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Comparison of NDT Data Fusion for Concrete Strength using Decision Tree and Artificial Neural Network

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Fusion of Non-Destructive Test (NDT) data results in more accurate estimation of concrete strength when compared to any single NDT data. Estimation of concrete strength from NDT results assumes importance for health assessment and evaluation of existing concrete buildings, particularly those near the end of their design life. Application of machine learning tools and response surface method has found popularity in recent years for this purpose. In this study, universally popular Artificial Neural Network (ANN) and relatively un-explored Decision Tree (DT) are applied to estimate concrete strength from rebound number and ultrasonic pulse velocity data collected from literature, in single and combined forms. A ranking system based on ratios of multiple performance measures was demonstrated for cases where different models are adjudged better considering different performance measures. From the results, it was concluded that fusion of NDT data resulted in better accuracy, for both ANN and DT. Comparing the selected performance measures as well as the ranks of the two machine learning tools, ANN models were found to perform better as compared to the DT models. The narrow range of multiple performance metrics obtained for three different data divisions (into modelling and evaluation sets) in all cases imparted confidence in the robustness of the approach of model development adopted in this study.

Keywords: Design life, Multiple performance measures, Non-destructive testing, Rebound number, Ultrasonic pulse velocity

Introduction

Assessment of strength of concrete for in-service buildings is an important activity today, with many of the concrete structures constructed during last few decades of twentieth century nearing the end of their design lives. Estimation of compressive strength of concrete of existing structures would give an indication of present health, as well as provide inputs (many concrete parameters are estimated from the characteristic strength of concrete using empirical expressions) for detailed analysis and evaluation. The most accurate estimation of the compressive strength can be obtained from the results of compressive tests conducted on the cores taken from all over the existing structure, but that would be a destructive test and it would, to a certain extent depending on the number of cores, weaken the structure. To avoid or reduce this effect, Non-Destructive Tests (NDT) come extremely handy. Rebound hammer test (yielding Rebound Number or RN) and the Ultrasonic Pulse Velocity (USPV) test are among the most commonly employed NDT on existing concrete structures for assessment of compressive strength.

Rebound Number is based on the resistance offered by the concrete surface to the impact of rebound hammer, whereas USPV is the velocity of ultrasonic wave passed through concrete. Thus, neither test can directly produce the compressive strength value for concrete. For that purpose, relationships are required to be established between RN and compressive strength or USPV and compressive strength – thereby estimating the compressive strength in an indirect manner. As the dependence of compressive strength on either of these two NDT results (RN or USPV) cannot be generalised, it is generally advocated that structure specific relationships be developed for better accuracy in strength estimates. Recently, fusion of different NDT data on concrete[1–6] has gained popularity due to improved accuracy of estimations.

Of the plethora of literature on strength estimation of concrete from NDT using traditional, and machine learning or Artificial Intelligence (AI) techniques, a few are mentioned here. These and references contained therein would provide an exhaustive literature on concrete strength estimation from NDT. Traditionally such correlation expressions have been developed using Statistical Regression (SR) techniques, in which the parameters of a certain

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assumed equation are evaluated from the concurrent NDT and core data.[1,3–7] Response surface method[7], stand-alone machine learning techniques (Artificial Neural Network or ANN[1,7–13], Support Vector Machine or SVM[11], Random forest or RF[14]; Boosted tree[15]) and hybrid machine learning techniques (Adaptive neuro-fuzzy technique or ANFIS[10]; Genetic algorithm combined with ANN or GA-ANN[16]) that employ no a-priori assumption of equation form has found many applications as well.

Compared to the regression based models that have been reported for laboratory data as well as data from existing structures, it is observed that the estimation of strength from NDT data or NDT fusion using machine learning techniques have been reported majorly from laboratory test results. This could be due to the requirement of a large database for development of machine learning models. From the literature review conducted, it was also noticed that Decision Tree (DT) was applied for prediction of concrete strength from ingredients[17–20] but application of DT for strength estimation from NDT data, either single or combined, is scarce. DT had been successfully employed for other civil and ocean engineering applications: estimation of capacity of single angle struts[21]; prediction of ocean currents[22]; and prediction of blast induced ground vibrations[23], among others. The present study therefore identified the research objectives as listed below.

