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Evaluation of the parameters affecting the Schmidt rebound hammer reading using ANFIS method

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Abstract. As a nondestructive testing method, the Schmidt rebound hammer is widely used for structural health monitoring. During application, a Schmidt hammer hits the surface of a concrete mass. According to the principle of rebound, concrete strength depends on the hardness of the concrete energy surface. Study aims to identify the main variables affecting the results of Schmidt rebound hammer reading and consequently the results of structural health monitoring of concrete structures using adaptive neuro-fuzzy inference system (ANFIS). The ANFIS process for variable selection was applied for this purpose. This procedure comprises some methods that determine a subsection of the entire set of detailed factors, which present analytical capability. ANFIS was applied to complete a flexible search. Afterward, this method was applied to conclude how the five main factors (namely, age, silica fume, fine aggregate, coarse aggregate, and water) used in designing concrete mixture influence the Schmidt rebound hammer reading and consequently the structural health monitoring accuracy. Results show that water is considered the most significant parameter of the Schmidt rebound hammer reading. The details of this study are discussed thoroughly.

Keywords: ANFIS; variable selection; Schmidt rebound hammer; structural health monitoring; concrete mix design

1. Introduction

Rebound hammer is a common nondestructive experimental method for investigating the structural health monitoring of a constructed concrete structure by many consultants (Amasaki 1991, Shariati *et al*. 2011, Brozovsky 2014, Breccolotti and Bonfigli 2015, Rubene and Vilnitis 2015, Selçuk and Yabalak 2015, Shariati and Schumacher 2015, Schumacher *et al*. 2017). Rebound hammer is widely used because it is reasonably cheap and has simple functioning procedures (Hamidian *et al*. 2011, Hamidian *et al*. 2012).

Investigations of several constructed concrete buildings with concrete show that concrete can penetrate in the deterioration under different conditions (Shariati *et al*. 2010, Arabnejad Khanouki *et al*. 2011, Mohammadhassani *et al*. 2014, Khanouki *et al*. 2016, Khorami *et al*. 2017).

Thus, the investigation and rehabilitation of concrete structures are of significant importance. Investigating the Schmidt rebound hammer is beneficial in identifying possible damage to structures and its reasons (Shariati 2008, Andalib *et al*. 2010, Hamidian *et al*. 2011, Shariati *et al*. 2011). The Schmidt rebound hammer has been used for a relatively long time in assessing cracks, damage, voids, and other corrosions of concrete structures (Khorami *et al*. 2017). This method can be effectively used to forecast the facility life of concrete structures, with consideration of their quality control. The rebound hammer can also determine concrete homogeneity. Concrete is a mixture of cement, fine and coarse aggregates, silica fume, and water, which influences its properties by the difference of mechanical strength and elastic stiffness (Mirmiran and Wei 2001, Bazzaz *et al*. 2012, Bazzaz *et al*. 2012, Jalali *et al*. 2012). With a remarkable number of variable factors, the Schmidt rebound hammer test became relatively helpful in measuring concrete quality (Hamidian *et al*. 2011, Hamidian *et al*. 2012, Shariati 2013, Andalib *et al*. 2014, Shariati *et al*. 2015). As mentioned, this method has been used in structural health monitoring for a long time, but understanding which parameters of concrete mix design have the most influence on the results of Schmidt rebound hammer and consequently on the health of concrete buildings has become a topic of interest by some researchers (Andalib *et al*. 2011, Caglayan *et al*. 2012,

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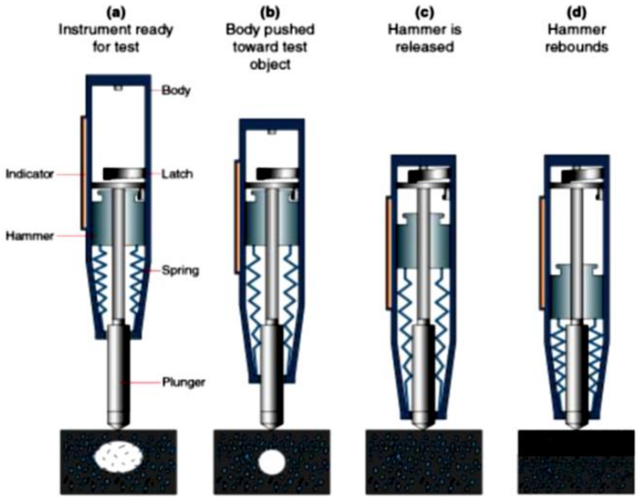

Fig. 1 Schematic processing of Schmidt rebound hammer test

Khorramian *et al*. 2015, Kibar and Ozturk 2015, Khorramian *et al*. 2017).

