1-15-2016

Advancing Concrete Strength Prediction using Non-destructive Testing: Development and Verification of a Generalizable Model

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Original Citation

Amini, K., Jalalpour, M., and Delatte, N. (2016). "Advancing concrete strength prediction using non-destructive testing: Development and verification of a generalizable model." Constr.Build.Mater., 102, Part 1 762-768.

Advancing concrete strength prediction using non-destructive testing: Development and verification of a generalizable model

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1. Introduction

Estimating the in-situ compressive strength is imperative for evaluating the quality of existing concrete structures during their service lives. In many cases, however, the actual condition of the materials used in construction is highly variable, and no information exists regarding the specifications of the concrete. This information includes age, concrete ingredients, construction quality, curing method, and concrete mechanical properties. Non-destructive tests (NDTs) can be used in such situations to estimate the in-situ physical properties of concrete to circumvent the need for in-situ sampling and compressive testing of concrete cores [1]. Due to the increase in the need for assessment of damaged concrete structures, NDT has gained popularity in recent years, and many NDT methods are available such as cast in-place cylinder test, ultrasonic pulse velocity (UPV), rebound hammer (RH), and resonant frequency test [2]. The procedures for performing these NDTs are outlined in ACI 228.1R-13 [3]. This paper focuses on RH and UPV.

Rebound hammer testing is a simple NDT method that provides an approximate indication of concrete quality and is deemed as a supplementary and in-place technique for estimating compressive strength of cast-in-place concrete [4]. Test results are measured as rebound number (RN). Many researchers attempted to establish a relationship between RN and compressive strength [5–8]. Szilágyi et al. [5] added to the fundamental understanding of the rebound surface hardness of concrete by introducing a phenomenological constitutive model that can be formulated for the surface hardness of concrete as a time dependent material property. Their results indicated that RN is significantly affected by the near surface properties of the hardened concrete such as smoothness, carbonation, size and type of the aggregates, and age of the concrete. Similar results are reported by ACI committee 228 [6]. Hence, RH is considered as a non-electronic, supplementary, in-place technique to predict the compressive strength of hardened concrete [4,8]. Qasrawi [7] also reported the unsuitability of the individual use of rebound hammer to estimate concrete strength.

Ultrasonic pulse velocity (UPV) method measures elastic properties of concrete and has been used to estimate the quality of in-situ concrete including the dynamic modulus of elasticity and therefore, compressive strength [9–11]. Yildirim et al. [12] investigated the effects of water to cement ratio, maximum aggregate size, aggregate type, and fly ash addition on the dynamic modulus of elasticity of low quality concrete using UPV. Based on their results, a strong relationship was achieved between the modulus of elasticity and ultrasound pulse velocity. However, the UPV test has been generally used to detect discontinuities in hardened concrete and is more sensitive to internal properties including density of concrete [4]. The empirical issues of using this method such as materials constitutions and calibration are explained in [13,14].

A combination of NDTs therefore, may be advantageous for predicting concrete strength, because the results obtained from a single test, as discussed above, might be inconclusive [15]. However, early investigations on this combined usage yielded mixed results. For instance, Breysse [16] concluded that the effectiveness of combining the evaluation of two or more NDTs has been controversial. Moreover, Carvalho et al. [17] applied statistical techniques to evaluate the reliability of UPV and RH to evaluate the compressive strength of the concrete in bridges. Their results revealed lack of consistency in the correlation of UPV and RH on four tested bridges. ACI 228.1R-03 [6] also reported that a combination of NDTs only provides marginal improvements over a single method. Nevertheless, recently, there is a growing literature on documenting the advantages of application of multiple NDTs to increase reliability and accuracy of predictions [7,18–21]. Ravindrajah et al. [22] reported promising results on compressive strength estimation of recycled-aggregate concrete using combined UPV and RH. Kheder [23] investigated concrete strength prediction using UPV and RH in conjunction with concrete mix proportions and density. They compared their results with cores taken from actual structures, and observed good predictive accuracy. The advantage of using a combination of RH and UPV, for example, can be described by the fact that the results of each test is influenced by different properties of the hardened concrete [7,21,24,25]. A number of regression models using a combination of UPV and RH to predict compressive strength have been developed recently [26–29]. The seminal work by Huang et al. [19] developed a multivariate regression model to predict compressive strength using the combined UPV/RH for a comprehensive data on the mixture proportions, curing conditions, and age of the concrete. They showed that their proposed model yields more accurate predictions in comparison with other regression models.