Research Contribution

This study aims to address the following:

- Explore a relatively less employed machine learning tool: DT–for NDT data fusion and compare the performance with universally popular ANN.
- Examine fusion of NDT data from existing buildings using machine learning tools (ANN and DT) targeted towards accurate estimation of compressive strength of concrete.
- Demonstrate a performance ratio based method for ranking the models, when evaluating different models with multiple (possibly contradicting) performance measures.

Materials and Methods

Data

Data employed in this study included the RN, USPV and (equivalent cube) compressive strength obtained from the cores taken from existing structures, and was collected from literature.[3] A sum total of 205 data sets was available, and the data statistics are presented in Table 1. For further details of the sample collection and measurements, readers may refer the original article.[3] The compressive strength data is plotted against RN in Fig. 1a and against USPV in Fig. 1b, where the generic pattern and high correlation of the basic data (0.88 for RN and 0.84 for USPV) can be noted.

This set of 205 data was split randomly into two sub-sets: modelling and evaluation, which are also

Table 1 — Descriptive statistics of data used in study

Statistic	RN	USPV (km/s)	Compressive strength (MPa)
Maximum	46.00	4.48	36.94
Minimum	21.94	2.61	5.21
Mean	34.09	3.66	18.62
Median	33.49	3.71	17.74
Standard deviation	5.76	0.44	6.53
Coefficient of variation	0.17	0.12	0.35

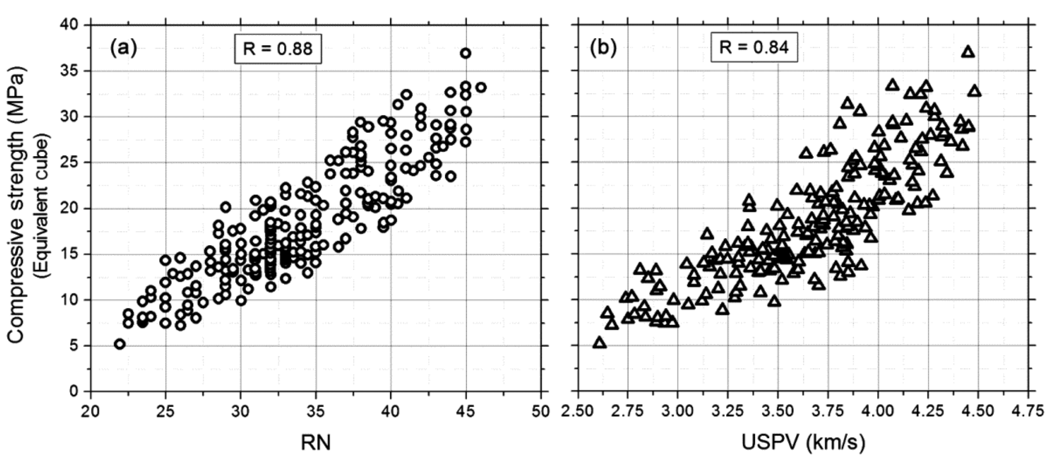

Fig. 1 — Basic data scatter for NDT data a) RN b) USPV

known as training and testing data in AI terminology. The modelling set contained around 75% of the data (154 nos.) with the remaining data (51 nos.) falling in the evaluation set. In order to evaluate whether any bias was introduced in the performance of DT or ANN models due to data division, three such random data divisions were performed for analysis and DT / ANN models were developed for each of them. The range (smaller would be better) and closeness (closer would be better) of the various performance indices would be examined for this aspect.

Performance Measures

The performance of the empirical or machine learning models are generally evaluated quantitatively with one or more performance measures (such as correlation coefficient or root mean square error, alternately called metric or index), and concurrently examined qualitatively with graphical tools such as scatter plot or variable plot. In this study, following the principles of data-driven model development, the models are developed with a sub-set of the data (as explained earlier) and the evaluation of the performance is performed with a different sub-set of data. As the evaluation data would be totally fresh for the model, such performance evaluation gives good indication of the predictive capability of the model.

For this study the following performance measures were selected:

- Correlation coefficient (R): indicates the degree of linear association of the observed and estimated values;
- Root Mean Squared Error (RMSE): penalized the larger deviations of estimates from the observed more;
- Mean Absolute Error (MAE): an error measure on absolute values of the estimates;
- Mean Absolute Relative Error (MARE): an absolute error measure on relative scale;
- Root Mean Square Relative Error (RMSRE): a relative error measure that penalizes the larger deviations of estimates from the observed more.

