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Nondestructive Concrete Strength Estimation based on Electro-Mechanical Impedance with Artificial Neural Network

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Abstract

Concrete is one of the most common materials used to construct a variety of civil infrastructures. However, since concrete is susceptible to fractures, it is essential to confirm the strength development of concrete during the curing process, in order to prevent unexpected collapse. To address this issue, this study proposes an artificial neural network (ANN)-based strength estimation technique using several kinds of strength related factors of concrete materials. In particular, the variations in mechanical properties of concrete were measured through electro-mechanical impedance (EMI) change using an embedded piezoelectric sensor. The ANN was trained to estimate the strength of concrete by using water-cement ratio, curing time and temperature, maturity from internal temperature, and 1-CC of the EMI signals. The trained ANN was verified with conventional strength estimation models throughout a series of experimental studies. According to the comparison results, it is noted that the proposed technique could be very effectively applied to estimate the strength of concrete.

1. Introduction

Concrete is one of the most common materials used to construct civil infrastructures, due to its availability, low cost, flexibility of handling, and being able to shape into any desired form. However, concrete is also one of the most difficult materials to manage, because it is a mixture consisting of cement, water, sand, gravel, and other aggregates. Due to its heterogeneous property, it is difficult to mathematically predict the compressive strength of concrete during and/or after the curing. In particular, predicting the compressive strength during the curing process is important in reducing the construction time and cost, because it can determine the appropriate curing time to achieve sufficient strength to safely progress to the next phase. The in situ strength of concrete structures can be determined with high precision, by performing strength testing and material analysis on core samples removed from the structure (Irie et al. 2008). However, this method can lead to destruction of the integrity of the host concrete structure. To overcome this problem, a range of nondestructive testing (NDT) methods and mathematical analysis have been developed to estimate the strength of concrete, without damaging the host structure.

Ultrasonic-based methods are generally used NDT methods for the monitoring of concrete. The properties of ultrasonic vibration or wave propagation, such as velocity or attenuation, are affected by the change of physical properties. Thus, the strength development can be monitored, by tracking the change of ultrasonic signals (Gu et al. 2006; Jonsson and Olek 2004; Oh et al. 2016; Shin et al. 2008; Kim et al. 2013, 2015; Tawie et al. 2010). Furthermore, a range of methods based on the acoustical, electrical, magnetic, optical, radiographic, and other mechanical properties of concrete have been studied (ACI Committee 228 2003; Lamond and Pielet 2006).

Mathematical prediction of the concrete strength is being marked as an active area of research. Many studies are being carried out in this area (Zain et al. 2010). Different approaches using regression functions have been proposed for predicting the concrete strength (Snell et al. 1989; Oluokun et al. 1990; Popovics 1998). Traditional modeling approaches are established based on empirical relation and experimental data, which are improving day by day. Some smart modeling system, utilizing artificial neural network (Kasperkiewicz et al. 1995; Vahid and Mohammad 2010) and support vector mechanics (Gupta 2007), have been developed for predicting the compressive strength of concrete.

This study proposes a novel model to estimate the strength development of concrete, by incorporating the NDT technique with mathematical analysis. To estimate strength of concrete, an artificial neural network model was trained by using electromechanical impedance, water-cement ratio, and curing conditions. The proposed ANN model was verified by comparing with conventional strength estimation models, through experimental study.
2. Theoretical backgrounds

2.1 Factors to have influence on the strength development

(1) Water-cement ratio
Strength of concrete depends primarily on the strength of cement paste. Strength of cement paste depends on the dilution of paste; in other words, the strength of paste increases with cements content and decreases with air and water content. The relationship between water-cement ratio and strength is popularly known as Abrams’ water-cement ratio rule, which was presented in 1918.

\[ f_c = \frac{w}{k_2} \]

where \( w/c \) represents the water-cement ratio of concrete mixture, and \( k_1, k_2 \) are empirical constants.

(2) Curing conditions
Curing of concrete is a technical process involving a combination of conditions that promote the cement hydration, such as time, temperature, and humidity immediately after the placement of a concrete mixture into formwork. Among many conditions, the curing time and temperature dominantly affect the strength.

