Canadian Journal of Civil Engineering

Developing SonReb models to predict the compressive strength of concrete using different percentage of recycled brick aggregate

Journal:	<i>Canadian Journal of Civil Engineering</i>
Manuscript ID	cjce-2020-0631.R2
Manuscript Type:	Article
Date Submitted by the Author:	16-Mar-2021
Complete List of Authors:	Thapa, Sheetal; National Institute of Technology Agartala, Civil Engineering Sharma, Richi; National Institute of Technology Agartala, Civil Engineering Halder, Lipika; National Institute of Technology Agartala, Civil Engineering Department
Keyword:	recycled brick aggregate, non destructive test, artificial neural network, static modulus, dynamic modulus
Is the invited manuscript for consideration in a Special Issue? :	Not applicable (regular submission)

SCHOLARONE™
Manuscripts

Developing SonReb models to predict the compressive strength of concrete using different percentage of recycled brick aggregate

Sheetal Thapa¹, Richi Prasad Sharma² and Lipika Halder³

Department of Civil Engineering, National Institute of Technology, Agartala, Tripura, 799046, India

Sheetal Thapa (Corresponding author)

sheetalthapa186@gmail.com

Research scholar, Civil Engineering,
NIT Agartala, India.
0000-0002-3388-0820

Richi Prasad Sharma

rps.civil@nita.ac.in

Professor, Civil Engineering,
NIT Agartala, India.
0000-0001-9955-123X

Lipika Halder

erlhalder@yahoo.co.in

Assistant Professor, Civil Engineering,
NIT Agartala, India

Abstract

The study was conducted to obtain the relationship between non-destructive and destructive tests in concrete cubes using different ratios of normal stone and recycled brick as a coarse aggregate. Variations in the grade of concrete, density, and age were considered to make the model prediction more efficient in places where uses of recycled brick aggregate are common. Normal concrete M20, M25, and M30 grades were considered having density variation by replacing stone into recycled brick aggregate, and age by testing concrete strength at 7, 28, and 84 days. The regression model was created using artificial neural networks and multiple regression analysis. The study shows that the regression model developed using an artificial neural network predicted better results. The obtained models from the experiment were compared with other models provided by different authors. The study also considers the effect of using recycled brick aggregate in nondestructive tests and modulus of concrete.

Keywords: recycled brick aggregate, compressive strength, NDT, ANN, multiple regression, static and dynamic modulus

1. Introduction:

In some areas due to scarcity of normal stone aggregates like northeast India and Bangladesh, the concrete has been cast using brick or recycled brick aggregate (RBA). The concrete cast using recycled brick aggregate has a

40 lesser density in comparison to conventional concrete. This also enables one to make concrete members with a
41 lighter weight reducing the dead load of the structure. Since the north-eastern part of India is a high seismic zone
42 (IV and V) according to BIS 1893 part-1 (2002) using this type of aggregate in concrete is that it helps to reduce
43 losses and damages due to earthquakes. The other advantage of using recycled brick aggregate in concrete is that
44 it makes the concrete more resistant to heat with low thermal conductivity. The density of this type of concrete
45 typically varies from 2000 kg/m³ to 2100 kg/m³ [Uddin M.T. et al. 2014; Bravo M. et al. 2017; Khalaf F.M. et al.
46 2004]. Though lightweight concrete has many advantages, it also comprises several disadvantages. Some of the
47 main problems using RBA are placing and finishing problems due to low workability of concrete instigated by
48 angularity and porosity of aggregate, take more mixing time than normal concrete, incapable to
49 provide the reliable density and compressive strength all over the complete area, bleeding takes place some rich
50 mix, etc [Mehta P.K. et al. 2006; Aker D.J. et al. 2003].

51 Another benefit of implementing RBA in concrete helps to reduce the consumption of stone aggregate, which
52 ultimately prevents damage to the surrounding environment due to excavation from the stone quarry and also
53 helps to address disposal problems for construction industries [Khalaf F.M. et al. 2004; Cachim P.B. 2009].

54 Due to the porous and less crushing strength of RBA, concrete major mechanical properties i.e. compressive
55 strength, elastic modulus, and a density decrease, and permeability increases [Cachim P.B. 2009; Zheng C et al.
56 2018; Khalaf F.M. 2006]. Consequently, a high rate of structure deterioration takes place in comparison
57 to that made with normal stone aggregate concrete [Adamson M. 2015]. Thus, frequent health monitoring is
58 required to keep the structure in safe and sound conditions.

59 Due to the limited study of recycled brick aggregate concrete, this study focused on developing a model to predict
60 compressive strength using common non-destructive test methods. The study also compares the obtained model
61 with previously well-established formulae. The effect in non-destructive test results due to uses of RBA as an
62 alternative to stone aggregate in concrete had also been discussed. Dynamic and static modulus of concrete had
63 also been studied using longitudinal pulse velocity test.

64 **2. Methodology:**

65 **2.1 Ultrasonic Pulse Velocity (UPV):**

66 The ultrasonic pulse velocity test is achieved by adopting two piezoelectric transducers (transmitter and receiver)
67 and one electronic time measuring circuit. Transmitting transducers convert ultrasonic pulse to mechanical stress
68 wave and deliver to the specimen. On the other hand, the receiving transducer converts mechanical stress to an
69 ultrasonic pulse and delivers it to a time measuring circuit. The time measuring circuit measures the time of travel
70 of a wave in the specimen and by measuring the length of travel, the pulse velocity of the specimen can be
71 calculated. BIS: 13311(1) – 1992 provides the test procedure to obtain UPV in a concrete specimen. The outcome
72 of UPV is greatly influenced by the surface and moisture condition of the concrete, path length, temperature,

stresses, and reinforcing bars [BIS: 13311(1) – 1992]. The length of travel increases with the presence of voids and cracks in the structure, resulting in less pulse velocity. In this work longitudinal pulse velocity (V_p) of concrete cube filled with different percentages of stone and brick aggregate is determined using portable ultrasonic pulse velocity tester shown in Fig. 1.