The real conditions of the structures may be highly variable spatially due to the variability of materials received, their properties and sporadic supervision [1,7]. Therefore, realistically, information about concrete mixture proportions and construction might not be available for in-situ predictions. However, a look at the above body of work reveals most of the developed models use this information. In the present article, accurate predictive models for compressive strength of concrete specimens are derived using only NDT results. Through rigorous statistical tests with threefold cross-validation, both UPV and RN were determined statistically significant variables for predictive modeling. Therefore, a multivariate regression model based on a combination of these NDT results was proposed and verified for accuracy through prediction of independent data. Finally, concrete quality classification using RN and UPV is proposed based on unsupervised machine learning k-means clustering method.

2. Experimental procedures and independent data collection

A total of 84 concrete cylinders with unknown information about their age, mixing ratios, and without any prior knowledge of their expected compressive strength were first tested in a laboratory using the following NDTs.

The rebound hammer (RH) test was conducted in accordance with ASTM C805 [31]. The test began by a careful selection and preparation of the sample surface for testing. Once the plunger of the RH is pressed to the concrete surface, a spring-pulled mass rebounds back with a rebound distance. The extent of the rebound is a measure of the surface hardness. This measured value is designated as the rebound number (RN), which is on a graduated scale. At least 10 readings for each sample were performed and their average was used to determine the RN for each sample. A concrete with high strength and high stiffness absorbs less energy, leading to a higher rebound value and a higher RN [6].

The ultrasonic pulse velocity (UPV) test was conducted according to ASTM C597 [30]. The UPV test can be conducted by three different methods; direct, semi-direct, and indirect method, out of which the direct method is the most accurate method [3] and was used in this work. However, in the field, using a direct method is impractical, and the indirect method is used instead. This test determines the required time for a vibration pulse of an ultrasonic frequency to travel through a concrete specimen with known dimensions. The pulse velocity is, therefore, determined and reported. Based on the obtained velocity, the uniformity, quality, and strength of tested specimens can be estimated. The changes in the wave speed indicate the variability of the dynamic modulus of elasticity and the density of the material [3]. RH and UPV tests were repeated three times on each specimen and the average values were reported. All the cylinders were secured from movement and all the tests were conducted on the center of the surface of the cylinders.

After all the NDTs were conducted, the compressive strengths of all the specimens were destructively determined according to ASTM C39 [32]. For this test, the cylinders were placed in a compression machine and were loaded until failure and the maximum compressive strength was recorded for each concrete cylinder. The combination of UPV, RH, and compressive test results forms the "in-house" data for this study.

An additional 88 data points were also collected from six different research papers [26,33–37]. These data are termed the "independent" data, and will be used for testing the proposed models.

3. Data modeling and classification approach

For all of the analyses in this paper, the UPV reading was scaled by dividing by 10^3. We begin with single variable linear regression analysis to establish the relation between compressive strength with RN and UPV separately. A regression model is expressed as follows:

$$\boldsymbol{y} = \mathbf{X}\boldsymbol{\beta} + \epsilon \tag{1}$$

where $\boldsymbol{y}$ is the vector of responses, $\mathbf{X}$ is the matrix that collects all the exogenous variables, which are hypothesized to predict or influence the response, $\boldsymbol{\beta}$ is the vector of model parameters that will be estimated based on the available data, and $\boldsymbol{\varepsilon}$ is the vector of noise or random fluctuations. In this study, the response data are concrete compressive strengths, and exogenous variables include RN, UPV and possibly their exponents with an intercept (constant) term. Important assumptions in regression models are as follows. It is assumed that responses are independent, and the random noise vector is zero-mean, uncorrelated and follows normal distribution. This last assumption also means that the residuals from any fitted model (difference between predictions and actual observations) should not show an identifiable structure [38,39]. Therefore, before making inferences using regression models, one should perform residual analysis. If these assumptions are met, then the model predicts the expected value or average of the response given the observed exogenous data. The most widely used models for compressive strength are: (1) second order polynomial, (2) power, and (3) exponential [16,26,40,41]. These models, for the case of *RN*, are expressed respectively as follows.