The graphical evaluations (qualitative performance measures) employed in this study included scatter plot of observed and estimated values; and residual plots. In a scatter plot, points lying closer to the 1:1 diagonal would indicate the better fit. The residual plot would help to identify the dependence of residual on the value of the estimate, if any. In both the plots, the estimates are examined whether they fall outside one standard deviation on either side of the observed values, as a measure of acceptability.[24] Using all these performance measures in conjunction would help to evaluate the developed models comprehensively for comparison.

Confusion matrix is an elegant method for pictorial representation of the performance of machine learning technique as well as for comparing the performance of different methods.[25] While primarily introduced for classifiers[26], confusion matrix can be applied to predictive models – by defining several classes for the predicted variable/s.[27] In the present study, the entire range of predicted variable (compressive strength) has been divided into six classes for developing the confusion matrix.

Methodology of Model Development and Comparison

For a particular modelling sub-set (say, RN and compressive strength; data division no. 1) the DT model is developed with modelling sub-set and the performance of the model is evaluated with the evaluation sub-set. For details of structure, functioning and development of DT models, readers may refer literature.[28–31] This exercise is repeated for each of the three data divisions, and the various performance indices of estimations are recorded for comparison (for example, Table 2, discussed later). For correlation coefficient, higher value being better, normalisation is performed by dividing the individual values by the maximum correlation obtained for all the models (in Table 2). In case of all other performance indices, lower value being better, the normalisation is performed by dividing the individual values by the minimum value, and taking the reciprocal of the number so obtained. Taking reciprocal for the indices for which lower value is better, ensures that the better model would have higher normalised performance index, and therefore, these may be combined with the normalised

Table 2 — Comparison of evaluation performance of DT models based on RN for different divisions of data

Evaluation set	R	MAE (MPa)	RMSE (MPa)	MARE	RMSRE	Rank
1	0.88 (0.98)	2.52 (1.00)	3.06 (1.00)	0.16 (0.81)	0.20 (0.85)	3 (4.64)
2	0.89 (0.99)	2.54 (0.99)	3.06 (1.00)	0.16 (0.81)	0.19 (0.89)	2 (4.69)
3	0.90 (1.00)	2.60 (0.97)	3.23 (0.95)	0.13 (1.00)	0.17 (1.00)	1 (4.92)

correlation to obtain the combined performance metric for ranking of the models. The models may be ranked now based on the summation of all normalised performance indices, with the higher value of the summation would be considered better. Now this exercise is performed for the other two modelling sub-sets (USPV and compressive strength; RN, USPV, and compressive strength) in a similar fashion. The ranges of performance metrics (obtained for corresponding evaluation sub-sets) of each of the models are recorded.

For development of ANN model, only one hidden layer was considered in this study and for obtaining the optimum number of neurons in the hidden layer, models were developed with varying number of neurons in hidden layer (1 to 10). The readers may refer textbooks[32–34] for the details of ANN, structure and functioning. The ANN models were ranked according to the philosophy (summation of relative performance indices) explained earlier. The Table 3 enumerates the individual performance metrics obtained for ANN models developed using RN and USPV together as inputs, as well as the overall ranks – for varying number of neurons in the hidden layer (1 to 10). The first position is claimed by the model architecture 2-2-1 and therefore, this architecture was used subsequently for RN-USPV based ANN model development. Similar exercises for the other two ANN models (RN-based and USPV-based) were performed to select the number of neurons in hidden layer for those ANN models. It was noted that in general, the best ANN models contained typically two to three neurons in the hidden layer. This could possibly due to the good correlation in the basic data (0.89 for RN and 0.84 for USPV). Performance of the best ANN models for the different input datasets (RN/USPV/RN and USPV) for the three data divisions would be noted (say, Table 4, discussed later). Subsequently for each combination of NDT technique (RN; USPV; RN and USPV) the range of performance obtained from ANN models are recorded for comparison (for example, Table 5, discussed later).

