

PREDICTION OF GEOPOLYMER CONCRETE COMPRESSIVE STRENGTH UTILIZING ARTIFICIAL NEURAL NETWORK AND NONDESTRUCTIVE TESTING

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Abstract

A promising substitute for regular concrete is geopolymer concrete. Engineering mechanical parameters of geopolymer concrete, including compressive strength, are frequently measured in the laboratory or in-situ via experimental destructive tests, which calls for a significant quantity of raw materials, a longer time to prepare the samples, and expensive machinery. Thus, to evaluate compressive strength, non-destructive testing is preferred. Therefore, the objective of this research is to develop an artificial neural network model based on the results of destructive and non-destructive tests to assess the compressive strength of geopolymer concrete without needing further destructive tests. According to the artificial neural network analysis developed in this study, the compressive strength of geopolymer concrete can be predicted rather accurately by combining the results of the non-destructive with R^2 of 0.9286.

Keywords:

Artificial neural network;
 Geopolymer concrete;
 Nondestructive test;
 Ultrasonic pulse velocity;
 Schmidt rebound hammer.

1 Introduction

A form of concrete called Geopolymer Concrete can be utilised to build any type of civil engineering or structural engineering project [1]. It is referred to as sustainable concrete since it can be used as a substitute for traditional concrete and uses industrial solid wastes like slag and fly ash as a binding material in the mixture, which indirectly reduces CO₂ emissions [2]. After the geopolymerisation reaction, an inorganic chemical bond is formed between silica and alumina. The highly alkaline conditions, in which the geopolymerisation reaction occurs, further activate the pozzolanic materials. The GPC uses pozzolanic materials high in alumina and silica content as a binding material [3]. Earlier studies have shown that GPC can achieve quite high Compressive Strength (CS) values up to 68 MPa [4]. Universal compression testing machines are generally used to impart destructive compression load on the cylindrical or cubic specimens, for evaluating the compressive strength of GPC. On the other hand, for in-situ compressive strength evaluation, compression testing using universal machines requires taking cores from the structural element which may harm the structure. Thus, other in-situ compressive strength evaluations should be considered such as non-destructive tests [5].

Non-Destructive Tests (NDT) are preferred over destructive testing techniques as they are rapid, inexpensive, easy to implement and do not cause any structural damage [6, 7]. Many researchers have used NDTs of concrete since there are considered a way to assess the strength, homogeneity, durability, and other characteristics of the existing concrete structures [8]. As several physical qualities of concrete are connected to its CS, several NDT evaluation techniques have been developed. Numerous researchers have investigated the application of NDTs for testing the GPC samples. The suitability of the non-destructive approach to determine the CS of various mixes with the grand granulated blast furnace-based GPC at various grades was examined by Patil et al. [9]. They noted a regression curve for all grades, between the CS results and the *RN* outcomes. Many researchers like Ravali et al., Yahya et al., and Muslum et al., investigated the possibility of using

NDTs such as the Ultrasonic Pulse Velocity (*UPV*) and the Schmidt Rebound Hammer (*SRH*) to forecast the *CS* of GPC. These studies revealed that, as in conventional concrete, there are correlations between the GPC *CS* and both *RN* and *UPV* [10, 11]. Many NDTs are combined and frequently used empirically, yet, owing to the limited number of existing NDTs, they were seen to be inaccurate. *CS* estimates are most frequently improved by combining two or multiple procedures; this is done based on the correlation between the observed measurement and desired value [12].

Combining different NDT results can be extremely helpful in generating concrete structure quantitative assessments [13]. In the past, popular NDTs like the *UPV* and the *SRH* have been used to detect *CS*. Additionally, their combination is regarded as a useful tool for evaluating the traditional concrete *CS* [14]. The combination of different NDT results to assist the geopolymer concrete *CS* was recently studied by several researchers. Sreenivasulu et al. used a linear regression technique, based on the *SRH*-Rebound Number (*RN*) and *UPV* data to forecast concrete *CS* during their study. Their results indicated that using multiple NDTs improves correlation and assists in the accurate assessment of concrete strength [15]. Also, Non-linear regression was utilised in combining *UPV* and *SRN* to anticipate the *CS* of GPC with different mixing proportions [16]. However, more accurate methods are required to predict the *CS* based on the NDT results.