$$E[f'_c|\mathrm{RN}] = \beta_0 + \beta_1 RN + \beta_2 RN^2 \tag{2}$$

$$E[f'_c|\mathrm{RN}] = \beta_0 RN^{\beta_1} \tag{3}$$

$$E[f'_c|\mathrm{RN}] = \beta_0 e^{\beta_1 RN} \tag{4}$$

In the above equations, f'_c is the compressive strength, $E[.]$ is the expected value operator, *RN* is the reported rebound number, and the coefficients (β) are estimated from the data using, for example, maximum likelihood method. Equations for the case of UPV are similar. These models were fitted to the data obtained in this study, and then residuals were evaluated and analyzed.

Multivariate regression models were also developed. Prior to this analysis, a power transformation analysis was also conducted and it was determined that there is no need to transform the compressive strength values. With the goal of deriving models generalizable to prediction of new data, a threefold cross-validation data partitioning scheme was pursued. First, the in-house data was randomly partitioned into three groups (each with 28 data points), and then two of these groups were used as "training sets" for fitting a regression model. The remainder of the dataset ("test set" or "cross-validation set") was then predicted using this developed model. This procedure was repeated three times, until each group was used exactly once in the test set. This phase of research was also used to assess the predictive contribution of the following exogenous variables RN, UPV, RN^2, UPV^2, $RN \times UPV$ using forward substitution and backward elimination [42]. This procedure began with choosing a statistical significance level of $\alpha = 0.05$. For this discussion, a full model is defined as the model with at least one more exogenous variable in comparison to the nested model, which is the same model with one variable removed. A full model is fitted first. The residual sum of squares for this model is then computed using the following equation:

$$\mathrm{Rss}_1 = \sum_{i=0}^{n} (\hat{y}_i - y_i)^2 \tag{5}$$

where $\hat{y}_i$ is the model prediction, y_i is the actual data point, and $n = 28$ is the number of test data. Next, a variable is removed creating a nested model with p_2 variables and the Rss_2 is evaluated for this model. The null hypothesis is that the full model does not provide a significantly better prediction. Therefore, the test statistics under this null hypothesis follows F distribution with $n - p_2$ degrees-of-freedom and is expressed as [38]:

$$F = \frac{\mathrm{Rss}_1 - \mathrm{Rss}_2}{\frac{\mathrm{Rss}_2}{n-p_2}} \tag{6}$$

If the above test statistic was greater than the critical value for F distribution--at the chosen significance level--the variable under study is retained in the model. Otherwise, the variable is removed. This procedure was performed for all the variables individually. For the forward substitution phase, the analysis began with a null model consisting only of the average of responses (intercept term, which is a vector of ones) and new variables are then added to the model sequentially. If prediction improvement was statistically significant, the new variable was added to the model. This process continued until all the variables were assessed.

One can imagine that including higher order polynomial terms in proposed models may improve prediction accuracy. For example, a third-order model including linear, quadratic and cubic terms for RN may outperform a quadratic model. Therefore, using the partitioned in-house data, the optimal model order was established with the following procedure as well. The training error is determined as:

$$J_{\mathrm{tr}} = \frac{\sum_{i=0}^{n_{\mathrm{tr}}} (\hat{y}_i - y_i)^2}{n_{\mathrm{tr}}} \tag{7}$$

where n_{tr} is the number of samples in the training set (i.e. 54 samples). The cross-validation error is also defined similarly. These errors were then evaluated and averages as a function of model order were plotted. Models up to order four were investigated (four sets of errors). It is noted, as expected, that the average training error decreases with increasing the model order. However, the average cross-validation error appears as a polynomial function with a local minimum which indicates the optimal model order. This is because the purpose of this phase was to avoid "overfitting" models to the in-house data. This bias-variance tradeoff is common in statistical predictive modeling [39].