Finally, the best performance obtained for DT and ANN model for the three sets of NDT (RN; USPV; RN and USPV), are compared with the corresponding Statistical Regression (SR) models. Confusion matrices

Table 3 — Comparison of evaluation performance of ANN models based on RN and USPV, for different number of neurons in hidden layer

Number of neurons in hidden layer	R	MAE (MPa)	RMSE (MPa)	MARE	RMSRE	Rank
1	0.94	1.79	2.15	0.11	0.13	2
2	0.94	1.74	2.12	0.11	0.13	1
3	0.94	1.79	2.24	0.11	0.14	3
4	0.93	1.88	2.30	0.11	0.14	4
5	0.92	2.10	2.59	0.13	0.17	7
6	0.92	1.91	2.48	0.11	0.15	5
7	0.91	2.02	2.60	0.13	0.17	6
8	0.84	2.58	4.00	0.15	0.22	8
9	0.76	3.28	5.13	0.19	0.27	10
10	0.75	2.51	5.49	0.15	0.28	9

Table 4 — Comparison of evaluation performance of best ANN models based on RN & USPV, for different divisions of data

Evaluation set	R	MAE (MPa)	RMSE (MPa)	MARE	RMSRE	Rank
1	0.94	1.74	2.12	0.11	0.13	2
2	0.94	1.78	2.25	0.10	0.12	1
3	0.93	2.08	2.49	0.13	0.16	3

Table 5 — Range of performance metrics for DT and ANN models for different NDT techniques

NDT technique	R	MAE (MPa)	RMSE (MPa)	MARE	RMSRE
DT models					
RN	0.88 – 0.90	2.52 – 2.60	3.06 – 3.23	0.13 – 0.16	0.17 – 0.20
USPV	0.85 – 0.88	2.48 – 2.69	3.12 – 3.28	0.13 – 0.16	0.18 – 0.20
RN & USPV	0.91 – 0.93	1.88 – 2.13	2.49 – 2.76	0.11 – 0.12	0.14 – 0.15
ANN models					
RN	0.91 – 0.92	2.19 – 2.42	2.62 – 3.10	0.13 – 0.14	0.16 – 0.18
USPV	0.87 – 0.89	2.28 – 2.70	2.91 – 3.22	0.12 – 0.16	0.15 – 0.20
RN & USPV	0.93 – 0.94	1.74 – 2.08	2.12 – 2.49	0.10 – 0.13	0.13 – 0.16

Table 6 — Confusion matrix for best SR (RN & USPV) model (in percentage: All – 205 data)

Range of compressive strength (MPa)	5 to <10	10 to <15	15 to < 20	20 to < 25	25 to < 30	30 to < 37
5 to < 10	71	29	0	0	0	0
10 to < 15	6	65	29	0	0	0
15 to < 20	0	16	71	14	0	0
20 to < 25	0	0	27	59	15	0
25 to < 30	0	0	0	40	47	13
30 to < 37	0	0	0	10	60	30

SR: Ali-Benyahia *et al*., 2017

Table 7 — Confusion Matrix for Best DT (RN & USPV) Model (in Percentage: Testing – 51 data)

Range of compressive strength (MPa)	5 to < 10	10 to < 15	15 to < 20	20 to < 25	25 to < 30	30 to < 37
5 to < 10	50	50	0	0	0	0
10 to < 15	11	50	39	0	0	0
15 to < 20	0	8	75	17	0	0
20 to < 25	0	0	0	36	64	0
25 to < 30	0	0	0	0	67	33
30 to < 37	0	0	0	0	50	50

DT: this study

Table 8 — Confusion matrix for best ANN (RN & USPV) Model (in percentage: testing – 51 data)

Range of compressive strength (MPa)	5 to < 10	10 to < 15	15 to < 20	20 to < 25	25 to < 30	30 to < 37
5 to < 10	50	50	0	0	0	0
10 to < 15	15	62	23	0	0	0
15 to < 20	0	9	73	18	0	0
20 to < 25	0	0	17	50	33	0
25 to < 30	0	0	0	40	40	20
30 to < 37	0	0	0	0	100	0

ANN: this study

(Table 6, Table 7, and Table 8) for these three predictive tools are presented for individual as well as relative evaluation of their predictive performance. Classes of 5 MPa have been defined to cover the entire range of compressive strength, from 5 MPa to 37 MPa – with the last class slightly wider (30–37 MPa). Numerical accuracy are examined with the performance metrics reported in literature (say, Table 9, discussed later) for these models as well. The relative merits and demerits of the approached can be discussed based on this comparison table.

Results and Discussion

The results of the study are presented in this section. As a demonstration of development of the predictive models using the two tools (DT and ANN), development of DT models with RN data; and development of ANN model with combined RN and USPV data are discussed in detail. Subsequently, the summary of results of the various models developed for the three combinations of inputs (RN; USPV; RN and USPV), three random data divisions, and the two tools (DT and ANN) are compared and discussed.