[Insert Fig. 1]

2.2 Schmidt's Rebound Hammer (SRH):

Schmidt's Rebound hammer (SRH) is the earliest nondestructive method. The instrument helps to provide approximate compressive strength by judging the surface hardness of the concrete specimen. Rebound hammer works on the principle that when a plunger of the hammer is pushed in the concrete specimen its mass attached to the plunger rebounds, producing a specified amount of force that will be absorbed by the surface of the specimen. The rebound of the mass is converted into the rebound number. The test is described in BIS: 13311(2)–1992 and shown in Fig. 2. The outcome of SRH is greatly influenced by the type of cement, type of aggregate, surface condition, moisture condition, carbonation, and reinforcing bars.

[Insert Fig. 2]

2.3 Artificial Neural Network (ANN):

ANN is a complex analytical tool to predict the output (dependent) variable using the input (independent) variable. ANN structure is made up of complex, parallel interconnected neurons, weights, and biases inspired by the biological neural structure found in animal brains. This complex structure helps to create a model to predict future output by acquiring knowledge from the experience. The ANN network structure in this work uses a feed-forward back-propagation algorithm, in which the difference between the predicted output from ANN and actual experimental output is calculated from each iteration and back-propagated to adjust weight and biases until the difference between the two output (actual and predicted) reaches minimum value [Basheer I.A. et al. 2000; Kewalramani M.A. et al. 2006]. ANNs are made up of multiple layers interconnected with each other. The first neuron layer consists of input variables, those neurons send the information to the second layer (hidden layer) consisting of artificial neurons, weight, and biases, which later send the information to the third layer (output) shown in Fig 3 (a). Each hidden layer neuron is connected with the previous neuron, weight, biases, and next or future neuron as shown in Fig. 3 (b). The number of hidden layers depends upon the number of inputs (independent variable) and their complex relationship with the output (dependent variable). Each neuron goes through a training algorithm to change the weight and biases of the next neuron to minimize the predicted and actual output difference (error). Different learning algorithms when applied in the neural model have a different rate of convergence, which should be carefully selected. Some of the common algorithms in the neural model are Levenberg-Marquardt (trainlm), Bayesian Regularization (trainbr), and Scaled conjugate gradient (trainscg).

[Insert Fig. 3]

2.4 SonReb:

Using a single NDT method for the prediction of strength or other mechanical parameters of concrete lacks efficient results due to drawbacks associated with the test. These NDT tests are subjected to influence by various concrete and environmental parameters. Thus, the combination of using different NDT tests simultaneously reduces errors in the results [Nobile L. et al. 2013; Nobile L. 2015; Jain A. et al. 2013]. Many authors developed different models to predict compressive using the SonReb technique, some of which are discussed in this paper.

2.5 Dynamic modulus:

The dynamic modulus of concrete is one of the most essential parameters for structure analysis subjected to time-varying loadings (earthquake, wind, and blast). Dynamic pulse wave from ultrasonic pulse velocity tester is helpful to find the dynamic modulus, and shown in equations (1) and (2) below;

$$V_{p1} = \sqrt{\frac{D_e}{d}} \dots \dots \dots (1)$$

$$V_{p3} = \sqrt{\frac{D_e(1-\mu)}{d(1+\mu)(1-\mu)}} \dots \dots \dots (2)$$

where, V_{p1} and V_{p3} stand for one and three-dimensional longitudinal pulse velocity; d and D_e stands for density and dynamic modulus of concrete (Lu et al., 2013), and μ stands for Poisson ratio. Equation (1) is applicable for finding dynamic modulus (D_e), since the specimen of concrete acts as a finite bar element Diogenes H.G.F. (2011).

2.6 Static modulus:

Empirical equations between dynamic and static modulus of structural concrete for both light and normal weight had been presented in equation (3) given by Popovics S. (1975) below;

$$S_e = \frac{446.09 D_e^{1.4}}{d} \dots \dots \dots (3)$$

Where; D_e = dynamic modulus (GPa) and S_e = static modulus (GPa)

3 Experimental Procedure:

3.1 Materials:

For casting concrete specimens, OPC 43 grade, two different kinds of aggregate (recycled brick and stone), and zone 3 sand are used. Stone and RBA used in the casting of the concrete specimen are shown in Fig. 4.

[Insert Fig. 4]

Table 1 shows the different material properties of concrete. The codes used for finding out different properties of material obtained in table 1 are BIS 2386 -1, 3, and 4 [BIS 2386-1; BIS 2386-3; BIS 2386-4 1963 R-2016].

3.2 Samples preparation and testing procedure:

After completion of the testing of material properties, the trial mix was conducted for normal environment conditions using BIS: 10262 - 2009 and BIS: 456- 2000. The mix proportion obtained for the 75 mm slump value had been presented in Table 2. For the specimen with different ratios of stone and recycled brick aggregate, the mix proportion ratios presented in Table 2 were also used in the same aggregate ratios for casting the specimen. At the time of casting, hand mixing was done for all specimens to avoid attrition between two different kinds of aggregate. Extra 10 % cement was added for hand mixing as per BIS: 456 - 2000 recommendation. After ensuring proper mixing, the mix was placed into the molds and was kept on a vibration table for proper compaction. Molds were kept in the air for 24 hours so that the concrete is properly set. After sufficient setting time of concrete cubes, molds were removed and submerged into the water for different curing periods, i.e. 7 days, 28 days, and 84 days. After proper curing, the cubes are taken out and kept in the air for 3 to 4 hours so the sample becomes dry. Dried samples are weighted in the digital weighing machine and the sample density range was found. UPV (longitudinal) and SRH tests are then carried out following BIS: 13311 (1) - 1992 and BIS: 13311 (2) –1992 standards. UPV test readings obtained from each specimen were the average value of three readings taken from different directions of the cubes. The rebound number obtained from each specimen was the average value of 18 points (nine points each opposite face under the compression machine). Tested samples are taken for destructive testing for finding out their compressive strength. Later, the dynamic and static modulus of concrete was determined using equations (1) and (3).