Finally, to classify the comprehensive data obtained in this study, a variant of k-means clustering method was applied using combined NDT results. Number of clusters were chosen iteratively through an optimization procedure outlined in [43]. The algorithm (kMeans++) iteratively minimizes the sum of distances from each observation to its cluster centroid over all clusters to partition the data into mutually exclusive clusters [44].

4. Results and discussion

4.1. Univariate models using individual NDT results

Regression lines using univariate models to predict the in-house compressive strength data with UPV and RN are shown in Fig. 1. It appears that power and exponential models overestimate compressive strength when RN and UPV values are greater than 35 and 3800 m/s, respectively. The situation is more pronounced for the case of RN. On the other hand, the second-order polynomial model may predict negative values for compressive strength when the RN is less than 10 and/or UPV is less than 3000 m/s. These negative predictions of compressive strength can be attributed to the scarcity of the available data in this range or to the fact that lower strengths of concrete increases the prediction intervals of the true compressive strength [7].

Fig. 2 illustrates the residuals of these models versus the predicted compressive strength of the cylindrical specimens. It can be seen that the residual plots of exponential and power models show systematic trends indicating that these models are not adequate to predict the compressive strength of the concrete specimens. Moreover, it can be seen that for both UPV and RN the residual requirements are only met by second order polynomial model. Therefore, it appears that only polynomial models may be adequate for statistical inference and predictions. These two models were next used for independent data prediction.

4.2. Independent data prediction using univariate polynomial models

Following the goal of this study (prediction of independent data), polynomial models from the previous section were used to predict the independent data collected from different research papers [26,33–37]. The predictions along with residual plots are shown in Fig. 3. While the model with UPV seems to predict the

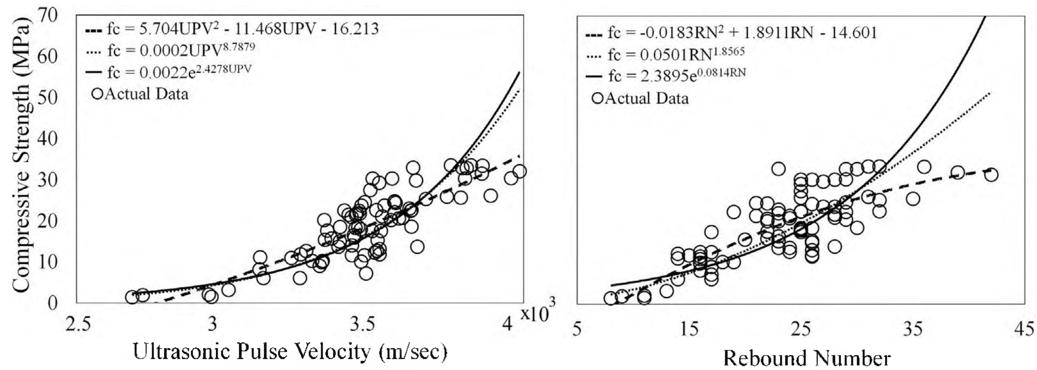

Fig. 1. Accuracy assessment of the developed univariate models based on: exponential, power, and second order polynomial laws.