Artificial Neural Networks (*ANN*) was one of the novels Machine Learning (*ML*) prediction techniques used in recent decades. *ANNs* refer to algorithms that replicate human neurons. The neurons are displayed as conceptual building blocks for circuits that might execute computational operations as well as models of actual neurons. An *ANN* processes information using a connectionist method and is made up of interconnected clusters of artificial neurons. Additionally, because *ANN* uses a non-linear activation function, it can characterise and recognise subtle non-linear relationships among many variables in incredibly complicated datasets. Additionally, it can relate and associate various factors to one another by storing the data in connection weights, which eliminates the challenges brought on by the absence of theoretical principles [17]. *ANN*, as a prediction tool, is widely used by the researchers in the field of concrete properties prediction. Almasaeid and Salman utilised *ANN* modelling in the anticipation of permeable concrete properties. Their study results proved that *ANN* is able to predict the properties of different types of concrete with acceptable accuracy [18]. Demir used the *ANN* technique for predicting the concrete *CS*, based on the *UPV* and *RN* results. The study showed that *ANN* can correlate the *CS* to *RN* and *UPV* with high accuracy reaching an R^2 of 0.975 [19]. Also, Almasaeid et al. utilised *ANN* modelling along with *UPV* and *SRN* to assist fire-damaged concrete by predicting the concrete compressive strength after high-temperature damage. Their study showed that the *ANN* has a high prediction ability to anticipate the concrete compressive strength with an R^2 of 0.87 [20]. On the other hand, the prediction of GPC compressive strength based on combining several NDTs using *ANN* was not studied by researchers before.

In this study, the researchers developed an *ANN* model for predicting the *CS* of the geopolymer concrete using data from the NDT processes based on the *SRH* and *UPV* results published in earlier studies. The developed *ANN* model provides a reliable, fast, and inexpensive alternative for regular *CS* destructive test.

2 Non-destructive tests

In this study, both ultrasonic pulse velocity (*UPV*) and Schmidt rebound hammer (*SRH*) as testing results are used to predict the *CS* of geopolymer concrete.

2.1 Ultrasonic Pulse Velocity (*UPV*)

The technique entails using a generator and receiver transistor to gauge the *UPV* value through the concrete. These tests are implemented on samples either in-situ or in a laboratory. Various factors can influence the results of the *UPV* test, like the surface and maturity of the concrete, the wave's travel distance, the age of the concrete, the proportion of the mixture, the kind and size of the aggregates, presence of reinforcement, the moisture content, etc. ASTM C597 has described this test in further detail [21]. There are three possible ways to perform *UPV*:

- directly (*D*),
- semi-directly (*S*),
- indirectly (*I*).

The differences between these three setups are shown in Fig. 1.

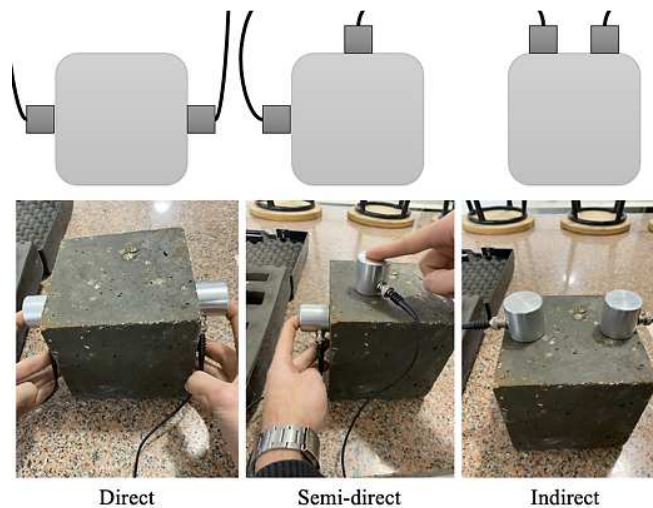


Fig. 1: Direct, semi-direct, and indirect *UPV* test setups.

2.2 Schmidt Rebound Hammer (SRH)

SRH is the oldest and most well-known NDT technique that is typically used to evaluate the concrete *CS* indirectly by comparing the concrete in different areas of the structure. The hammer, which weighs around 1.8 kg, is adequate to use, both in the field and in a laboratory. An elastic mass's ability to rebound is influenced by how stiff the surface that it impacts. ASTM C805 provides detailed information about this test. Many factors influence the SRH test results like the smoothness of test surface, sample age, shape, size, and rigidity of samples, type of cement, the surface and internal moisture condition of the concrete, type of coarse aggregate, and carbonation of the concrete surface, etc. [22]. Fig. 2 describes the setup of the SRH test.



Fig. 2: SRH test setups.