At a given water-cement ratio, if longer moist curing period is applied, higher strength is obtained. The evaluation of compressive strength with time is very important to structural engineers. ACI Committee 209 (2008) recommends the following relationship for moist-cured concrete made with normal Portland cement.

\[ f_{cm}(t) = f_{28c} \left( \frac{t}{4 + 0.85t} \right) \]

where \( f_{cm}(t) \) is mean compressive strength at age \( t \) days, and \( f_{28c} \) is 28-day compressive strength.

Also, CEB-FIP Models Code suggested the time-strength relationship using the following equation.

\[ f_{cm}(t) = \exp \left[ s \left( 1 - \frac{28}{\sqrt{t/t_f}} \right) \right] f_{cm} \]

where \( f_{cm}(t) \) is mean compressive strength at age \( t \) days; \( f_{cm} \) is 28-day compressive strength; \( t_f \) is mean early strength cements, 0.25 for normal hardening cement, and 0.38 for slow hardening cements (Mehta and Monteiro 2006).

Concrete cured in high temperatures gains strength faster than the concrete cured in low temperatures. When concrete is casted and cured at a specific constant temperature, within the range of 5 to 46°C, it is generally observed that for up to 28 days, the cement hydration and the strength gain occurs more rapidly with the higher the temperature (Ksenija et al. 2011).

2.2 Conventional Strength Estimation model

(1) Time-strength estimation model
Two types of time-strength relationships, ACI 209 model and CEB-FIB model as shown in equation (4) and (5), were utilized for strength estimation. It is hard to apply these models to in-situ concrete, because they were actually designed for moist-cure at 20°C. To use these models for concrete in different conditions, the coefficients should be experimentally re-calculated. The general form of ACI model and CEB-FIB model are expressed as the following equations.

\[ f_c(t) = f_{28c} \left( \frac{t}{a + bt} \right) \]

\[ f_c(t) = \exp \left[ a \left( 1 - \frac{28}{\sqrt{t}} \right) \right] f_{28c} \]

where \( f_c(t) \) is compressive strength at age \( t \) days; \( f_{28c} \) is 28-day compressive strength; and \( a, b \) are constants.

(2) Maturity model
The maturity method can estimate concrete strength based on the time-temperature history of the concrete. Strength increases as cement hydrates. The amount of cement hydrated depends on the duration and temperature the concrete has been cured at. Maturity is a measure of how far the hydration has progressed (Mcintosh 1949; Nurse 1949; Saul 1951).

The commonly known Nurse-Saul maturity function is defined in ASTM C 1074 and was used to calculate the maturity of concrete.

\[ M = \sum_{0}^{t} (T_c - T_o) \cdot \Delta t \]

where \( M \) is a maturity index at age \( t \); \( T_c \) is the average concrete temperature during the time interval \( \Delta t \); and \( T_o \) is datum temperature.

Among many functions proposed by different researchers to model strength-maturity relationship, the hyperbolic function was used in this study. (Carino 1981)

\[ f_c = f_{28c} \frac{k(M - M_o)}{1 + k(M - M_o)} \]

where \( M_o \) is maturity index when strength development is assumed to begin, and \( k \) is the rate constant.

(3) Limitation of conventional strength estimation model
The conventional non-destructive concrete strength estimation was not being actively used in construction site due to its low accuracy caused by the assumption in estimation model. The time-strength models, ACI and CEB-FIB model, were assumed the strength of concrete was dominantly affected by the time of curing and the
curing temperature was 20°C. The maturity model was assumed the strength development is only affected by the hydration reaction of cement. Also due to the equation, these models cannot estimate the strength over the designed strength (28-day compressive strength). Thus it is need to novel NDT technique for strength estimation to measure the strength development in construction site using sensors and estimation algorithm.

3. Concrete strength estimation using embedded sensor and ANN

3.1 Embedded Piezoelectric Sensor

Piezoelectric sensors can interconvert mechanical energy and electrical energy. Due to this piezoelectric effect, piezoelectric sensor can be used simultaneously as both actuator and sensor. This study employs lead zirconate titanate (PZT) to generates vibration and waves to the concrete structure, and measure the dynamic responses of the concrete (Park et al. 2008; Bhalla and Soh 2004). Table 1 shows the size and major properties of the PZT used in this study.

