig 5 show RMSE values depending on the number of hidden layer neurons \( (K) \) and the hidden layer activation function, determined for the analyzed artificial neural networks A, B and C in respectively training and testing. The ANN with number of hidden layer neurons \( K \) in a range of 3–10 and with the tanh, logistic, exponential and sine function was analyzed.

It appears from Fig. 5a-c that the lowest RMSE value (below 0.002) determined in the training process characterizes network C (the unidirectional multilayer error back propagation network with QUASI-NEWTON algorithm and 9 and 10 hidden layer neurons and the tanh or logistic hidden layer activation function) while the highest RMSE value (above 0.005) characterizes network A.

It appears from Fig. 5d-f that also Network C is characterized by the lowest RMSE (below 0.002) for testing, whereas network A has the highest RMSE (0.004–0.005). According to Fig. 5c, unidirectional multilayer error back propagation network C with the QUASI-NEWTON algorithm, with 7, 9 and 10 hidden layer neurons and the tanh or logistic hidden layer activation function ensures the lowest RMSE for testing.
Fig. 5. Average RMSE depending on number of hidden layer neurons and hidden layer activation function, determined in (a) training – network A, (b) training – network B, (c) training – network C, (d) testing – network A, (e) testing – network B, (f) testing – network C.

Fig. 6. Average linear correlation coefficient $R$ depending on number of hidden layer neurons and hidden layer activation function, obtained in (a) training – network A, (b) training – network B, (c) training – network C, (d) testing – network A, (e) testing – network B, (f) testing – network C.
Fig. 6 shows the averages of linear correlation coefficient $R$ depending on number of hidden layer neurons $K$ and the hidden layer activation function, obtained for the analyzed artificial neural networks A, B and C in respectively the training and testing process. The number of hidden layer neurons $K$ in the ANNs ranged from 3 to 10 and the tanh, logistic, exponential and sine hidden layer activation functions were used.

It appears from figure 6a-c that in the training process network C is characterized by the highest average linear correlation coefficient $R$ (0.965), whereas network A shows the lowest coefficient $R$ (0.950). Unidirectional multilayer error back propagation network C with the QUASI-NEWTON algorithm, with 10 hidden layer neurons and the tanh hidden layer activation function ensures the highest linear correlation coefficient $R$ for training.

According to Fig. 6d-f, also in the testing process Network C is characterized by the highest average of linear correlation coefficient $R$ (above 0.975), whereas network A is characterized by the lowest coefficient $R$ (0.960). According to Fig. 6c, the unidirectional multilayer error back propagation network with the QUASI-NEWTON algorithm, with 6, 7 and 10 hidden layer neurons and the tanh or logistic hidden layer activation function ensures the highest linear correlation coefficient $R$ for testing.

On the basis of the above analysis, covering in total 96 configurations of the selected artificial neural networks denoted with the letters A, B and C, respectively, network C was chosen for the training and testing aimed at the nondestructive identification of pull-off adhesion $\bar{f}_{b}$. This is a unidirectional multilayer error back propagation network with the QUASI-NEWTON algorithm, with 10 hidden layer neurons and the tanh hidden layer activation function. The structure of this ANN is shown in Fig. 7. The five parameters experimentally determined by the three nondestructive methods constitute the input layer of network C.

![Fig. 7. Structure of unidirectional multilayer error back propagation ANN with QUASI-NEWTON algorithm tanh hidden layer activation function adopted for training and testing aimed at nondestructive identification of pull-off adhesion $\bar{f}_b$.](image)

### 6. Results of training, testing and experimental verification of network C

Fig. 8 shows the correlation between pull-off adhesion $\bar{f}_{b}$ determined by seminondestructive pull-off method and pull-off adhesion $\bar{f}_{cb}$ identified by network C – a unidirectional multilayer error back propagation network with the QUASI-NEWTON algorithm, with 10 hidden layer neurons and the tanh hidden layer activation function. Two hundred epochs were adopted.

The above correlation for training and testing is shown in respectively Fig. 8a and 8b. It appears from Fig. 8 that network C correctly maps the training data and correctly identifies the testing data, as evidenced by the situation of the points along the regression line, corresponding to the ideal mapping. It is important that very high linear correlation coefficient $R$ values (respectively 0.9775 and 0.9725) were obtained in both training and testing.

As mentioned in sect. 4, 69 sets of experimental results were selected for the experimental verification of network C. The values of parameters $S_a$, $S_p$, $N_{av}$, $K_d$ and $f_T$ in each of the 69 randomly selected test points (16 for surface I, 16 for surface II, 12 for surface III and 25 for surface IV) were input into the previously trained and tested ANN.

Fig. 8c shows the correlation between experimentally determined pull-off adhesion $\bar{f}_{b}$ and pull-off adhesion $\bar{f}_{cb}$ identified by network C in the experimental verification process. The results show that network C correctly maps the randomly selected verification data, as evidenced by the situation of the points along the regression line corresponding to the ideal mapping, and by the high linear correlation coefficient $R$ (amounting to 0.9481).
7. Conclusions

The following conclusions were drawn from the obtained results of the experimental and numerical studies:

- Artificial neural networks with an appropriately matched structure and training algorithm are suitable for the nondestructive identification of pull-off adhesion $f_{c,b}$ between the top layer and the structural layer in concrete floors on the basis of parameters evaluated using the state-of-the-art nondestructive methods, i.e. the optical method and the acoustic methods. As demonstrated, the unidirectional multilayer error back propagation network with the QUASI-NEWTON algorithm is particularly suitable for this purpose.

- Pull-off adhesion $f_{c,b}$ of the concrete layers in floors can be reliably identified by means of the three nondestructive methods: the optical method and the two acoustic (impulse-response and impact echo) methods on the basis of the parameters: $S_a$, $S_p$, $K_d$, $N_{av}$ and $f_T$ determined by the methods. As mentioned above, the unidirectional multilayer error back propagation network with the QUASI-NEWTON algorithm and 9 and 10 hidden layer neurons and the tanh hidden layer activation function is suitable for this purpose, as evidenced by the very high values of linear correlation coefficient $R$, amounting to 0.9775, 0.9725 and 0.9481 for respectively training, testing and experimental verification and by the very low values of relative error $RE$, mostly below 0.08 for training. Below 0.10 for testing and below 0.12 for verification.

- The method proposed here is not intended to completely replace the currently commonly used way of identifying the pull-off adhesion of the concrete layers in floors by the seminondestructive pull-off method. The proposed method represents a new approach consisting in the neural identification of the value of this adhesion on the basis of jointly five parameters: two parameters describing base layer roughness, evaluated by the optical method, and three parameters evaluated on the surface of the floor by the nondestructive acoustic methods.
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