3 Data collection

In order to develop an ANN model predicting the GPC compressive strength based on NDT testing results, the datasets are collected from the following literatures:

3.1 Sreenivasulu et al. [15]

Sreenivasulu et al. (2018) examined many GPC mixtures with various fine aggregate blending techniques in their study. They combined differing ratios of granite fines and sand and granite slurry. 20- and 10-mm coarse aggregates are combined in a 60:40 ratio. The researchers combined the ground granulated blast furnace slag and the fly ash (class F) in a 50:50 ratio and used this mixture as a geopolymer binder. They further used a solution of sodium silicate and sodium hydroxide 8M as the alkaline activator. Results of SRH and *UPV* testing were recorded after curing the samples for 7, 28, and 90 days [15], before determining the compressive strength of the samples. Table 1 lists Sreenivasulu et al. samples mixing proportions and testing results [16].

Table 1: Sreenivasulu et al. samples mixing proportions and testing results.

Mix	Fly ash/ metakaolin [kg/m ³]	Coarse aggregate [kg/m ³]	Sand [kg/m ³]	Granite fines [kg/m ³]	NaOH molarity	Extra water [kg/m ³]	Age [days]	RN	UPV [km/sec]	CS [MPa]
100:0 7D 1	204.5	1290	459	0	8	92.5	7	30.6	3.1	30.89
100:0 7D 2	204.5	1290	459	0	8	92.5	7	29.8	3.02	27.78
100:0 7D 3	204.5	1290	459	0	8	92.5	7	29.9	3.07	28.58
100:0 28D 1	204.5	1290	459	0	8	92.5	28	41.2	3.26	45.33
100:0 28D 2	204.5	1290	459	0	8	92.5	28	45.7	3.27	48.4
100:0 28D 3	204.5	1290	459	0	8	92.5	28	40	3.22	43.87
100:0 90D 1	204.5	1290	459	0	8	92.5	90	43.5	3.62	51.47
100:0 90D 2	204.5	1290	459	0	8	92.5	90	45.4	3.69	55.91
100:0 90D 3	204.5	1290	459	0	8	92.5	90	43.8	3.68	53.2
80:20 7D 1	204.5	1290	439.2	109.8	8	92.5	7	31.6	3.13	32.58
80:20 7D 2	204.5	1290	439.2	109.8	8	92.5	7	32.4	3.09	31.29
80:20 7D 3	204.5	1290	439.2	109.8	8	92.5	7	32.6	3.15	32.04
80:20 28D 1	204.5	1290	439.2	109.8	8	92.5	28	44.5	3.44	50
80:20 28D 2	204.5	1290	439.2	109.8	8	92.5	28	44.4	3.41	46.22
80:20 28D 3	204.5	1290	439.2	109.8	8	92.5	28	43.9	3.47	48
80:20 90D 1	204.5	1290	439.2	109.8	8	92.5	90	47.3	4.08	55.73
80:20 90D 2	204.5	1290	439.2	109.8	8	92.5	90	45.8	4.16	57.11
80:20 90D 3	204.5	1290	439.2	109.8	8	92.5	90	45.8	4.12	58.22
60:40 7D 1	204.5	1290	329.4	219.6	8	92.5	7	32.5	3.2	32.62
60:40 7D 2	204.5	1290	329.4	219.6	8	92.5	7	32.8	3.22	34.22
60:40 7D 3	204.5	1290	329.4	219.6	8	92.5	7	33.7	3.23	35.07
60:40 28D 1	204.5	1290	329.4	219.6	8	92.5	28	46.7	3.55	54
60:40 28D 2	204.5	1290	329.4	219.6	8	92.5	28	46.6	3.52	51.42
60:40 28D 3	204.5	1290	329.4	219.6	8	92.5	28	46.2	3.47	48
60:40 90D 1	204.5	1290	329.4	219.6	8	92.5	90	47.3	4.35	58.04
60:40 90D 2	204.5	1290	329.4	219.6	8	92.5	90	47.6	4.37	58.4
60:40 90D 3	204.5	1290	329.4	219.6	8	92.5	90	46.5	4.37	63.33
40:60 7D 1	204.5	1290	219.6	329.4	8	92.5	7	24.6	3.01	20.84
40:60 7D 2	204.5	1290	219.6	329.4	8	92.5	7	25.8	3.07	23.42
40:60 7D 3	204.5	1290	219.6	329.4	8	92.5	7	25.5	3.04	22.89
40:60 28D 1	204.5	1290	219.6	329.4	8	92.5	28	30.2	3.23	34.84
40:60 28D 2	204.5	1290	219.6	329.4	8	92.5	28	26.8	3.21	32.04
40:60 28D 3	204.5	1290	219.6	329.4	8	92.5	28	30.6	3.17	34.53
40:60 90D 1	204.5	1290	219.6	329.4	8	92.5	90	31.2	3.48	43.24
40:60 90D 2	204.5	1290	219.6	329.4	8	92.5	90	31.6	3.42	34.53
40:60 90D 3	204.5	1290	219.6	329.4	8	92.5	90	32.6	3.44	37.87