[Insert Table 2]

[Insert Fig. 5]

3.3 Specimen Details:

To carry out testing, concrete cubes with 150 mm on each side had been cast taking a different proportion of brick and stone aggregate. Seven different proportions between stone and RBA were used for preparing the specimen for the experiment i.e. fully stone, St: RBA (80:20), (60:40), (50:50), (40:60), (20:80) and fully RBA. For each type of proportion, 27 cubes were cast, with nine cubes for each grade of concrete (i.e. M20, M25, and M30), which were tested for 7, 28, and 84 days respectively. A total of 189 numbers of cubes were cast to complete the experiment. Table 3 shows the cast specimen details with its density range.

[Insert Table 3]

3.4 Multiple Regression Analysis.

The obtained test results from both nondestructive test (independent variable) and destructive test (dependent variable) had been used to create a regression model. Multiple regressions had been used to find the relation between the independent (longitudinal pulse velocity and rebound number) and dependent (compressive strength) variable. Following are some of the common equations used to correlate the independent variable with the dependent variable of concrete.

$$f_{ck} = a.(V_p^b).(RN^c) \dots\dots\dots(4)$$

$$f_{ck} = a + b.V_p + c.RN \dots\dots\dots(5)$$

Where, f_{ck} is the compressive strength of concrete (MPa); V_p is longitudinal pulse velocity (m/Sec); RN is Rebound Number; and a, b and c are constant parameters.

Equation (4) is commonly known as the double powered method and equation (5) known as a bilinear method. The bilinear model was solved using MS Excel data analysis tool pack and a double powered model was solved using L. Nobile (2015).

For validation of the developed model k-fold validation technique was used by dividing the total sample into 21 different segments (9 samples each). Iterations (training and testing instances) were done 21 times, each time taking a single unique segment for validation and the remaining 20 segments for model preparation.

3.5 Artificial Neural Network:

ANN is used to create a model between destructive (output) and non-destructive testing (input). In this study, a feed-forward back-propagation training algorithm was used in a two-layer network shown in Fig. 6 (a). The learning algorithms used are trainlm, trainscg and trainbr. The learning, testing, and validation phases are 70%, 15%, and 15% of the total data sets (selected randomly), shown in Fig. 6 (b). The neural model with the highest correlation (R) value between the predicted output from ANN and actual output from testing, and minimum MSE (mean square error) had been selected as an optimum model. The different parameters used to create a model for finding out the optimum neural model are presented in Table 4.

[Insert Table 4]

4 Results and discussion:

With increasing uses of recycled brick aggregate in the concrete, the resulting structures become less resistant to environmental and mechanical loading effects. Thus frequent health monitoring is needed for such types of structures. Concrete compressive strength one of the major mechanical factors. The results obtained below are some of the models for the prediction of compressive strength using common non-destructive tools. The model to predict the modulus of concrete using pulse velocity wave is also discussed below.

4.1 Bilinear and double powered regression model

MSE values (i.e. score) obtained from the testing section from 21 different training and testing instances in the k-fold validation method for both bilinear and double powered models are presented in Fig. 7. The dotted line shows the average value of 21 different MSE scores.

[Insert Fig. 7]

Fig. 8 shows the bilinear and double powered regression model and Table 5 shows the statistical results obtained from the models. The regression model and its statistical values presented in Table 5 are the average value obtained from 21 different k-fold validation approaches from training instances.

[Insert Fig. 8]

204 [Insert Table 5]

205 From adjusted R^2 and SE values from training and MSE score from testing sets, presented in Table 5, the double
206 powered model shows the less reliable result in comparison to the bilinear model considering the change in
207 physical parameters of concrete.

208 4.2 ANN model

209 Results obtained from different neural network models are shown in Table 6. The optimum model was obtained
210 using Levenberg-Marquardt (trainlm) with 6 hidden neurons, showing the least MSE values between predicted
211 and actual output. The scaled conjugate algorithm (trainscg) shows the least correlation strength with the highest
212 number of hidden neurons required to achieve optimum results. The obtained results are particularly valid for
213 concrete cast using recycled brick aggregate.

214 [Insert Table 6]

215 The results obtained from the optimum neural model are presented in Fig. 9 (a) and (b). MSE and R values
216 at different stages during optimum neural modeling can be obtained from Fig 6 (c) above.

217 [Insert Fig. 9]

218 Weights and biases obtained from the optimum neural model are presented in Fig. 10. From weights obtained
219 from the model, it can be concluded that the rebound numbers show more importance in the prediction of
220 compressive strength compared to pulse velocity. This may be due to the effect of unreliable density of using
221 both types of aggregate which indirectly hampers the effectiveness of using pulse velocity.

222 [Insert Fig. 10]**223 4.3 Comparison between multiple regression and ANN model**

224 Predicted results obtained from ANN and multiple regression models are compared with actual experimental
225 results. The statistical results obtained from the different models are presented in Table 7, ANN shows the best
226 prediction results followed by the bilinear model and double powered model.