Table 9 — Comparison of performance for different methods and NDT techniques

NDT Type	Method	Correlation	RMSE (MPa)	Rank
	DT	0.90	3.23	7
RN	ANN	0.92	2.62	4
	SR	0.88	3.06	5
	DT	0.85	3.25	8
USPV	ANN	0.87	3.02	6
	SR	0.85	3.44	9
	DT	0.93	2.49	3
RN & USPV	ANN	0.94	2.25	1
	SR	0.93	2.42	2

DT: this study; ANN: this study; SR: Ali-Benyahia *et al*., 2017

Development of DT Model with RN Data

As explained in the methodology section, three random data divisions (modelling and evaluation sets) were considered for each NDT technique. The evaluated performance of the DT models so developed for the RN data, are listed in Table 2. The ranking for the DT models are evaluated according to the method explained in methodology section. The relative values of the performance metrics are given in brackets for each performance metric. The summation of the relative performance metrics is used to determine the rank, the sum is provided in brackets in the 'rank' column. The closeness of all the evaluation performance metrics obtained for the three random data divisions indicates that the adopted method is robust for the various data divisions. A sample set of plots (Fig. 2) are presented for the first evaluation set. It is noted in Fig. 2a that only a single estimate (out of 51) falls outside the acceptable bounds. The residual plot (Fig. 2b) confirms that the errors are independent of the variable value, that is, there is no proportional error involved in the estimates with the DT model. Similar plots were examined for evaluation of performance but are not included here for brevity.

Development of ANN Model for Combination of RN and USPV Data

As explained in the methodology, different numbers of neurons in hidden layer were explored to identify the best suited ANN architecture. An example of the results for this exercise is provided in Table 3 for ANN models based on combined RN and USPV data. Employing the performance ratio method explained in the methodology, the ranks are obtained for the various network architectures. The best architecture identified for this particular dataset is 2-2-1. Similar exercise was repeated for each ANN model that was developed in this study, and the best model has been reported. It may be mentioned that the best-suited number of neurons in hidden layers for the various ANN models were in the range 2 to 3, and no major improvement in performance could be observed for higher numbers explored. The evaluated performance of the ANN models based on RN and USPV, so developed for the three different divisions of data, are listed in Table 4. The closeness of all the evaluation performance metrics obtained for the three random data divisions indicates that the adopted method is robust for the various data divisions. A sample set of plots (Fig. 3) are presented