The data obtained from Schmidt rebound hammer test are investigated using adaptive neuro-fuzzy inference technique (ANFIS) (Bazzaz 2010, Mohammadhassani *et al*. 2013, Mohammadhassani *et al*. 2014, Toghroli Ali *et al*. 2014, Shah *et al*. 2015, Safa *et al*. 2016, Toghroli *et al*. 2016, Mansouri *et al*. 2017) to find the most significant factors affecting its results. The variable selection process comprises different approaches that determine a subsection of the total verified factors for the best estimation. ANFIS was applied to achieve a flexible search in this study. Afterward, the method was applied to examine how the five factors (namely, age, silica fume, fine aggregate, coarse aggregate, and water) affect the readings of Schmidt rebound hammer.

2. Methodology

2.1 Data collection

Schmidt rebound hammer test examines surface hardness. Its operation method is that flexible bulk rebound depends on the rigidity of the surface against the bulk imposed. Fig. 1 depicts the schematic process of Schmidt rebound hammer test. Concrete strength and the Schmidt rebound numbers have no significant theoretic relationship; however, experiential correlations have been specified between strength properties and Schmidt rebound number (Ansari *et al*. 2015, Bazzaz *et al*. 2015, Rubene and Vilnitis 2015). In this study, three parts of a concrete structure, namely column, beam, and slab, are tested using the rebound hammer method.

2.2 Testing details

Horizontal and vertical readings were used for Schmidt rebound hammer. Five readings were obtained at each point for both positions, and then the average of the readings is calculated and used in strength estimation. For beam testing, horizontal and vertical positions were used to test the slab in the vertical position. Both positions were used for column readings.

2.3 Variables used as input and output of research

For this analysis, five input factors were selected, namely, age, silica fume, fine aggregate, coarse aggregate, and water. These parameters were considered potentially significant on the results of Schmidt rebound hammer readings and consequently the structural health of the concrete structure. The parameters include of age, silica fume, fine aggregate, coarse aggregate, water, rebound hammer compressive strength.

To construct a system with the best features, the essential subsection of the parameters is initially identified, which is called the variable selection process. This process is aimed at obtaining a subsection of factors that show good estimation capability. The tool of the multipart system is modelled with neural network as a function of calculation and regression. The neural network is accomplished by adaptive processing of structures that are parallel and are unified over the organized networks. Thus, the correctness of the method's models relies on the capability of the selected sensor data in demonstrating the model system, which is formed as a result of the sensor data. To generate an effective ANFIS model that is accomplished with approximately a singular procedure output, the collection procedure for the subsection of relevant factors is vital. The mentioned important issue is addressed in the variable selection. As previously mentioned, the aim of variable selection is to identify a subsection of all factors that provide estimation capability (Castellano and Fanelli 2000, Dieterle *et al*. 2003, Bazzaz *et al*. 2015). The difficulties confronted in the procedure of the collection of factors could perhaps be determined by combining previous information and separating and eliminating irrelevant factors (Bazzaz *et al*. 2011, Singh *et al*. 2012, Verma and Singh 2013). Then, a more refined method should discover an optimized process over the procedure of genetic algorithm (Verma and Maheshwar 2014, Tripathy *et al*. 2015, Bazzaz 2018). The impartial is to select the correct input factors, thereby decreasing the error that occurs among the practical values, and the model approximations of those clarified variables. ANFIS is one of the most efficient neural network systems. The results of this method were utilized to obtain the aim of the current study using the variable selection (Kwong *et al*. 2009).

ANFIS was applied in a factor search to determine how the main factors influence the structural health monitoring of existing concrete structure using Schmidt rebound hammer test. A few researchers have used ANFIS (Jang 1993, Trivedi *et al*. 2015) in different systems, such as modeling (Khandelwal *et al*. 2005, Petković *et al*. 2012, Singh *et al*. 2012), estimation (Sivakumar and Balu 2010, Singh *et al*. 2016), and control (Tian and Collins 2005, Kurnaz *et al*. 2010, Ravi *et al*. 2011, Petković *et al*. 2012). The application of neuro-adaptive learning procedure provides more information on the collected data for fuzzy modeling procedure (Aldair and Wang 2011, Dastranj *et al*.

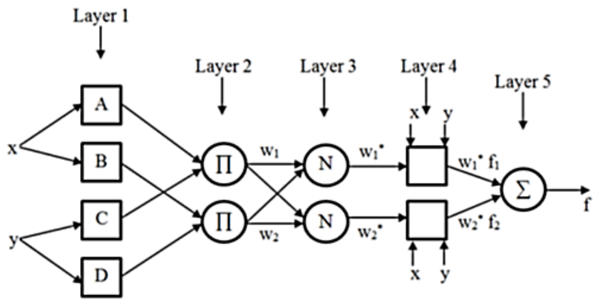

Fig. 2 Schematic structure of ANFIS model

2011). Applying ANFIS aims to establish the fuzzy interference system (FIS) by examining available pairs of input or output data (Grigorie and Botez 2009, Manoj 2011). This method provides fuzzy logic that corrects the membership function (MF) factors. Consequently, this method is the best in enabling those related FIS identify the available pairs of input or output data (Moustapha and Krishnamurti 2001, Akcayol 2004).