3.2 Noori et al. [16]

Noori et al. investigated the relationship between the compressive strength and NDTs by testing two types of GPC (Fly ash and metakaolin). GPC mixes with three different molarity concentrations of sodium hydroxide NaOH and three different amounts of source material were tested using UPV and SRH. Table 2 lists Noori et al. samples mixing proportions and testing results [16].

Table 2: Noori et al. samples mixing proportions and testing results.

Mix	Fly ash/ metakaolin [kg/m ³]	Coarse aggregate [kg/m ³]	Fine aggregate [kg/m ³]	NaOH molarity	Extra water [kg/m ³]	RN	UPV [km/sec]	CS [MPa]
M1	400	1200	650	8	48	27.1	3.26	27.25
M2	500	1200	650	8	60	30.2	3.37	29.52
M3	350	1200	650	8	42	25.6	3.19	25.93
M4	400	1200	650	12	48	30.8	3.41	30.41
M5	500	1200	650	12	60	31.9	3.53	33.2
M6	350	1200	650	12	42	28.1	3.31	29.1
M7	400	1200	650	16	48	33.7	3.58	34.52
M8	500	1200	650	16	60	35.8	3.69	37.44
M9	350	1200	650	16	42	31.5	3.5	31.96
F1	400	1200	650	8	40	29.5	3.82	39.77
F2	500	1200	650	8	50	32.2	3.9	41.68
F3	350	1200	650	8	35	28.2	3.71	38.27
F4	400	1200	650	12	40	33.2	3.93	42.86
F5	500	1200	650	12	50	35.6	4	45.47
F6	350	1200	650	12	35	30.6	3.84	40.53
F7	400	1200	650	16	40	36.2	4.04	45.9
F8	500	1200	650	16	50	38.5	4.12	49.34
F9	350	1200	650	16	35	33.9	3.93	43.1

3.3 Muslum [11]

In Muslum's study, physical, mechanical, and microstructural characteristics of several GPC mixes were investigated. The GPC samples were prepared by mixing furnace blast slag, brick powder and slaked lime along with NaOH solution. The mechanical investigation included sample testing using UPV and SRH to estimate the GPC compressive strength along with the compression test. The mixing proportions and testing results for collected from Muslum's study are listed in Table 3 [11].

Table 3: Muslum's samples mixing proportions and testing results.

Mix	Furnace blast slag [g]	Lime [g]	Brick [g]	NaOH molarity	RN	UPV [km/sec]	CS [MPa]
G8M - 1 %	2000	20	200	8	36	3.5	31
G8M - 3 %	2000	60	200	8	37	3.8	29
G8M - 5 %	2000	100	200	8	39	3.9	33
G8M - 7 %	2000	140	200	8	38	3.7	32
G10M - 1 %	2000	20	200	10	35	3.4	25
G10M - 3 %	2000	60	200	10	36	3.4	26.5
G10M - 5 %	2000	100	200	10	34	3.3	24.5
G10M - 7 %	2000	140	200	10	31	3	22
G12M - 1 %	2000	20	200	12	35	3.2	16
G12M - 3 %	2000	60	200	12	33	3.2	23.5
G12M - 5 %	2000	100	200	12	39	3.7	29
G12M - 7 %	2000	140	200	12	36	3.4	26.5

The relationship between the CS of the GPC samples and the above-mentioned test results are presented in Fig. 3. Furthermore, the correlation between the results of the UPV and SRH test methods has been described in Fig. 4.