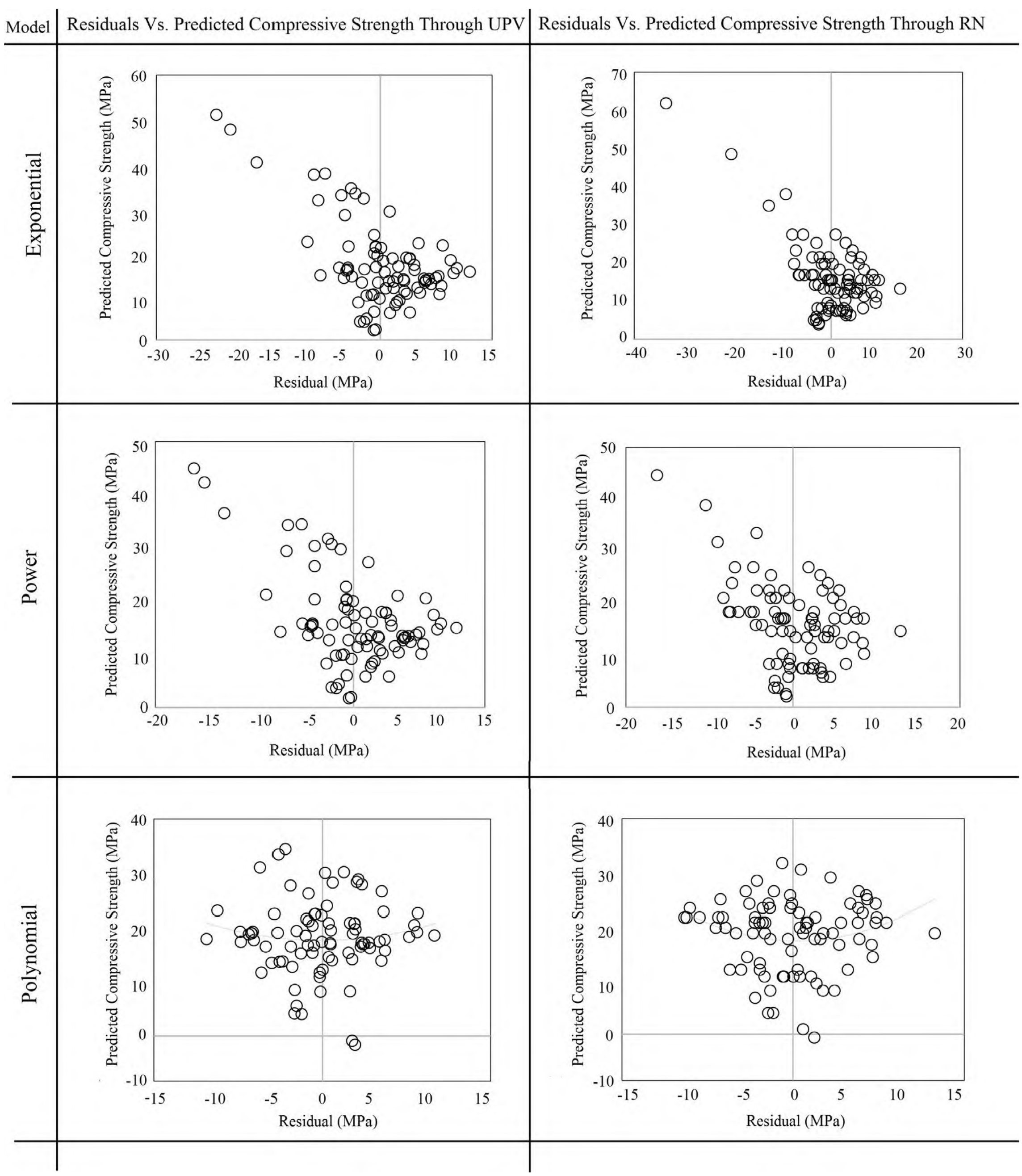

Fig. 2. Predicted compressive strength versus residuals for different models based on UPV and RN results of the in-house data.