2.4 Variable selection

A set of fuzzy if-then rules should be constructed to produce a subset of pre-determined input-output data. This set of rules must be accompanied with a proper MF. As a basis for this requirement, ANFIS is the best solution. In this case, input-output pairs of data are considered the converted MF. ANFIS uses the primary FIS to generate input-output data and regulate the primary FIS by a backpropagation algorithm. The main modules of FIS consist of three mechanisms, namely, database, rule base, and reasoning. The first mechanism allocates the MFs that are used in fuzzy rules, which are the components of the second mechanism. The last mechanism is the reasoning process, which infers a feasible outcome based on the inputs. A mixture of systems and information together with a wide range of sources comprises these intelligent systems, which amend to make improvements in the rapidly changing world. These systems can be compared with human intelligence in explicit domain. To consider the rapidly changing world, ANFIS can distinguish designs and contributions. FIS can combine human understanding, fix interface, and create results.

FIS in MATLAB was applied to accomplish the procedure. To predict structural health monitoring of constructed concrete structures, the most significant factors are the analyses of Schmidt rebound hammer in an ANFIS model for two input variables. This schematic structure of the ANFIS model is shown in Fig. 2.

For this study, the fuzzy if-then procedure of Takagi and Sugeno's class along with the two inputs was utilized. The two first-order Sugeno inputs are as follows

$$If\ x\ is\ A\ and\ y\ is\ V, then\ f_1 = p_1x + q_1y + r_1 \tag{1}$$

The input factors of MFs were used to prepare the first layer, which helps to provide the inputs for the next layer. An adaptive node was measured by every node, which requires the following node function

$$O = \mu_{AB}\left(x\right) and\ O = \mu_{CD}\left(x\right),$$

Where $\mu_{AB}(x)$ and $\mu_{CD}(x)$ are defined as membership meanings. The funcions of bell-shaped membership obligating the minimum of (0.0) and the maximum of (1.0) are specified as

$$\mu(x) = bell(x; a_i, b_i, c_i, d_i) = \frac{1}{1 + [(\frac{x - c_i}{a_i})^2]^{b_i}} \tag{2}$$

Where $\{a_i, b_i, c_i, d_i\}$ are defined as presumption parameters. Inputs to the nodes in this case are X and y, which are the representatives of the combination of the effective variables on the Schmidt rebound hammer readings in the prediction of structural health monitoring.

The second layer (membership layer) of nodes gathers the receiving signals from the former layer and sends non-adaptive results in the form of $w_i = \mu_{AB}(x) \times \mu_{CD}(y)$. This layer weights the function of every membership. Each output node exhibits the firing strength of a rule.

The third layer is identified as the rule layer. All neurons perform as the pre-condition matching the fuzzy rules. In other words, when the number of fuzzy rules is equal to the number of layers, the rule's activation level is deliberated.

Standardized weights were calculated in every node. Likewise, the nodes in the third layer were measured as non-adaptive. Each node calculated the significance of the rule's firing strength over the sum of firing strengths of all rules in the form of $w_i^* = \frac{w_i}{w_1 + w_2}, i = 1, 2.$

The results were referred as the standardized firing strengths.

To conclude the rules, the fourth layer was liable for supplying the result values. Each node in the fourth layer, which was identified as the defuzzification layer, was an adaptive node, which required the node function of $O_i^4 = w_i^* xf = w_i^*(p_i x + q_i y + r_i)$. The variable set in this layer is $\{p_i, q_i, r\}$ which is appointed as the resultant parameters.

In the final layer (fifth layer), all the receiving inputs from the previous layer were collected. This layer is the output layer. Subsequently, the fuzzy organization results were adjusted into a crisp. The single node of the fifth layer was considered non-adaptive. In this node, the total output was analyzed as the sum of all receiving signals.

$$O_i^5 = \sum_i w_i^* xf = \frac{\sum_i w_i f}{\sum_i w_i} \tag{3}$$

Hybrid learning algorithms were utilized to identify the variables of the ANFIS method. The functional signals continued until the fourth layer where the hybrid learning algorithm passes. Additionally, the consequent variables were initiated by the least-squares approximation. To synchronize presumption variables through the gradient decline order, the error rates circulated backward.