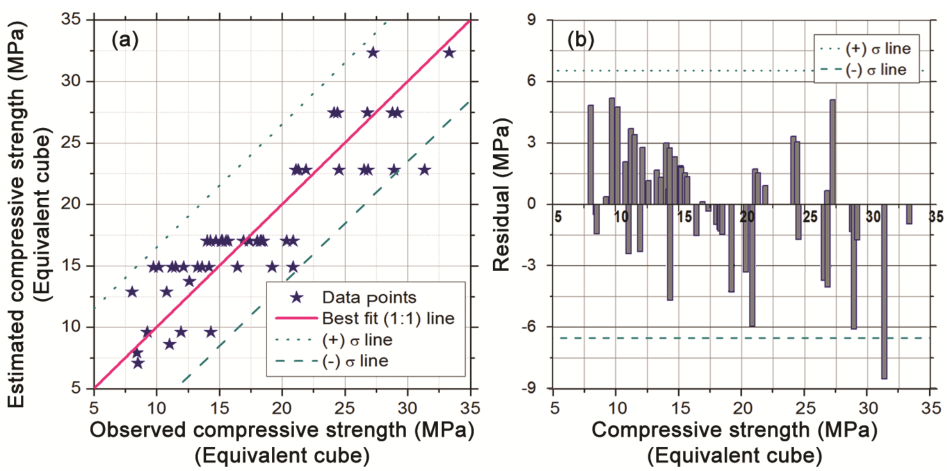

Fig. 2 — Model performance for DT based on RN a) Scatter plot b) Residual plot

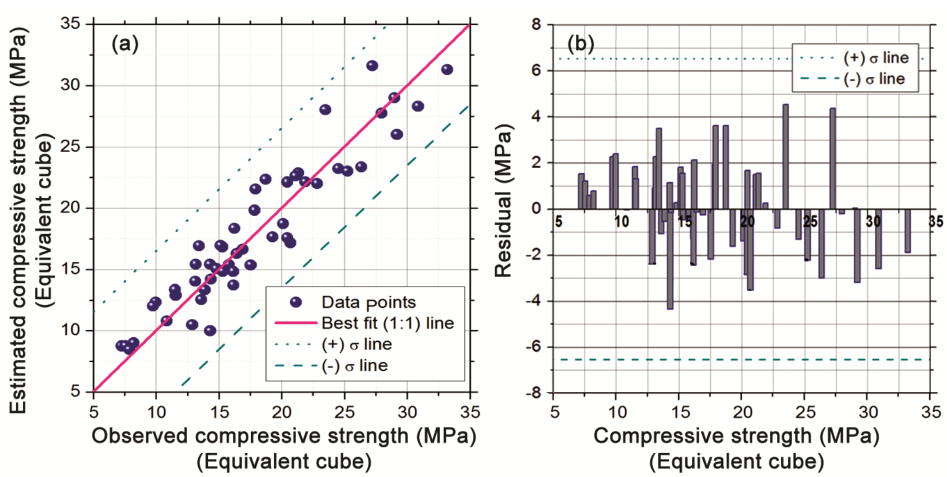

Fig. 3 — Model performance for ANN based on fusion of RN and USPV a) Scatter plot b) Residual plot

for the first evaluation set. The scatter plot (Fig. 3a) shows that the estimates all fell well within the acceptability bounds. The residual plot (Fig. 3b) shows that the residuals for the different values of compressive strength are much less than those observed for the RN-based DT models, and are within the one standard deviation bounds. Similar plots for other data divisions are omitted for brevity.

Evaluation of Performance for DT and ANN Models Using Various NDT Techniques

The exercise explained in earlier sub-section for DT model for RN data, is carried out for DT models developed for USPV data and combined RN-USPV data, and the ranges of performance metrics obtained are summarised in Table 5. In a similar fashion as explained in earlier sub-section for ANN model for RN-USPV data, the ranges of performance metrics obtained for ANN models developed for RN or USPV data are also included in the Table 5. The scatter plots are presented for the three combinations of NDT data in Fig. 4, Fig. 5, and Fig. 6 respectively for RN, USPV, and RN-USPV based estimations of compressive strength. The individual residual plots were also examined, but not included here for brevity. For the RN based models (Fig. 4), a couple of estimates of DT models and one estimate of ANN models fell outside the acceptability bounds. For the USPV based models (Fig. 5), the numbers outside the acceptability bounds went up for DT models to seven, and it was a single estimate from ANN models. When the NDT data fusion was implemented with RN-USPV based models (Fig. 6), the estimates were well within the bounds for ANN models, whereas for DT based models, there were five estimates outside the bounds. However, as was ascertained earlier with the various performance measures (Table 5), the overall performance of the NDT data fusion models was adjudged better.

Specifically, the ANN models had mean absolute percentage errors in the range of 10% to 13% for the combined RN-USPV model, 13% to 14% for the RN model, and 12% to 16% for the USPV model. For the models developed using DT, the corresponding ranges were 11% to 12% (RN-USPV), and 13% to 16% (for