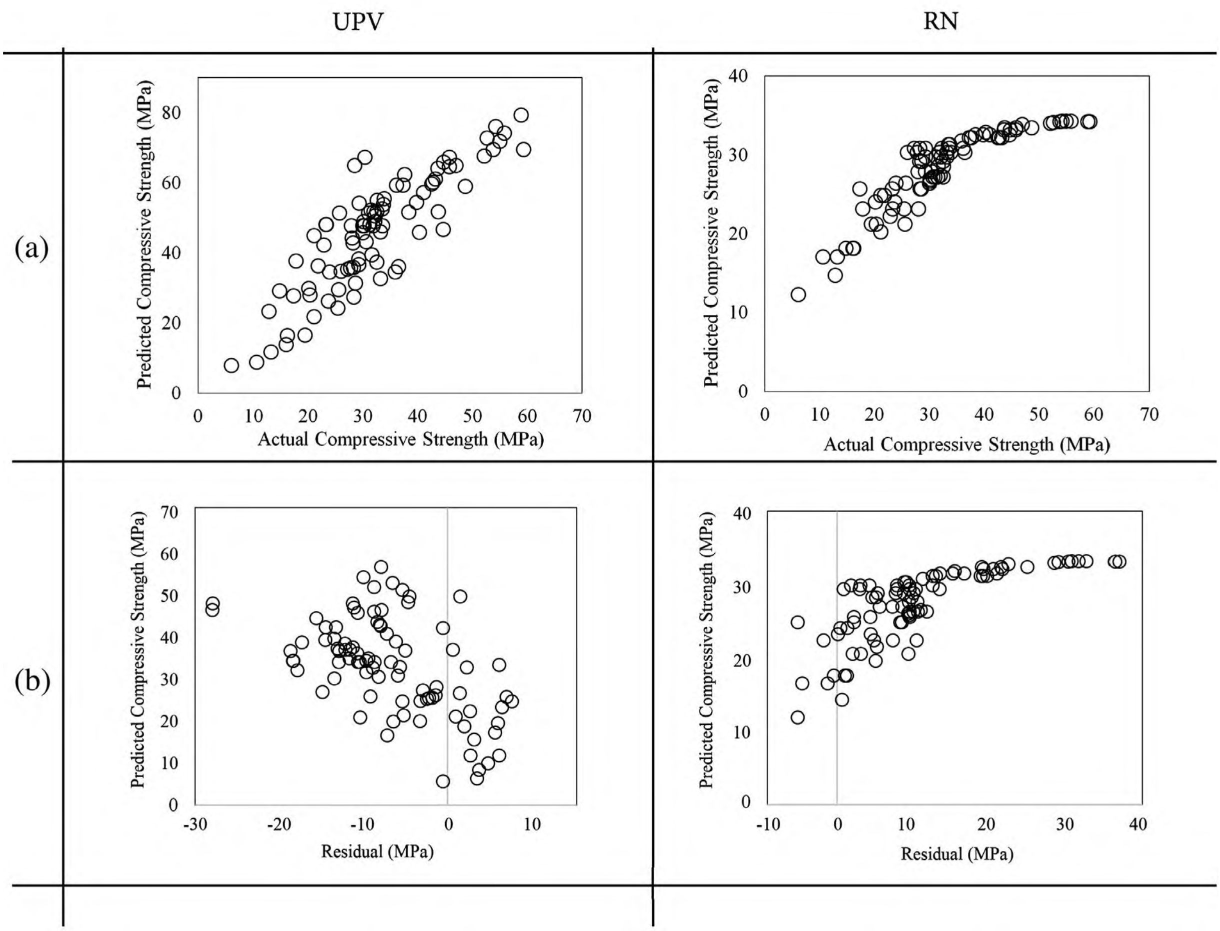

Fig. 3. Application of second order polynomial model based on UPV and RN on the independent data: (a) predictions versus actual data and (b) predictions versus residuals.

data with acceptable accuracy, the residuals appear to have a structure, which implies that the model may have a systematic bias when applied on independent data. Moreover, it can be seen on the right panel of Fig. 3(a) that the model based on RN significantly underestimates the actual independent data, specifically at higher values. For instance, an actual compressive strength of 50 MPa is predicted at 32 MPa.

Therefore, using a single NDT result seems inadequate to predict the independent data. This result is in agreement with results of other research in this field, where it is argued that the individual NDT may not yield reliable models [7,21,45].

4.3. Predictive models using combined NDT results

For these analyses, the in-house data was partitioned into three sets, and then optimal order selection began. The model order was systematically increased from linear to cubic term for both UPV and RN variables, and training and cross-validation errors were determined. The results indicated that the optimal model order was quadratic polynomial as the average test error was minimized at this model order.