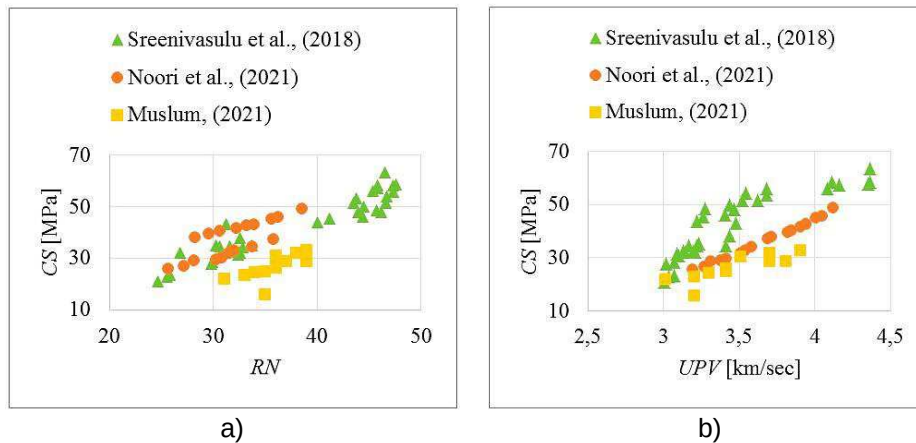


Fig. 3: Relation between NDT and GPC compressive strength: a) CS vs RN, b) CS vs UPV.

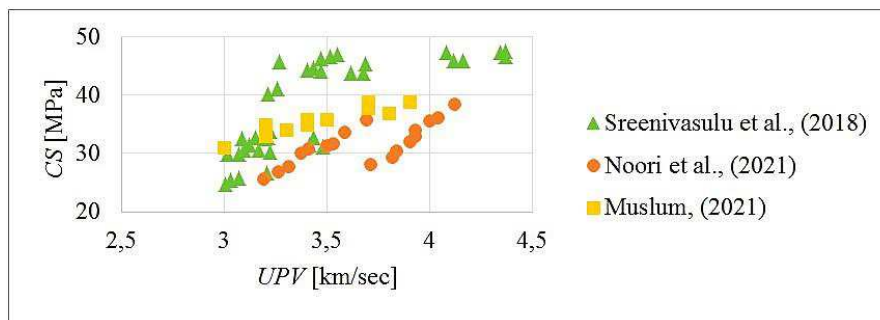


Fig. 4: Relation between SRN and UPV tests results.

4 Artificial neural network modeling

4.1 Data and model structure

The ANN model in this study is built using a training method known as Feed-forward error Back-propagation (FB). The FB networks have a layered structure, with a particular number of nodes in each layer. The nodes in the input layer represent the input variables that can influence the outputs. Nodes representing the input variables are found in the output layer. Amongst these layers, a few hidden layers have nodes (hidden) that permit data to flow from inputs to outputs. However, most FB ANN applications consist of integrated network designs that include just one hidden layer. There are three stages included in the FB network training process: feed-forward of the input training pattern, the connection link weights adjustment, and the error back-propagation and estimation of the relative error [23].

An ANN model is constructed to forecast the GPC compressive strength, i.e. CS. 66 experimental test results were used to develop this ANN model. The datasets are test results collected from the three different cited literatures. This model is set up with a single hidden layer that has a sigmoidal function.

If inputs and outputs are both normalised and scaled in such a way that the total data range between 0.1 and 0.9 before modelling, the ANN training model can display effective results. The output of the ANN model must be denormalised for generating results because scaling the inputs will also scale the output. The parameters, their maximal and minimal values, and the ANN-selected maximum and minimum values are listed in Table 4. All the parameters utilised in the ANN model are defined in Table 5.

The ANN_{max} and ANN_{min} values are used for data scaling from 0.1 to 0.9. The forecast made by the ANN model will be limited to the actual maximal and minimal values. The data are normalised and denormalised using equations (1) and (2), respectively [24]:

$$Normalized\ parameter_n = \frac{Parameter_n - ANN_{min}}{ANN_{max} - ANN_{min}}, \quad (1)$$

$$Parameter_n = (Normalized\ value \cdot (ANN_{max} - ANN_{min})) + ANN_{min}. \quad (2)$$

Table 4: Utilized datasets characteristics.

Parameter	Max.	Min.	ANN_{max}	ANN_{min}	$Scaled_{max}$	$Scaled_{min}$	Mean	Standard deviation
RN	47.6	24.6	53	20	0.836	0.139	35.74	6.64
UPV [km/sec]	4.37	3	4.6	2.75	0.876	0.135	3.51	0.36
CS [MPa]	63.33	16	70	10	0.889	0.1	37.88	11.27

Table 5: ANN model inputs and outputs.