To obtain dynamic responses from the inside of concrete structures, the sensors should be embedded within the concrete. However, the PZT can be easily broken by stresses, such as the thermal stress and shrinkage stress of concrete. To protect the PZT in the concrete, an embedded piezoelectric sensor has been developed (Song et al. 2008). The novel embedded piezoelectric sensor is fabricated to improve the signal quality, using a hemispherical hollow Styrofoam case, as Fig. 1(a) shows. The embedded piezoelectric sensor allows one side of the PZT to maintain free boundary condition, even though the sensor is embedded within the concrete media. Thus, the embedded piezoelectric sensor can measure the electromechanical impedance as if it were attached to the concrete surface. The electromechanical impedance is measured using a single sensor with a self-sensing technique, and the harmonic wave propagation is measured using two sensors; one is used to generate the harmonic waves, and the other senses the propagated waves. The embedded piezoelectric sensor module consists of two embedded piezoelectric sensors to simultaneously measure the impedance and harmonic wave propagation. Fig. 1(b) shows the size of the sensors.

3.2 Electro-mechanical impedance

The electro-mechanical impedance (EMI) method was used for structural health monitoring, damage detection and NDE (Giurgiuţiu and Rogers 1997; Kim et al. 2012; Lee et al. 2015; Park et al. 2011). The mechanical impedance of concrete can be expressed as the following equation.

\[ Z_{\text{conc}} = i\omega m_{\text{conc}}(\omega) + c_{\text{conc}}(\omega) - i\kappa_{31}(\omega) \frac{k_{\omega}(\omega)}{k_{\text{PZT}} + k_{\omega}(\omega)} \]  

(8)

If the piezoelectric transducer (PZT) is closely attached to the host structure and an alternating electric voltage is applied to the PZT, the elastic waves generated by the PZT are transmitted to the host structure. The responses on the waves represent the mechanical impedance of the host structure. Through the mechanical coupling between the PZT and the host structure, and through the electro-mechanical transduction inside the PZT, the structural impedance directly reflects the effective electrical impedance. The EMI of the PZT, as coupled with the host structure, is given by

\[ Z(\omega) = \frac{1}{i\omega C} \left( 1 - \kappa_{31} \frac{k_{\omega}(\omega)}{k_{\text{PZT}} + k_{\omega}(\omega)} \right)^{-1} \]  

(9)

where, \( Z(\omega) \) is the electro-mechanical impedance; \( C \) is the zero-load capacitance of the PZT; \( \kappa_{31} \) is the electro-mechanical cross coupling coefficient of the PZT; \( k_{\omega}(\omega) \) is the dynamic stiffness of the structure; and \( k_{\text{PZT}} \) is the stiffness of the PZT.

During the strength development of concrete, the dynamic stiffness and resonant frequency are changed according its strength. Therefore, the EMI is changed according to the strength of host concrete structures.

Table 1 Properties of PZT material.

| APC 850 WFB Series |   |   |
|---------------------|---|---|
| Size (mm)           |   |   |
| Diameter            | 30.00 |   |
| Thickness           | 0.508 |   |
| Electromechanical Coupling Factor | \( \kappa_{33} \) | 0.72 |
|                     | \( \kappa_{31} \) | 0.36 |
| Piezoelectric Charge Constant (10^-12 m/V) | \( d_{33} \) | 400 |
|                     | \( d_{31} \) | -175 |

(a) Schematic of the embedded piezoelectric sensor.

(b) The size of the embedded piezoelectric sensor.

Fig. 1 Embedded piezoelectric sensor.
The cross correlation coefficient (CC) was utilized to quantify EMI variation due to the strength change. 1-CC can be calculated using the following equation.

\[
1 - CC = 1 - \frac{1}{N-1} \sum_{i=1}^{N-1} \frac{(\text{Re}(Z_i) - \text{Re}(\bar{Z}_i))(\text{Re}(Z_j) - \text{Re}(\bar{Z}_j))}{\sigma_{Z_i} \sigma_{Z_j}}
\]

where \( \text{Re}(Z) \) is the real part of impedance function when strength development is assumed to begin; \( \text{Re}(Z) \) is the real part of impedance measured at curing time \( t \); \( \bar{Z} \) are the mean values of each data; \( N \) is the total number of dataset; and \( \sigma_{Z_i}, \sigma_{Z_j} \) are the standard deviations of each dataset.