Next, testing statistical significance for these variables was performed. For brevity, results for forward selection are only presented here. The null model was chosen to be the intercept only, and each variable contribution was assessed in isolation. The results show that both RN and UPV produce a significantly better prediction as can be seen with the p-value matrix shown in Table 1. The interaction variable ($UPV * RN$) was not significant in any of the partitions. Therefore, based on the data obtained in this study, predicting the strength of concrete may be more accurate with results from a combination of RN and UPV. Moreover, backward elimination on this full model indicated that no variable could be removed. All these analyses were repeated with a fivefold cross-validation with no changes on the inferences.

Table 1
p-Value matrix.

Variable	Partition		
	1	2	3
RN	0.000	0.003	0.000
UPV	0.000	0.030	0.000
RN^2	0.000	0.001	0.000
UPV^2	0.000	0.019	0.000

Finally, each model (obtained by fitting to 2/3 of the data) was used to predict its corresponding test set of the data. The predictions are presented in Fig. 4, where the accuracy of models can be verified. The best model from these analyses is chosen as the average of the three, and is expressed as:

$$E[f'_c|RN, UPV] = 10^3(0.10983 + 0.00157\mathrm{RN} - 0.79315\mathrm{UPV} - 0.00002RN^2 + 1.29261UPV^2) \quad (8)$$

4.4. Independent data prediction using the proposed multivariate model

As mentioned before, the true power of NDTs may lie in their capabilities for independent data predictions. Therefore, the proposed model is used for prediction of the independent data

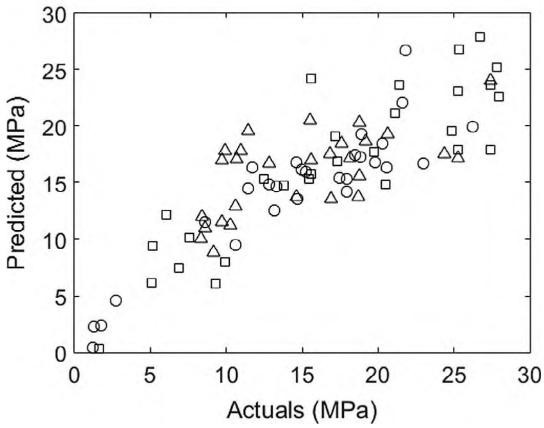

Fig. 4. Cross-validation prediction results for multivariate models using combined NDTs for the in-house compressive strength data.

acquired in this study. Fig. 5 shows the predicted values against the actual compressive strength data. The two diagonal dashed lines show the upper and lower 95% prediction interval depicting the range one expects actual responses to fall in. It can be observed that the majority of the points lie close to the predicted mean, the solid diagonal line, which verifies accuracy of the proposed model. The average of the ratio between measured and predicted values for compressive strength is 0.955. There are, however, a few outliers. As another method to verify model predictions, we can define model error as the absolute value of difference between actual data and predictions. Using this criterion, about 65% of the independent data are predicted with less than 10% error, 75% with less than 15% error, and 82% with an error of less than 20%. Overall, the proposed model appears to predict independent data with acceptable accuracy, and may be useful for prediction of a wide range of new data. Fig. 6 demonstrates the residual plot of the developed model using combined UPV and RN. It can be observed that residuals appear to be zero-mean without a structure. Therefore, the proposed model seems adequate for predictions and inferences.

4.5. Concrete quality classification based on clustering

Leslie and Cheesman [46] reported that the qualitative condition of the concrete can be classified as a function of UPV. Their results indicated that the variation of UPV as a function of concrete soundness might be used to classify the quality of concrete as either very good, good, fair, poor, and very poor. Because the results obtained in this study support combined usage of NDT results, a combined NDT-based concrete classification scheme using both the in-house and independent data was proposed. The authors chose to use all of the data to develop more comprehensive results. The optimal number of clusters were found to be four using a variant of k-means clustering. Table 2 shows the centroid of these four clusters in the three-dimensional space of *UPV*, *RN*, and f'_c. The data in each cluster are visually shown in Fig. 7, where each cluster is signified with a different symbol. The trend line between UPV and RN is also depicted in this figure. The trend line also confirms the direct relationship between these two tests. It can be seen in the figure that there are some intersections between the clusters indicating that specimens with same UPV/RN values may have different strength specifications. In other words, neither UPV nor RN by itself can provide accurate prediction of the compressive strength of concrete. Overall, the result of this concrete classification is expected to be useful for the field engineers and researchers for a rough estimation on concrete strength and quality.