	Parameter	Definition
Inputs	RNn	Normalized rebound number from Schmidt rebound hammer
	$UPVn$	Normalized ultrasonic pulse velocity
Outputs	CS	Normalized GPC compressive strength

Training datasets are used to optimise the weights of the network connections for various networks with hidden nodes ranging between 1 and 12. Various statistical parameters like the Mean Absolute Relative Errors ($MARE$), Average Squared Errors (ASE), and the coefficient of determination R^2 are estimated and presented for each trained network. The trained network having the minimal ASE value is referred to as the network having the optimum number of hidden nodes [25]. Following optimisation, the model is checked and validated by comparing its outputs to the validation datasets that were not included in the model's construction. A schematic diagram of the 2-n-1 ANN model (two inputs, n hidden nodes, and one output) is shown in Fig. 5. Also, this 2-n-1 ANN model can be mathematically expressed as shown in equations (3) and (4).

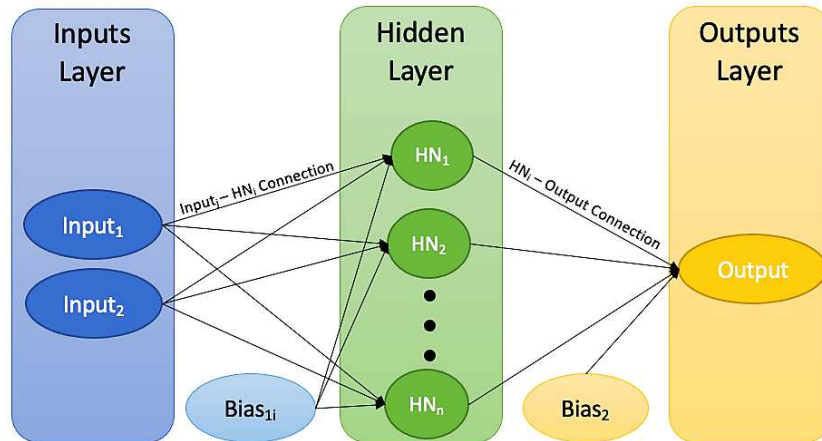


Fig. 5: Schematic of 2 inputs, n hidden nodes, and 1 output ANN model.

$$Output = \frac{1}{1 + e^{-\sum_{i=1}^n HN_i * (HN_i - Output Connection) + Bias_2}}, \quad (3)$$

$$HN_i = \frac{1}{1 + e^{-\sum_{j=1}^2 Input_j * (Input_j - HN_i Connection) + Bias_{1i}}}. \quad (4)$$

4.2 Model training and optimizing

For network optimisation, 66 sets of data are utilised. The dataset is divided into 50 sets of data for model training, and 16 sets of data for validation. Fig. 6 displays the statistical accuracy metrics for an ANN model trained with various numbers of hidden nodes. The network's optimum number of hidden nodes is found to be 5, based on the displayed values since it showed the lowest $ASE_{training}$ value. Hence, the model is denoted by its architecture as 2-5-1 with $ASE_{training} = 0.002876$, $MARE_{training} = 8.15$, and $R^2_{training} = 0.928$. Table 6 lists the connection links' weights between the nodes in different layers.