227 [Insert Fig 11]**228 [Insert Table 7]**

229 From the actual strength (experimental) plot shown in Fig. 11, the first 27 specimens represent a fully stone
230 aggregate sample and the last 27 specimens represent fully RBA aggregate. The specimens in between represent
231 sample cast from the different mix ratios of stone and RBA aggregate. In each type of sample (27 specimen
232 intervals) we observe two or three peaks, the first peak represents 7 days, the second peak represents 28 days
233 and the final peaks represent 84 days of compressive strength variation for three different grades of concrete.
234 The difference between 28 days (2nd peak) and 84 days (3rd peak) compressive strength values increases with
235 increasing RBA percentage in the figure. This may be due to the porous texture of aggregate, which helps to
236 retain water for hydrations of cement for a longer period in comparison to normal stone aggregate concrete.
237 The increase in the strength of percentage from 28 to 84 days for different types of the concrete specimen is as

238 follows: for fully stone 1.56 percent, 3.47 percent for 20 percent RBA, 4.08 percent for 40 percent, 4.25
239 percent for 50 percent, 4.33 percent for 60 percent, 4.78 percent for 80 percent and 5.12 percent for fully RBA.
240 The rate of gaining strength with age i.e. 7, 28, and 84 days for all different type of specimen remain almost the
241 same (gradient) which satisfies with the study given by F.M. Khalaf (2006).

242 **4.4 Comparison of the different model obtained from previous authors with the experimental models** 243 **models**

244 Table 8 shows the different models considered in this study, the number of specimens, and the range of results
245 from the specimen to obtain the Son-Reb relationship.

246 **[Insert Table 8]**

247 ***Bilinear Model Comparison***

248 Data used to develop different Son-Reb models by previous authors are applied in a bilinear model developed in
249 this study (experimental model). This is followed by a comparison of the model obtained in the present research
250 with those by previous researchers. The root mean square error (RMSE) obtained from the difference between
251 predicted and actual strength due to using unknown results into each other models for comparison are presented
252 in Fig. 12.

253 **[Insert Fig. 12]**

254 From the RMSE comparison, it was observed that the model developed in this study using the k-fold validation
255 approach shows better results in predicting compressive strength compared to other models developed by
256 different authors. Among different selected models Kheder G.F. (1999) and Amini K. et al (2016) show better
257 results. This could be due to the fact that the model by G.F. Kheder incorporated varying densities of concrete
258 and that K. Amini et al. used the optimal higher-order polynomial for the prediction of strength.

259 ***Neural Model Comparison***

260 Comparison between authors were conducted using results obtained from different experiments presented in
261 Table 8 to the optimum model developed from neural network training presented in Fig. 6 (a). Table 9 shows the
262 comparison in terms of MSE and R^2 between predicted and actual compressive strength.

263 **[Insert Table 9]**

264 From Table 9, it can conclude that data used from Kheder G.F. (1999) shows the best correlation with the
265 present studies.

266 **4.5 Relationship between compressive strength and nondestructive test**

267 The regression model between compressive strength, pulse velocity and rebound number for different ratios of
268 stone and RBA aggregate concrete with its statistical values are presented in Table 10. From the table, it
269 can be observed that with an increasing percentage of RBA in the specimen, SE and RMSE values
270 increases for the regression model representing strength and pulse velocity. This may be due

271 to an increased amount of voids and fissures in the specimen with increasing RBA
272 percentage, which finally results in unreliable pulse velocity readings.

273 From statistical results, it was observed that the prediction of compressive strength using rebound hammer is
274 maximum for a single type of aggregate, and decreases with the increasing ratios showing minimum value at
275 an equal ratio of stone and RBA aggregate specimen. This is due to the fact that the hardness of the sample
276 varies drastically in small regions for equal mix aggregate (i.e. 50% replacement).

277 **[Insert Table 10]**

278 **4.6 Relationship between modulus and pulse velocity**

279 The regression relationship and its corresponding statistical results between pulse velocity and static/dynamic
280 modulus of concrete were obtained from equations (1) and (3), and are presented in Table 11. From the
281 statistical results, it can conclude that the prediction of modulus of concrete using pulse velocity decreases with
282 increasing RBA percentage in concrete. This is due to the increased variation of density of the specimen with
283 increasing RBA content.

284 **[Insert Table 11]**

285 The entire linear regression model presented from Table 10 and 11 was validated using k-fold validation
286 approach. This approach was conducted to make the models more reliable in very limited sets of data. The
287 models with 27 samples were segmented into 9 folds (3 samples each on the single fold). Training and testing
288 were conducted 9 times with a unique set of folds for each time. The results obtained in the table were the
289 average values from conducting 9 iterations.

290 **5. Conclusion:**

291 The model developed in this study helps to predict the compressive strength and modulus of concrete using
292 common nondestructive tools. Some of the conclusion obtained from this study is described in the section
293 below;

- 294 • ANN model shows the most reliable tools to predict compressive strength in comparison to the multiple
295 regression models considering the effect of physical change in concrete. Rebound number was given more
296 importance to predict compressive strength in comparison to pulse velocity. Among different training
297 functions, the Levenberg-Marquardt algorithm was most efficient in predicting compressive strength.
- 298 • The multiple regression models obtained in this study show better prediction results for concrete cast with
299 recycled brick aggregate in comparison to all other models developed by previous researchers.
- 300 • The model created by G.F. Kheder gives the best prediction of compressive strength with varying physical
301 parameters of concrete.
- 302 • With increasing RBA percentage in a concrete member, the time required to reach ultimate compressive
303 strength increases.

- 304 • The rebound hammer test shows better results for the uniform type of aggregate-based concrete. Pulse
 305 velocity prediction strength decreases with increasing RBA percentage in the specimen. With
 306 increasing variation in density of the specimen, reliability of using pulse velocity for prediction of
 307 compressive strength decreases in comparison to rebound number test.
- 308 • A regression model between modulus and pulse velocity of concrete was presented. From the
 309 model, it can be observed that with increasing RBA percentage prediction of modulus using pulse wave
 310 decreases.