3.3 Artificial neural network based concrete strength estimation model

The strength of concrete is affected by numerous factors such as waver-cement ratio, aggregate size and mineralogy, admixture types, specimen geometry, curing condition, and mechanical conditions. The factors of water-cement ratio and curing time and temperature, and the electro-mechanical impedance of concrete were selected to model the strength development phenomena, since they dominantly contribute to the strength of concrete and can be controlled and/or measured by design engineer. The aforementioned conventional models considered only the curing time and temperature, hence the coefficients should be re-calculated for each concrete. In order to overcome this limitation, a complex model that can include all factors, is proposed by applying artificial neural network (ANN). Concrete is a complex material that consists of cement, water, and aggregates. Because of this heterogeneity, the strength model cannot be clearly derived algebraically by mapping the factors and the actual strength. The ANN algorithm, which is a pattern recognition method, was utilized to overcome the complex properties of concrete (Worden and Tomlinson 1992; Lippmann 1987; Lopes et al. 2000).

To achieve ANN model for concrete strength estimation, the network was trained using the set of inputs that represents the condition of the concrete, and the target was compressive strength. The inputs consist of water-cement ratio, curing time, curing temperature, maturity, and 1-CC of impedance signal. The input factors were selected according to following terms; 1. The factors should be measurable data or controllable value. 2. The factors should be affected by the strength development. In detail, the W/C ration is one of dominant factor that determine the strength of concrete. The curing time and temperature are major parameter to estimate the strength of concrete. The maturity can represent the change of internal temperature change. Also the 1-CC of impedance is changed according to the strength development of concrete. The target data was experimentally acquired by using destructive test. The ANN model could be a solution for concrete with different conditions after training for using several experimental tests.

| Specimen No. | 1  | 2  | 3  |
|--------------|----|----|----|
| W/C (%)      | 40 | 34 | 34 |
| C            | 324| 228| 137|
| FA           | 81 | 0  | 0  |
| SP           | 0  | 228| 296|
| SF           | 0  | 0  | 23 |
| S            | 722| 717| 723|
| G            | 965| 723| 966|
| AD (%)       | 0  | 0.9| 0.007|
| AE (%)       | 0  | 0.8| 0.005|
| Curing Temp. (℃) | 5  | 20 | 40 |

Table 2 Mix proportions and curing temperatures of test specimens.

4. Experimental verification of the proposed strength estimation model

4.1 Experimental setup

An experimental study was performed to verify the strength estimation models. Three concrete specimens designed to get 55.16 MPa were casted using different mix proportions. The specimens were placed in the temperature-controlled chamber, and the curing temperature was controlled as 5, 20, and 40℃ for each specimen. Table 2 shows the mix proportions and curing conditions of specimens.

Table 2 shows the mix proportions and curing conditions of specimens.

The size of specimens were 1200×2000×1000 mm³, and the sensors for measuring the internal temperature and EMI signal were embedded in the specimen as shown in Fig. 2.
4.2 Test results

Table 3 shows the result of core test on the test specimens. The strength of specimens were rapidly increased during 1~7 days; and after then, they gradually converged toward maximum strength of each specimen. The designed strength of the three specimens was 55.16 MPa, but the 28-day strength was different due to the mix proportion and curing condition.

Figure 3 shows variation in the internal temperature of specimens during 28 days. The internal temperature is rapidly increased during 1~3 days, and it is decreased to the external curing temperature. The internal temperature change was caused by the hydration reaction, which is an exothermic reaction. The internal temperature variation was well-matched with the strength change of each specimen.

Figure 4 shows the result of impedance measurement during 28 days. The impedance signal also dramatically changed during 1~3 days. After then, during 14~28 days, the signal variation range decreased until it reached to almost zero. There were some differences between the specimens, which were caused by the different mixing and curing conditions, yet the variation patterns were almost the same. Also, the impedance variation pattern was well-matched with strength and temperature variation.

4.3 Verification of the proposed ANN model

To estimate the strength of test specimens, the constants of ACI, CEB-FIP, and maturity models were derived by regression using reference strength data which was measured by destructive test at 1, 3, 5, 7, 14, and 21 days. The constants of ACI model were \(a = 2.723\) and \(b = 0.8451\). The \(a\) was small, and the \(b\) was almost the same as the coefficient for moist-cured concrete made with normal Portland cement. The constant \(a\) of CEB-FIP model was 0.2876, which is slightly larger than the constant for normal hardening cement. The constant \(k\) of maturity model was 0.0000187 for specimen No. 1, 0.0000297 for specimen No.2, and 0.0000466 for specimen No.3. The ANN model was trained using tan-sigmoid transfer function in hidden layer and linear transfer function in output layer as shown in Fig. 5. The learning rule was Levenberg-Marquardt backpropagation and the number of hidden layer was 10 layers. The 15 set of input data consisted
of design strength, water-cement ratio, curing time and temperature, maturity, and 1-CC of impedance from three specimens as shown in Table 4.