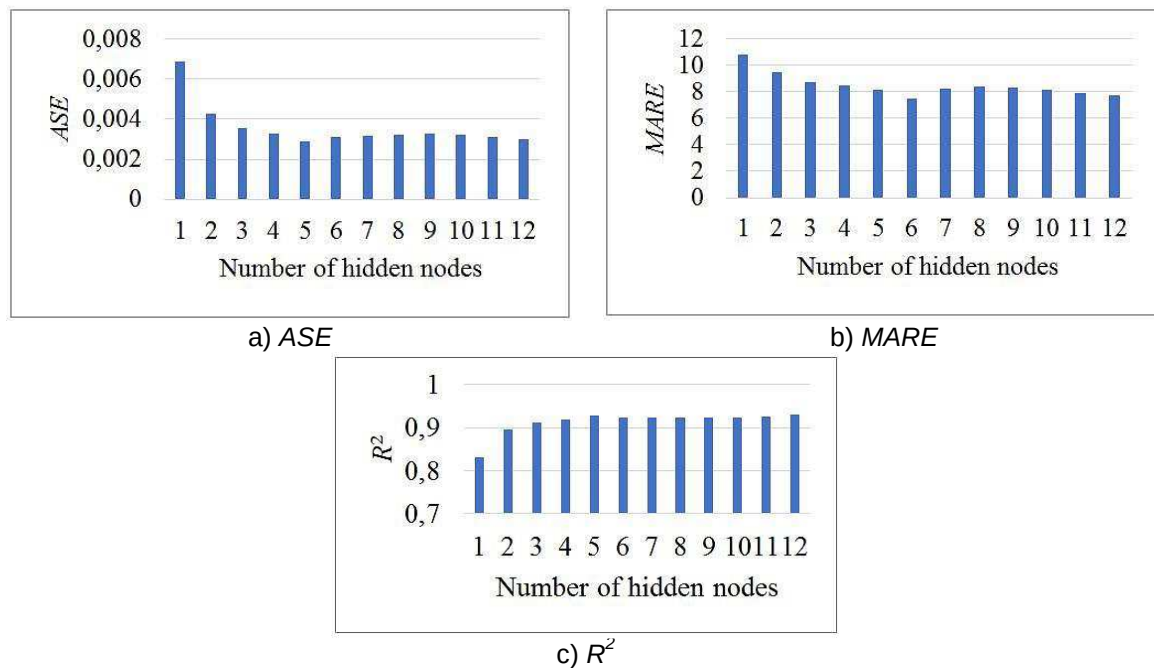


Fig. 6: The statistical accuracy measurements of the developed ANN model.

Table 6: Connection links weight used in 2-5-1 ANN model.

Input _i	Connection links weights between inputs and hidden nodes (<i>Input_i - HN_i</i> connection)				
	HN ₁	HN ₂	HN ₃	HN ₄	HN ₅
<i>RNn</i>	24.0660	2.2471	-4.3857	-1.1795	-1.3503
<i>UPVn</i>	-4.8405	-5.1543	-3.0684	-0.3532	-0.1430
<i>Bias_{1i}</i>	-13.3000	3.5688	-0.2343	-0.6313	-0.1786
Output	Connection links weights between hidden nodes and outputs (HN _i – Output connection)				
	HN ₁	HN ₂	HN ₃	HN ₄	HN ₅
<i>CSn</i>	1.6881	-4.8300	-2.9304	1.1737	1.4614
					<i>Bias₂</i>
					3.2539

5 Discussion

In order to check the accuracy and predictability of the developed model, the model is validated and tested using 16 validation datasets not included during the model training. The following statistical values were calculated as they represented the prediction accuracy model: $MARE_{validation} = 10.884$, $ASE_{validation} = 0.004941$, and $R^2_{validation} = 0.85042$. In addition, Fig. 7 illustrates a comparison between the experimental datasets and the ANN prediction outcomes for the validation results. Thus, validation projected versus experimental data results and the validation statistical accuracy measurements show that the 2-5-1 ANN model predictions are significantly acceptable and appropriate.

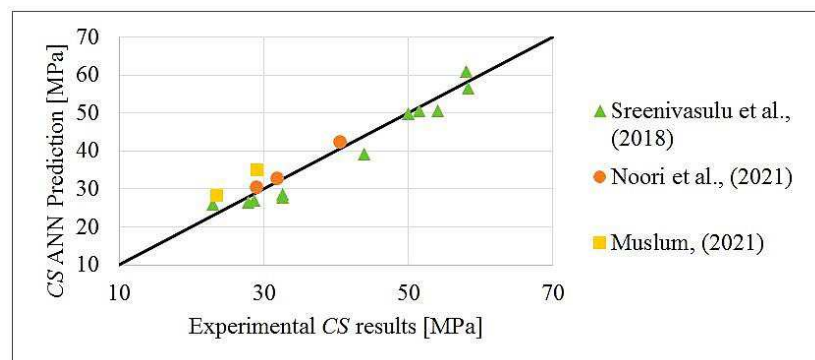


Fig. 7: CS validation data prediction results of the 2-5-1 ANN model vs experimental results from different cited literatures.

Moreover, the proposed 2-5-1 ANN model is compared to other published models used *UPV* and *SRH* to predict the *CS* of GPC. Table 7 lists the comparisons between the developed and the previously published models for the 66 sets of data used in this study. Also, Fig. 8 illustrates this comparison. The results in Table 6 and Fig. 8 show that the proposed 2-5-1 ANN model has outperformed the other models.

Table 7: Models' comparison.