311

Notation	Description
f_{ck}	Compressive strength (MPa)
V_p	Longitudinal pulse velocity (m/sec)
RN	Rebound Number
SE	Standard error
RMSE	Root mean square error
R^2	Correlation strength
p	Significant test
ANN	Artificial neural network
RBA	Recycled Brick Aggregate
N	Number of specimen
CA	Coarse Aggregate
FA	Fine Aggregate

312 **Acknowledgment:**

313 The authors wish to acknowledge the National Institute of Technology, Agartala (NITA), India for carrying
 314 out this research in the institute and all staff members of the concrete laboratory for their constant support and
 315 guidance. The research was fully self-funded.

316 **Data Availability Statement**

317 The data that support the findings of this study are available from the corresponding author upon reasonable
 318 request.

319 **References:**

- 320 Adamson, M., Razmjoo, A. and Poursaee, A. 2015. Durability of concrete incorporating crushed brick as
 321 coarse aggregate. Construction and building materials **94**: 426-432.
 322 doi.org/10.1016/j.conbuildmat.2015.07.056

- 323 Akers, D.J., et al. 2003. Guide for Structural Lightweight-Aggregate Concrete. ACI 213R-03. American
324 Concrete Institute (ACI), Michigan
- 325 Amini, K., Jalalpour, M. and Delatte, N. 2016. Advancing concrete strength prediction using non-destructive
326 testing: Development and verification of a generalizable model. *Construction and Building Materials* **102**:
327 762-768. doi.org/10.1016/j.conbuildmat.2015.10.131
- 328 Arioglu, E., Arioglu, N. and Girgin, C. 2001. A discussion of the paper “Concrete strength by combined
329 nondestructive methods simply and reliably predicted” by H.Y. Qasrawi. *Cement and Concrete Research*
330 **31**: 1239 – 1240. doi.org/10.1016/S0008-8846(01)00551-8
- 331 Basheer, I.A. and Hajmeer, M. 2000. Artificial neural networks: fundamentals, computing, design, and
332 application. *Journal of microbiological methods* **43**(1): 3-31. doi.org/10.1016/S0167-7012(00)00201-3
- 333 Benyahia, K.A., Ghrici, M., Kenai, S., Breysse, D. and Sbartaï Z.M. 2016. Analysis of the relationship
334 between nondestructive and destructive testing of low concrete strength in new structures. *Asian Journal of*
335 *civil engineering* **18**(2): 191-205. doi.org/10.4236/ojce.2012.21003
- 336 Bingol, S., and Cavdar, A., 2016. A new nomogram proposal to determine concrete compressive strength by
337 combined non-destructive test methods. *Research in Nondestructive Evaluation*, 1-38.
338 dx.doi.org/10.1080/09349847.2016.1195466
- 339 B.I.S. 13311-1 1992. Method of non-destructive testing of concrete using Ultrasonic pulse velocity [CED 2-
340 Cement and Concrete]. Bureau of Indian Standards, New Delhi, India
- 341 B.I.S. 13311-2 1992. Method of non-destructive testing of concrete using rebound hammer [CED 2 - Cement
342 and Concrete]. Bureau of Indian Standards, New Delhi, India
- 343 BIS 2386-1 1963 R-2016. Methods of test for aggregate for concrete – Part 1: Particle shape and size.
344 Bureau Indian Standards, New Delhi, India
- 345 BIS 2386-3 1963 R-2016. Methods of test for aggregate for concrete – Part 3: Specific gravity, density,
346 voids, absorption and bulking. Bureau Indian Standards, New Delhi, India
- 347 BIS 2386-4 1963 R-2016. Methods of test for aggregate for concrete – Part 4: Mechanical properties. Bureau
348 Indian Standards, New Delhi, India
- 349 BIS 10262 2009. Guidelines for concrete mix design proportioning [CED 2 - Cement and Concrete].
350 Bureau Indian Standards, New Delhi, India

- 351 BIS 456 2000. Indian Standards plain and reinforced concrete code of practice (Fourth Revision).
352 Bureau Indian Standards, New Delhi, India
- 353 Bravo, M., Brito, J.D. and Evangelista, L. 2017. Thermal performance of concrete with recycled aggregates
354 from CDW plants. *Applied Sciences* 7(7): 740. doi.org/doi:10.3390/app7070740
- 355 Cachim, P.B. 2009. Mechanical properties of brick aggregate concrete. *Construction and Building Materials*
356 **23**(3): 1292-1297. doi.org/10.1016/j.conbuildmat.2008.07.023
- 357 Chandak, N.R., and Kumavat, H.R. 2020. SonReb method for evaluation of compressive strength of
358 concrete. *Materials Science and Engineering* **810**: 012071. doi.org/10.1088/1757-899X/810/1/012071
- 359 Cristofaro, M.T., Viti, S. and Tanganelli, M. 2020. New predictive models to evaluate concrete compressive
360 strength using the SonReb method. *Journal of Building Engineering*, **27**: p.100962.
361 doi.org/10.1016/j.jobbe.2019.100962
- 362 Diogenes, H.G.F., Cossolino, L.C., Pereira, A.H.A., El Debs, M.K. and El Debs, A.L.H.C. 2011.
363 Determination of modulus of elasticity of concrete from acoustic response. *IBRACON structures and*
364 *materials journal* **4** (5): 803-813. doi.org/10.1590/S1983-41952011000500007
- 365 Hannachi, S., and Guetteche, M.N., 2012. Application of the Combined Method for Evaluating the
366 Compressive Strength of Concrete on Site. *Open Journal of Civil Engineering* **2**:16 -21.
- 367 Hobbs, B., and Kebir M.T. 2007. Non-destructive testing techniques for the forensic engineering
368 investigation of reinforced concrete buildings. *Forensic Science International* **167**: 167-172.
369 doi.org/10.1016/j.forsciint.2006.06.065
- 370 Jain, A., Kathuria, A., Kumar, A., Verma, Y. and Murari, K. 2013. Combined use of non-destructive tests for
371 assessment of strength of concrete in structure. *Procedia Engineering* **54**: 241-251.
372 doi.org/10.1016/j.proeng.2013.03.022
- 373 Kewalramani, M.A. and Gupta, R. 2006. Concrete compressive strength prediction using ultrasonic pulse
374 velocity through artificial neural networks. *Automation in Construction* **15**(3): 374-379.
375 doi.org/10.1016/j.autcon.2005.07.003
- 376 Khalaf, F.M. 2006. Using Crushed Clay Brick as Coarse Aggregate in Concrete. *Journal of Materials in*
377 *Civil Engineering* **18**: 518-526. doi.org/10.1061/(ASCE)0899-1561 (2006)18: (518)