3. Results

Table 1 Effects of each input parameter on the Schmidt rebound hammer readings

ANFIS model 1: in1 ⟶	trn=1762.4593, chk=1874.9520
ANFIS model 2: in2 ⟶	trn=1795.2248, chk=1864.5841
ANFIS model 3: in3 ⟶	trn=1750.4152, chk=1957.2586
ANFIS model 4: in4 ⟶	trn=1641.5241, chk=1704.6688
ANFIS model 5: in5 ⟶	trn=1603.2604, chk=2184.5130

Table 2 Combinations of two input parameters for the Schmidt rebound hammer readings

ANFIS model 1: in1 in2 ⟶	trn=1752.5995, chk=1874.4390
ANFIS model 2: in1 in3 ⟶	trn=1524.4381, chk=27675.1091
ANFIS model 3: in1 in4 ⟶	trn=1347.9230, chk=1893.5727
ANFIS model 4: in1 in5 ⟶	trn=1264.0688, chk=2255.0260
ANFIS model 5: in2 in3 ⟶	trn=1745.5854, chk=1968.7871
ANFIS model 6: in2 in4 ⟶	trn=1640.1069, chk=1708.0038
ANFIS model 7: in2 in5 ⟶	trn=1594.2183, chk=2204.1388
ANFIS model 8: in3 in4 ⟶	trn=1507.5879, chk=1585.8359
ANFIS model 9: in3 in5 ⟶	trn=1203.7260, chk=3000.3752
ANFIS model 10: in4 in5 ⟶	trn=1225.9724, chk=5080.7442

By employing the results of the Schmidt rebound hammer, an inclusive study was accomplished. To formulate a set of the best combination of inputs, given inputs and readings were selected, which also aims to identify the most significant output factor (Schmidt rebound hammer readings). Mainly, any ANFIS model is constructed by the tasks for each arrangement, which is prepared for a single period. Then, the finished work is reported. The most effective input in the output estimation is recognized from the outset, as shown in Table 1. The input variables with the smaller training error have the most significant influence on the results.

From the results shown in Table 1, Input Variable 5 is the most significant Schmidt rebound hammer reading. Both the checking and training errors are comparable, which implies an indirect signal. Therefore, no overfitting is observed. As a result, selecting several input factors in the structure of the ANFIS model can be discovered. The most relevant integration of two receiving factors can be shown for verification. Table 2 shows the optimal combination of two input features for the prediction of the structural health monitoring of an existing concrete structure. Two optimal input factors can then be extracted for further analysis.

To acquire the proper inputs using ANFIS quickly, the function used for all variables is the one with only one training for a single epoch. The number of epoch on an ANFIS training is 100, which can be improved after fixing the inputs. Furthermore, error curves are depicted for the two extracted input parameters and the 100 epochs of training and checking.

As can be seen in the graph of the model for the ANFIS input-output (decision), prediction of the Schmidt rebound hammer readings is a monotonic nonlinear surface. The figure shows the response of ANFIS model for the varying selected Input Parameters 3 and 5.

Some disadvantages are observed when different inputs are used. For example, the difficulty in defining the model, the disruptions, and the inaccuracies are caused by unrelated factors, thereby resulting in reduced generalization capacity of the model. Moreover, data collection is more prolonged. Thus, reducing the different number of inputs is necessary. To make the model efficient, reduction in complexity is an option, which makes better estimation and understanding in terms of the variables.

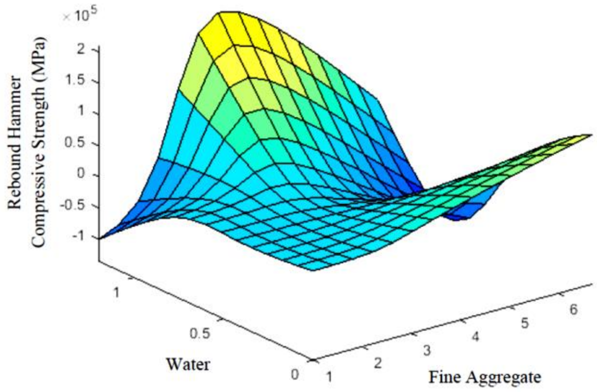

Fig. 3 ANFIS decision surfaces for the Schmidt rebound hammer readings for two selected parameters (3 and 5)

The use of ANFIS system has many valuable benefits, such as its adaptability of optimization and its computational efficiency. ANFIS can be combined with proficient systems and uneven sets for other applications. Complex systems with more multipart factors can be analyzed using ANFIS because the system is faster than other similar control plans. ANFIS has a highly compatible behavior that is useful in the tedious job of training MFs.

4. Conclusions

A systematic approach that uses ANFIS methodology is employed to identify the most significant factor in the results of Schmidt rebound hammer test reading of structural health monitoring. MATLAB program is used to simulate this system. The results were then checked on the equivalent output blocks.

Different ways were used in determining a subsection of all recorded parameters to obtain better predictions. An adaptive search is made using ANFIS. Then, the method is used to determine the influence of the five parameters (namely, age, silica fume, fine aggregate, coarse aggregate, and water) on the results of the Schmidt rebound hammer readings.

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