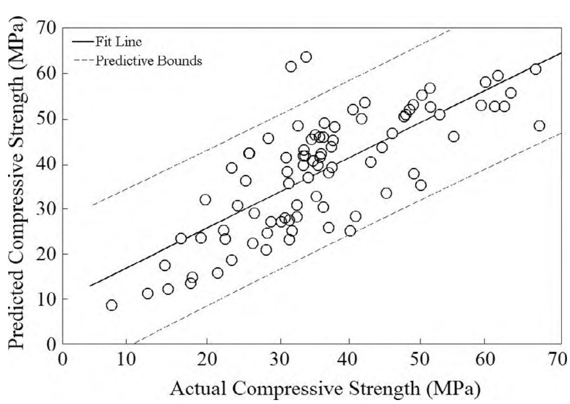

Fig. 5. Prediction of the independent data using the model proposed in Eq. (8).

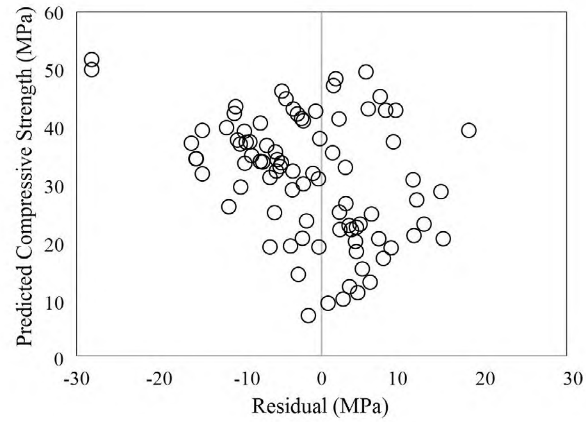

Fig. 6. Residuals plot of the model proposed in Eq. (8) applied to the independent data.

Table 2
Cluster centroids in space in all directions.

Cluster number	UPV (m/s)	RN	Compressive strength (MPa)	Concrete quality
I	5000	46	40	Very good
II	4500	35	30	Good
III	4000	27	20	Fair
IV	3500	19	10	Poor

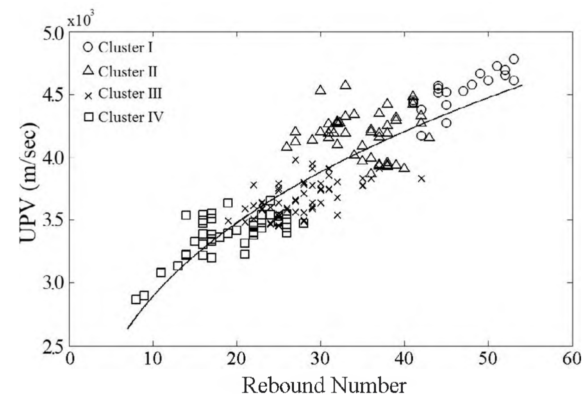

Fig. 7. Concrete quality classification results and relationship between UPV and RN.

5. Conclusions

This paper used solely results on UPV and RH for prediction and classification of concrete strength, without a need for information about the concrete history and mixture proportions. The intent was to align models for in-situ predictions of existing structures. A rigorous statistical analysis with threefold cross-validation and application to independent data showed that combined usage of UPV and RN appeared to outperform models based on a single test result. This may be because UPV and RN are sensitive to the different characteristic of concrete. Based on this observation, a model is put forward for predictions of concrete strength. The proposed model was tested on independent data, and showed a very good predictive accuracy. Moreover, a table was proposed for concrete quality classification based on combined UPV and RN results. This table may be useful for researchers and engineers in the field for a rough estimation of in-situ concrete strength.

Acknowledgment

The authors thank Mr. Andrew Lesak for assistance with conducting experiments.

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