- 378 Khalaf, F.M. and Devenny, A.S. 2004. Recycling of demolished masonry rubble as coarse aggregate in
379 concrete: Review. *Journal of Materials in Civil Engineering* **16**(4): 331-340. doi.org/10.1061/(ASCE)0899-
380 1561(2004)16:4(331)
- 381 Kheder, G.F. 1999. A two stage procedure for assessment of in-situ concrete strength using combined non-
382 destructive testing. *Material Structures* **32**: 410–417. doi.org/10.1007/BF02482712
- 383 Lorenzi, A., Silva Filho, L.C.P., Campagnolo, J.L., Strieder, A.J. and Caetano, L.F. 2004. Using Non-
384 Destructive Testing for Monitoring Concrete Elements of Sizable Structural Members. *Structural Materials*
385 *Technology (SMT): NDE/NDT for Highways and Bridges* **6**: 67-74. doi.org/10.13140/RG.2.1.4810.1607
- 386 Mehta, P.K. and Monterio, P.J.M. 2006. *Concrete structure, properties and materials*. 3th Edition, Mc Graw-
387 Hill Companies
- 388 Menditto, G., Bufarini, S., D’Aria, V. and Massaccesi, M. 2004. New correlation curves for the hammer,
389 ultrasound and combined method. In: *Concreto*, Maggioli Editor, Italy, **57**: 84–89.
- 390 Nobile, L. and Bonagura, M. 2013. Accuracy of non-destructive evaluation of concrete compression
391 strength. In *The 12th International Conference of the Slovenian Society for Non-Destructive Testing*,
392 Portorož, Slovenia
- 393 Nobile, L. 2015. Prediction of concrete compressive strength by combined non-destructive
394 methods. *Meccanica* **50**(2): 411-417. doi.org/10.1007/s11012-014-9881-5
- 395 Popovics, S. 1975. Verification of relationships between mechanical properties of concrete-like materials.
396 *Material and Constructions* **8**(3): 183–191. doi.org/10.1007/BF02475168
- 397 Uddin, M.T., Hasnat, A., Awal, M.A. and Bosunia, S.Z. 2014. Recycling of brick aggregate concrete as
398 coarse aggregate. *Journal of Materials in Civil Engineering* **27**(7): B4014005.
399 doi.org/10.1061/(ASCE)MT.1943-5533.0001043
- 400 Zheng, C., Lou, C., Du, G., Li, X., Liu, Z. and Li, L. 2018. Mechanical properties of recycled concrete with
401 demolished waste concrete aggregate and clay brick aggregate. *Results in Physics* **9**: 1317-1322.
402 doi.org/10.1016/j.rinp.2018.04.061

403 **Figures Legends:**

404 **Fig. 1** Pulse velocity test using PUNDIT (Portable Ultrasonic Non Destructive Tester)

405 **Fig. 2** Rebound number test using Schmidt’s Hammer

406 **Fig. 3** Unit processing element structures

Fig. 4 (a) Stone and (b) RBA aggregate used in preparation of concrete

Fig. 5 (a) Specimen preparation; (b) specimen curing; (c) density test; (d) destructive test and (e) destroyed specimen, taken from lab of NIT Agartala

Fig. 6 (a) Optimum neural model, (b) Sample distribution and (c) Results obtained from optimum network model, taken from MatLab

Fig. 7 MSE value from testing section of k-fold validation technique

Fig. 8 (a) Bilinear model and (b) Double powered model between destructive and nondestructive test

Fig. 9 (a) Regression and (b) Performance plot obtained from optimum neural model

Fig. 10 Weights and biases obtained from optimum neural model

Fig. 11 Comparison between actual strength and predicted strength from different obtained model

Fig. 12 Shows the RMSE values obtained from interchanging data into each other models

Tables Legends:

Table 1 Properties of materials used in concrete

Table 2 Concrete mix proportion

Table 3 Sample density of concrete specimen

Table 4 Configuration of neural network

Table 5 Regression model obtained after performing average k-fold validation between compressive strength and non-destructive parameters

Table 6 Performance test for different neural model with different optimization function

Table 7 Comparison between different models to predict compressive strength

Table 8 Different SonReb models with corresponding range of results

Table 9 Comparison with different authors using optimum neural network model

Table 10 Average regression relationship between compressive strength, pulse velocity and rebound number using K-fold validation

Table 11 Average regression relationship between compressive strength and modulus using k-fold validation

Figure & Figures Captions

Fig. 1 Pulse velocity test using PUNDIT (Portable Ultrasonic Non Destructive Tester)