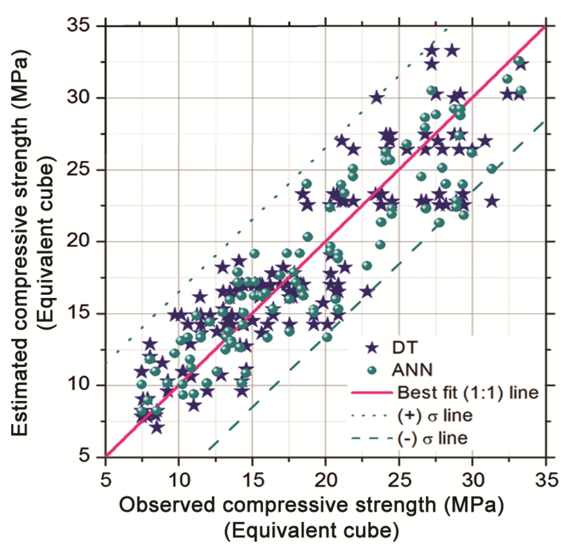

Fig. 4 — Scatter plot of model performance for DT and ANN models based on RN

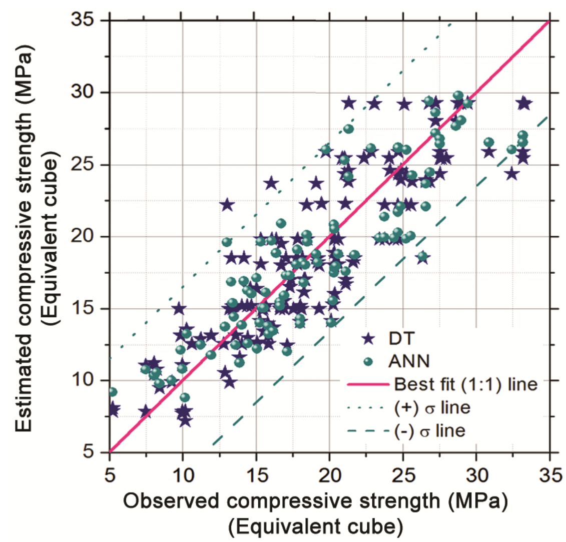

Fig. 5 — Scatter plot of model performance for DT and ANN models based on USPV

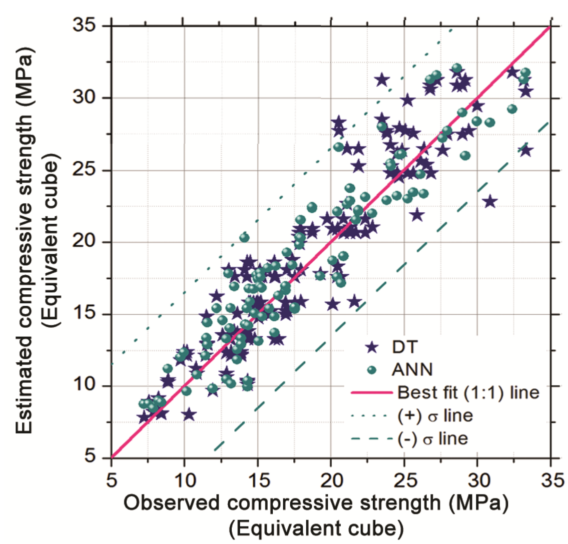

Fig. 6 — Scatter plot of model performance for DT and ANN models based on fusion of RN and USPV

both RN; and USPV). The root mean square percentage error (RMSPE), when examined for the models depicted similar picture. The values of RMSPE varied between 13% and 16% for the combined RN-USPV model, 16% to 18% for the RN model, and 15% to 20% for the USPV model – when developed using ANN. In case of models developed using DT, the values were slightly higher at between 14% and 15% for the combined RN-USPV model, 17% to 20% for the RN model, and 18% to 20% for the USPV model. Thus, the percentage errors considered matched well with the inferences from the proposed ranking system.

Therefore, it is concluded that the performance of the models developed using RN and USPV together results in better performance for both DT and ANN models, followed by models developed using RN and lastly, models developed using USPV data. This is similar to the observation made by Ali-Benyahia *et al.*[3] for the statistical regression (SR) models. It is hereby concluded that fusion of NDT data would be a good approach to improve the accuracy of prediction of compressive strength of concrete using statistical regression or machine learning tools. Among the two machine learning tools explored in this study, ANN models yield more accurate estimates compared to the DT, for all three combinations of NDT techniques, as indicated by the lower errors, and higher correlation for the ANN models.

The rebound number is better indicator of the quality of concrete, though it fails to capture the internal voids or deterioration. The USPV value, on the other hand, can capture the internal voids or deteriorations of concrete, but can be influenced by other factors, which might affect the compressive strength differently. Therefore, USPV is not as good an indicator of the actual concrete strength as RN. In this study too, the correlation observed (Fig. 1a: 0.88) between the basic data for RN (RN-compressive strength) was higher than that observed (Fig. 1b: 0.84) for USPV (USPV-compressive strength). Therefore, the fact that RN based models outperform USPV based models is easily explained. When the two NDT data are used in conjunction, the strengths of the two techniques (better correlation with the compressive strength of RN; internal assessment capability of USPV) are combined and that resulted in better predictive performance for the NDT fusion models (compared to RN based models) developed using any technique – DT or ANN.

Comparison of Performance for Best DT and ANN Models (This Study) and SR models[3] using Various NDT Techniques

As a final comparison, the best performance of the ANN and DT models developed in this study for the three sets of input data (RN; USPV; RN and USPV) are compared with the corresponding best regression model reported in literature.[3] For this purpose, three sets of performance measures are compared: the estimation/prediction in the correct class (confusion matrix – qualitative); the degree of linear association (correlation coefficient – quantitative); and the numerical accuracy (RMSE – quantitative).