Figure 6 shows the result of strength estimation using 4 types of strength estimation models. ACI model and CEB-FIB model approximately illustrate the trend of strength development without accurate strength estimation. These models could not reflect the curing condition or w/c ratio, because the models were derived by only using the relationship between time and strength. The maturity model could estimate the strength of specimens with a slight difference. However, the constant of maturity model should be calculated separately for each specimen, because maturity is different for every concrete. Thus, the maturity model is difficult to be a general solution for concrete strength estimation.

The strength estimation result using ANN model is illustrated with bold line in Fig. 6. The trained ANN model could estimate the strength of all specimens with

| W/C ratio | Curing time (Day) | Curing Temp. (℃) | Maturity | 1-CC | Measured strength (MPa) |
|-----------|------------------|------------------|----------|------|-------------------------|
| 40        | 1.0              | 5                | 4128.67  | 0.2077 | 12.54                   |
| 40        | 3.0              | 5                | 83619.12 | 0.2265 | 31.29                   |
| 40        | 7.1              | 5                | 403073.6 | 0.2259 | 43.71                   |
| 40        | 16.4             | 5                | 629821.9 | 0.2239 | 46.93                   |
| 40        | 27.2             | 5                | 832133.2 | 0.2232 | 47.35                   |
| 34        | 1.0              | 20               | 3435.41  | 0.2528 | 12.15                   |
| 34        | 3.0              | 20               | 64058.94 | 0.2869 | 31.05                   |
| 34        | 7.1              | 20               | 384974.1 | 0.2836 | 47.17                   |
| 34        | 16.4             | 20               | 665536.8 | 0.2836 | 57.52                   |
| 34        | 27.2             | 20               | 938418.4 | 0.2791 | 65.43                   |
| 34        | 1.0              | 40               | 2899.02  | 0.1490 | 14.11                   |
| 34        | 3.0              | 40               | 67643.05 | 0.2208 | 35.82                   |
| 34        | 7.1              | 40               | 449757.1 | 0.2213 | 52.27                   |
| 34        | 16.4             | 40               | 808950.6 | 0.2242 | 57.49                   |
| 34        | 27.2             | 40               | 1161456  | 0.2292 | 57.91                   |

Fig. 5 Artificial neural network model.

Fig. 6 Estimation results using strength estimation models.
To quantify the performance of each estimation model, the error was calculated as shown in Table 5. In specimen No. 1 and 2, the ANN model had shown smallest mean error while the maturity model had smallest error in specimen No. 3. Nevertheless, in all result, the ANN model is the most powerful in estimating the strength of concrete with different mix proportions and curing conditions, since it contains all of the major factors affecting the strength of concrete. Also the trained ANN could estimate the strength of concrete with different mix proportion so it can be applied to the other concrete specimen through inputting the W/C ratio and other input data. Thus, the proposed ANN model could be one of solutions for estimating the strength of concrete.

### 5. Conclusion

This study investigated the application of an ANN based concrete strength estimation method using several kinds of strength related factors. The strength related factors consist of conventional strength factors, such as water-cement ratio, curing time, curing temperature, and maturity, and EMI. The EMI changes according to the variation in mechanical properties of concrete during curing process thus it is possible to estimate the strength development by tracking the EMI variation during curing process. To quantify the EMI variations, the 1-CC value of EMI signals was used. The proposed ANN model was verified by being compared with conventional strength estimation models, such as ACI model, CEB-FIB model, and maturity model by performing experimental study. Three specimens were casted and cured at different temperatures, respectively. The EMI signal was measured using embedded piezoelectric sensor at every hour during the first 7 days, and they were measured at every 6 hours until 28 days. The reference compressive strengths were measured by compression test using cylinder at Day 1 and by core test at 3, 7, 14, and 28 days. The ANN model was trained using 5 strength factors and compared with the conventional strength estimation models. The ANN model can estimate the strength of concrete specimen with different mix proportion with negligible error. The results conclusively confirmed that the proposed approach could be very effectively used to estimate the strength development of concrete structures.

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