Fig. 2 Rebound number test using Schmidt's Hammer

Fig. 3 Unit processing element structures

Fig. 4 (a) Stone and (b) RBA aggregate used in preparation of concrete

Fig. 5 (a) Specimen preparation; **(b)** specimen curing; **(c)** density test; **(d)** destructive test and **(e)** destroyed specimen, taken from lab of NIT Agartala

(c)

Results

	Samples	MSE	R
Training:	133	9.31285e-0	8.78848e-1
Validation:	28	4.94297e-0	9.27807e-1
Testing:	28	7.60105e-0	9.49281e-1

Fig. 6 (a) Optimum neural model, (b) Sample distribution and (c) Results obtained from optimum network model, taken from MatLab

Fig. 7 MSE value from testing section of k-fold validation technique

Fig. 8 (a) Bilinear model and (b) Double powered model between destructive and nondestructive test

Fig. 9 (a) Regression and (b) Performance plot obtained from optimum neural model

Fig. 10 Weights and biases obtained from optimum neural model

Fig. 11 Comparison between actual strength and predicted strength from different obtained model

Fig. 12 Shows the RMSE values obtained from interchanging data into each other models

Table and Table Captions

Table 1 Properties of materials used in concrete

Concrete Ingredients	Specific Gravity	Water Absorption (%)	Sieve Analysis	Crushing Value	Fineness Modulus
Cement	3.09	n.a.	n.a.	n.a.	n.a.
Sand	2.6	2.7	Zone 3	n.a.	n.a.
Stone	2.65	2.85	20 mm down- 10 mm retained (60%) 10 mm down – 4.75mm retained (40%)	15.45	8.3
RBA	1.91	8.03		20.02	7.61

Table 2 Concrete mix proportion

Grade	Aggregate Type	Cement (Kg/m³)	F.A. (Kg/m³)	C.A. (Kg/m³)	Water (Kg/m³)	W/C Ratio
M20	Stone	359.5	589.6	1276.22	188.76	0.525
	RBA	363.2	595.65	1289.36	190.68	0.525
M25	Stone	404.9	546.61	1085.13	188.68	0.466
	RBA	407.3	549.85	1091.56	189.8	0.466
M30	Stone	458.3	508.71	847.85	192.94	0.421
	RBA	460.6	511.27	852.11	192.23	0.421

Table 3 Sample density of concrete specimen

Type of sample	Percent	Density (kg/m³)	Number of samples
Fully Stone	n.a.	2350 - 2450	27
Fully RBA	n.a.	1950 - 2050	27
RBA (%)	20	2300 - 2400	27
	40	2250 – 2350	27
	50	2200 - 2300	27
	60	2100 – 2200	27
	80	2050 - 2150	27

Table 4 Configuration of neural network

Parameter	Specification
Input layer	2
Hidden layer neuron number	2-18
Output layer	1
Transfer function	Tran-sigmoid / Pure-Linear
Performance function	Mean square error (MSE)
Training Function	Trainlm / Trainscg / Trainbr
Learning Function	Learngdm
Gradient	1×10^{-2}
Momentum	0.001
Max failure	6

Table 5 Regression model obtained after performing average k-fold validation between compressive strength and non destructive parameters

Model Type	Equations	Adjusted R ²	N	SE	p	MSE (N=9)
Training						Testing
Bilinear	$f_{ck} = -22.129 + 0.00675V_p + 0.674RN$	0.772	180	3.1	< 0.001	9.96
Double powered	$f_{ck} = \exp(-8.091) (V_p)^{1.047} (RN)^{0.779}$	0.768	180	3.15	< 0.001	10.5

Table 6 Performance test for different neural model with different optimization function

Model	Trainlm		Trainscg		Trainbr	
	MSE	R	MSE	R	MSE	R
2-2-1	8.017	0.885	9.55	0.8683	8.565	0.8747
2-4-1	7.505	0.8933	9.033	0.8801	8.088	0.885
2-6-1	4.943	0.9087	8.588	0.8866	7.565	0.893
2-8-1	5.11	0.8985	8.305	0.8855	7.015	0.8955
2-10-1	5.625	0.9055	7.664	0.8883	6.472	0.8995
2-12-1	6.331	0.8995	7.582	0.894	6.888	0.8982
2-14-1	7.074	0.9021	7.808	0.8905	6.92	0.8906
2-16-1	7.906	0.8933	7.955	0.8908	7.305	0.8906
2-18-1	8.18	0.8968	8.104	0.8864	7.63	0.881

Table 7 Comparison between different models to predict compressive strength

Model Type	Equations	R ²	MSE	N
ANN	Presented in Fig. 6 and Fig. 10	0.825	4.943	189
Bilinear	$f_{ck} = -22.129 + 0.00675V_p + 0.674RN$	0.772	9.96	189
Double powered	$f_{ck} = \exp(-8.091) (V_p)^{1.047} (RN)^{0.779}$	0.768	10.5	189