Literature	Expression for CS [MPa]	R^2
Sreenivasulu et al. [15]	$CS = 7.966UPV + 1.125RN - 27.759$	0.729
Noori et al. [16]	$CS = -96.341447RN^{-0.243311} + 0.049966UPV^{0.898066}$	0.610
Proposed ANN model	5 – 5 – 1 ANN	0.872

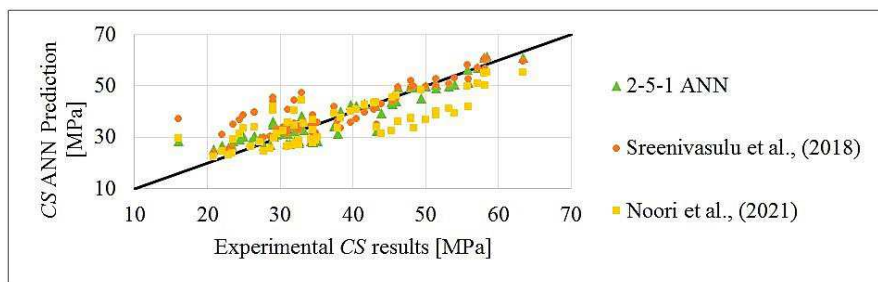


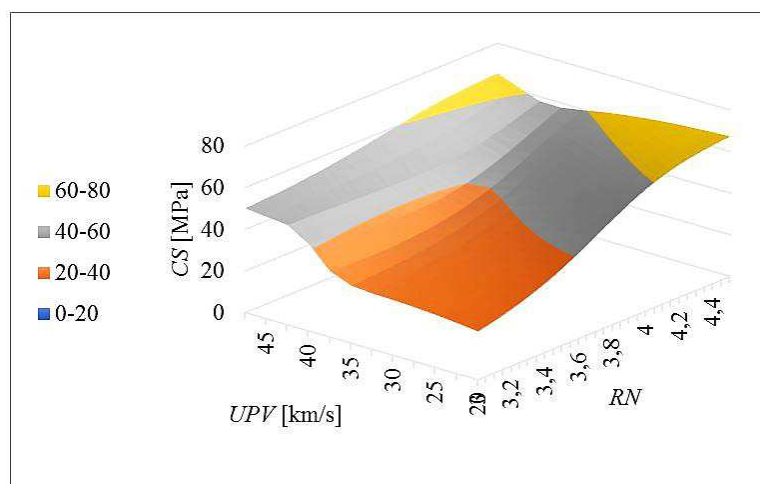
Fig. 8: Models' comparison.

Additionally, the connection weight-based importance factor approach, proposed by Olden and Jackson, is used to judge the importance of *RN* and *UPV* in the 2-5-1 ANN model. This method calculates the total connection weights of every input as the product of input-hidden and hidden-output connection link weights, existing between every input and output, and then adds the products for all hidden nodes to obtain the importance factor [24]. Table 8 lists the importance factor values of *RN* and *UPV* based on the connection links weights listed in Table 4. The importance factor values indicate that both inputs are important to the 2-5-1 ANN model. However, *RN* has a higher impact on the GPC *CS* prediction.

Table 8: The overall connection weight of *RN* and *UPV* in the 2-5-1 ANN model.

Input	<i>RN</i>	<i>UPV</i>
Importance factor	39.266	25.092

Also, the developed ANN model is used to generate contour map, this contour map describes the relation between *RN*, *UPV*, and GPC *CS*. Fig. 9 shows the relation between the NDTs and the GPC *CS*.

Fig. 9: Contour mapping between *RN*, *D-UPV*, and *CS*.

6 Conclusions

In this study, a single-hidden layer feed-forward error back-propagation artificial neural network model was trained, optimised, and validated in order to predict the geopolymer concrete compressive strength. The optimum model was found to have five hidden nodes with a sigmodal activation function. The utilized datasets in the modelling were collected from three cited literatures with a total of 66 testing results.

Based on the applied artificial neural network analysis, the researchers could model the relationship between non-destructive tests and the compressive strength of the geopolymer concrete for strength values ranging between 16 and 63 MPa, with a mean absolute relative error of 8.15, average squared error of 0.002876, and coefficient of determination R^2 of 0.9286. As non-destructive testing, the developed model utilized results of ultrasonic pulse velocity ranging from 3 to 4.37 km/sec and Schmidt rebound number ranging from 24 to 48. The model proposed in the study performed better than both the linear $R^2 = 0.729$ and the non-linear regression $R^2 = 0.0.610$ models that had been previously published in cited literatures. Since it incorporated the datasets from the earlier published studies, the ANN model developed here can be considered a generic model.

Reached from the previous conclusions, it is recommended to consider other geopolymer concrete mechanical properties such as elasticity modulus, flexural strength, and tensile strength in future ANN modelling.

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