The confusion matrices for the best models from the three techniques are presented in Table 6, Table 7, and Table 8 for SR, DT, and ANN respectively. It can be observed that considering the entire range of compressive strength (5 MPa to 37 MPa), SR emerges as the better predictor of class (57%), followed by DT (55%), and ANN (46%). However, considering the range (10 MPa to 30 MPa) that contains around 87% of the data, the difference in performances is reduced: SR (61%); DT (57%); and ANN (56%). Thus it might be concluded that the SR (RN-USPV) model emerges as the better model among the three modelling tools – as far as prediction of the correct class of compressive strength is concerned. The readers might note that these numbers would vary depending on the number of classes chosen and their ranges as well. Another point worth mentioning is that the SR model was presumably developed from the entire dataset, while the DT or ANN models were developed with only 75% of the entire data. More on this will be discussed subsequently.

The performance (correlation coefficient and RMSE) reported in literature for the SR models developed by Ali-Benyahia *et al.*[3] are presently compared in Table 9, to the same performance metrics (correlation coefficient and RMSE) of the best DT and ANN models in this study, obtained using evaluation data for each NDT technique (RN; USPV; RN and USPV). The ranks for the different combinations of input data and modelling methods are obtained in the similar way explained earlier, but using only correlation coefficient and RMSE in this case. The ranks are listed in the last column of Table 9. For reasons explained in the last section, use of fused RN and USPV data yielded better numerical accuracy of the estimates (indicated by lower RMSE) for all three methods. Regarding the tools used for development of the models, the best performance was obtained in both RN and USPV models as well as combined RN-USPV model for ANN-based models. This could be due to the model-free approach of ANN, wherein there is no a-priori assumed model structure and a high degree of flexibility. The second place was taken by SR (RN and RN-USPV) and DT (USPV) for different NDT data. Possibly when employed for well-correlated data (RN in this case) the SR models performed well. When the relationship between the variables (USPV and compressive strength) were not well-defined, the domain-splitting approach and separate models in different sub-domains, as adopted in DT based models, yielded better accuracy. But the performances obtained for DT were quite close to the SR performance even when SR was slightly better.

An important aspect of the performance comparison is highlighted here. Consideration would have to be given to the fact that the SR models by Ali-Benyahia *et al*.[3] were developed from 205 sets of data, whereas the DT or ANN models were developed with only 154 sets of data (around 75% of SR). Furthermore, the performance measures for the SR models by Ali-Benyahia *et al*.[3] reported in literature was apparently evaluated from the entire set of 205 data, which were also used for development of the SR models in the first place. Hence, though good indicators for the goodness of fit of the developed empirical equation(s) to the set of 205 data, these might not be the predictive performance of the SR models. For different datasets used for model development and evaluation, the correlation coefficient was reportedly lower and the RMSE was reportedly higher for the study by Ali-Benyahia *et al*.[3] In the models (DT and ANN) reported in this study, the evaluation data had not been used for development of that model, and therefore, these would be excellent indicators for the predictive performance of the DT or ANN models.

From the preceding discussion, it is concluded that using SR model reported in literature (developed with entire dataset), the strength can be estimated in the correct class 57% of times (entire dataset), whereas the DT and ANN model (developed with 75% of the dataset) would predict strength in correct class for 55% and 46% predictive cases (examined using remaining 25% of the dataset). Considering the quantitative performance measures (correlation coefficient and RMSE) for the same cases, it is concluded that whereas the ANN based models would definitely be more accurate in predictive performance among the three, the DT based models would be better than or as good as the SR based models for NDT data fusion as well.

Conclusions

The proposed ranking method using ratios of performance measures helped to discern between model performances when all performance measures did not completely agree. SR models could estimate the compressive strength of concrete in existing buildings in the correct class (57%), followed by DT (55%), and ANN (46%). Quantitative performance of DT models was found to be comparable to SR models for strength prediction from RN and USPV. In all cases (RN; USPV; and RN-USPV), ANN models provided better predictions compared to DT models, possibly due to its' model-free nature. As reported in literature for SR models, fusion of data (RN and USPV) would help development of better machine learning models (ANN & DT) for prediction of compressive strength of concrete in existing structures. Future studies can explore other machine learning tools and NDT techniques, individually or combined, for more accurate estimation of the strength parameters of concrete in existing structures.

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Data Availability Statement

All data used for the study is available in literature, as noted in the article.

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