Table 8 Different SonReb models with corresponding range of results

Author's	Model with range of data	No. of specimen
G.F. Kheder (Air Dry) [25]	$f_{ck} = 0.0158(V_p^{0.4254})(RN)^{1.1171}$ $f_{ck} = 12.9 - 52.1; V_p = 2587 - 5212; RN = 18 - 44$	108
E. Arigolu [26]	$f_{ck} = 0.00153\{(1000*V_p)^4 * RN^3\}^{0.611}$ $f_{ck} = 3.2 - 42.62; V_p = 2770 - 5070; RN = 15 - 36$	33
G. Menditto ($\alpha=0$) [27]	$f_{ck} = 0.00004(V_p^{0.8084})(RN^{1.8815})$ $f_{ck} = 2.3 - 107.3; V_p = 2350 - 4850; RN = 12.2 - 61$	1000
B. Hobbs [28]	$f_{ck} = -173.033-4.069(1000*V_p)^2+57.693(1000*V_p)+1.307*RN$ $f_{ck} = 19.5 - 49.5; V_p = 3950 - 4450; RN = 22.5 - 36.5$	25
S. Hannachi [29]	$f_{ck} = 121.3 - 0.0261RN + 0.5752V_p$ $f_{ck} = 25.5 - 38.5; V_p = 3710 - 4190; RN = 22 - 30$	18
K.A. Benyahia (water cured) [30]	$f_{ck} = 0.0435\{(1000*V_p)^{1.5672}\}(RN^{1.1892})$ $f_{ck} = 12.2 - 42.74; V_p = 3800 - 4900; RN = 20.5 - 41$	36
K. Amini [31]	$f_{ck} = 10^3*(0.11+0.0016RN-0.793V_p-0.00002RN^2+1.293V_p^2)$ $f_{ck} = 12.4 - 42.74; V_p = 2700 - 3980; RN = 22.5 - 36.5$	84
S. Bingol (28 days) [32]	$f_{ck} = -34.21-0.009V_p + 0.952RN$ $f_{ck} = 1.3 - 39; V_p = 2700 - 3980; RN = 8 - 42$	101
N.R. Chandak (lab) [33]	$f_{ck} = 0.0841(V_p^{0.945})(RN^{0.572})$ $f_{ck} = 9.4 - 41.2; V_p = 2060 - 4388; RN = 12.3 - 40$	27
M.T. Cristofaro [34]	$f_{ck} = -28.44 + 0.01174V_p + 0.37RN$ $f_{ck} = 11.04 - 48.9; V_p = 2207 - 4135; RN = 24.1 - 52.8$	78

29

Table 9 Comparison with different authors using optimum neural network model

Author's	MSE	R ²
G.F. Kheder [25]	4.19	0.829
E. Arigolu et al [26]	5.14	0.818
G. Menditto et al [27]	5.35	0.814
B. Hobbs et al [28]	8.33	0.74
S. Hannachi et al [29]	10.115	0.693
K.A. Benyahia et al [30]	7.312	0.786
K. Amini et al [31]	7.023	0.796
S. Bingol et al [32]	5.563	0.807
N.R. Chandak et al [33]	8.05	0.76
M.T. Cristofaro et al [34]	9.33	0.699

30

Table 10 Average regression relationship between compressive strength, pulse velocity and rebound number using K-fold validation

Specimen	%	N	R ²	S.E. (MPa)	P test	Regression Model	RMSE (N=3)
Training							Testing
Fully Stone	n.a.	24	0.84	2.62	< 0.001	$f_{ck} = -83.858 + 0.0255V_p$	2.716
			0.779	3.08		$f_{ck} = -20.78 + 1.502RN$	3.264
RBA (%)	20	24	0.825	2.66	< 0.001	$f_{ck} = -83.676 + 0.0255V_p$	2.9
			0.773	3.02		$f_{ck} = -3.812 + 1.051RN$	3.288
	40	24	0.81	2.72	< 0.001	$f_{ck} = -78.957 + 0.0244V_p$	3.03
			0.75	3.12		$f_{ck} = -2.99 + 0.977RN$	3.292
	50	24	0.8	2.78	< 0.001	$f_{ck} = -88.542 + 0.0267V_p$	3.07
			0.737	3.1		$f_{ck} = -4.54 + 1.104RN$	3.34
	60	24	0.796	2.81	< 0.001	$f_{ck} = -72.41 + 0.0236V_p$	3.13
			0.762	2.91		$f_{ck} = -5.05 + 1.114RN$	3.28
	80	24	0.785	2.85	< 0.001	$f_{ck} = -91.581 + 0.0297V_p$	3.2
			0.778	2.82		$f_{ck} = -6.68 + 1.23RN$	3.253
Fully RBA	n.a.	24	0.77	2.73	< 0.001	$f_{ck} = -92.33 + 0.03V_p$	3.35
			0.786	2.77		$f_{ck} = -10.27 + 1.4RN$	3.11

33

34

35

36

Table 11 Average regression relationship between compressive strength and modulus using k-fold validation

Specimen	%	N	Modulus	R ²	S.E. (GPa)	P test	Regression Model	RMSE (N=3)
Training								Testing
Fully Stone	n.a.	24	Static	0.997	0.054	< 0.001	$S_e = 0.0042V_p - 4.81$	0.052
			Dynamic	0.985	0.15		$D_e = 0.0051V_p - 0.798$	0.127
RBA (%)	20	24	Static	0.993	0.08	< 0.001	$S_e = 0.0043V_p - 5.161$	0.067
			Dynamic	0.977	0.167		$D_e = 0.005V_p - 0.027$	0.154
	40	24	Static	0.991	0.077	< 0.001	$S_e = 0.0043V_p - 4.934$	0.071
			Dynamic	0.974	0.178		$D_e = 0.0047V_p + 0.167$	0.169
	50	24	Static	0.986	0.1	< 0.001	$S_e = 0.00421V_p - 4.618$	0.075
			Dynamic	0.966	0.183		$D_e = 0.0047V_p + 0.235$	0.174
	60	24	Static	0.985	0.112	< 0.001	$S_e = 0.0041V_p - 4.03$	0.106
			Dynamic	0.955	0.22		$D_e = 0.0045V_p + 0.491$	0.211
Fully RBA	n.a.	24	Static	0.966	0.137	< 0.001	$S_e = 0.00435V_p - 4.754$	0.127
			Dynamic	0.947	0.273		$D_e = 0.005V_p - 1.69$	0.225