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# ANN- PSO modelling for predicting buckling of self-compacting concrete column containing RHA properties

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**ABSTRACT**

In recent decades, concrete technology has reached the broad-based areas of operations through the implementation of Self Compacting Concrete to increase the concrete performance. Due to high silica content, the pozzolonic characteristic of RHA makes it as a supplementary material for cement. In this paper, Cement was partially replaced with Rice Hush Ash of 5%, 10% 15%, 20%, 30% and 40% influencing the properties of SCC. The aim of this report is to explore the effect of cement replacement by RHA on the fresh and mechanical properties of SCC. In addition, the bucking behaviour of the axial loaded reinforced concrete column was predicted using Artificial Neural Network. Experimental data are collected and 100 experimental data is used for training the ANN model and 20 sets of data is utilized for testing. From the results it is observed that SCC blended with RHA shows the positive relationship between 30% replacement of RHA with an increase in the strength of compression and tensile strength of around 6. The buckling behaviour of the 70% Cement + 30% RHA SCC reinforced column was predicted by ANN- PSO is a precision and efficient model.

**Keywords:** Self-compacting concrete; Rice Husk Ash; Artificial Neural Network; Fresh properties; Mechanical properties; Buckling of Column.

## 1. INTRODUCTION

A homogeneous mixture which plays a essential role in the construction industry is concrete which is a mixture of cement, Fine aggregate, Coarse aggregate and water. Admixtures are added in the concrete to develop its workability. Many researchers have been carried out in increased in the performance of the concrete. One such advancement is the development of Self Compacting Concrete (SCC). In 1988, Self-Compacting Concrete was first developed by Japan, due to decreasing number of skilled labours in the construction industry [1]. Due to different applications and structural configurations, SCC has been widely used in many countries [2]. Compared with conventional concrete, SCC includes large amounts of binder, superplasticizer, and supplementary cementitious materials and various quantity of powder or viscosity modifying admixtures like rice husk ash, fly ash, and ground granulated blast furnace [3]. The term powder was defined by ANWAR [4]which is the materials of particle size smaller than 0.125mm which includes the fraction of aggregate, additions and cement [5]. SCC is a concrete that can flow within the formworks, pass through the reinforcing bars, and completely fill the mould, with no disintegration or exudation, and compaction produced simply by the weight of the concrete [6]. The structural properties of the SCC were improved by the addition of different mineral admixtures [7].

SCC has various numbers of advantages because it can able to flow due to its own weight [1]. Some of the advantages are listed below.

- Improved concrete quality and reduces the maintenance on site.
- Faster construction times.
- Health and the safety improvements are achieved by the reduction of vibrator Handling.
- Possibilities for the use of dusts, which are currently waste products and difficult to dispose.
- Quick positioning contributes to cost savings through reduced equipment and labour requirement.

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Rice husk Ash is the product obtained by burning the Rice husk generated from the rice mills. During milling of paddy, the husk has generated which contains 75% of organic volatile materials and leaving 25% converted in to ash, known as RHA obtained during the burning process. The RHA has 85 to 90% amorphous silica [8]. Many investigations have made on the usage of RHA in concrete productions and had the results positive [9]. The silica extraction process and pozzolanic materials are some of the commercial uses of the RHA in self-compacting concrete [9]. The high reactivity in cement is due to finely ground RHA and is used to decrease both the porosity and thickness of the interfacial region of the transition [10, 11]. Due to improper disposal, RHA leads to environmental hazard [12]. The fineness of RHA affects the activation process of pozzolanic properties of crystalline type of RHA [13, 14]. Research to substantiate the feasibility of low – cost SCC production using RHA was carried out. The SCC compressive strength with RHA of 10% and 20% in comparison with normal concrete of two water-binder ratio of 0.4 and 0.35 was studied at the age of 180days [15]. The increase in compressive strength at the age of 58days due to inclusion of RHA was observed because of the micro filling ability and pozzolanic activity of RHA [16]. By enhancing the pore structures and packing density, the compressive strength of the SCC is improved with the addition of minerals like limestone powder and coal fly ash along with RHA is due to filler effect of mineral additives [17].

In the world of Civil Engineering, developments in the field of artificial intelligence continue to have the strong impact. New techniques and algorithms are developing that enable Civil Engineers to be able to use computing in various forms [18]. ANN, which is a computational instrument, is an alternative method determines the buckling load of the columns. ANN aims to model the human brain and the neuron systems design. ANN technique is used to many engineering structural problems like predicting the compressive strength and Modulus of elasticity [19, 20], Structural analysis and Design 2000, Non Destructive testing of materials, Prediction of Ultimate strength of reinforced beams [21]. No literature is there for the prediction of deflection of the column subjected to axial load with the applications of ANN. Hence this was the motivation of this present study.

The main aim of this research work was to utilize rice husk ash in SCC and to find out the fresh properties and hardened properties like compressive and split tensile strength at the different levels of the cement replacement (5%, 10%, 15%, 20%, 30% and 40%) along with the rice husk ash. In addition to this, Artificial Neural Network (ANN) model is used to predict the deformation for the axial load capacity of the reinforced RHA induced self-compacting concrete column.

## 2. MODEL DETAILS

### 2.1. Artificial Neural Network (ANN)

ANN is the emerging new modelling techniques applicable for the various technology fields and particular for the problems where the simple equations cannot be directly related to the input and output values. A functional abstraction of the biological neural systems of the human brain is the Artificial Neural Network (ANN) and was developed in the early 1980s which is the new branch of artificial intelligence. The processing unit, learning rules and connection formula characterize the basic components of ANN [22, 23]. ANN models consist of three or more layers, including an input layer, an output layer and a hidden layer in which the neurons of different weights are linked with each other [23, 24]. ANN can be trained to solve the problems in any fields and its architecture is classified as feedback network and feed-forward network [24, 25]. A multilayered feed-forward neural network with the back propagation algorithm which is a most widely used algorithm was used in this present investigation. Figure 1 presents the typical structure of an ANN.

Artificial Neural Networks, with their ability to model complex nonlinear relationships, can be trained to learn the underlying patterns and correlations within the available data. By feeding the neural network with input data (e.g., material properties, geometric parameters, etc.) and their corresponding buckling outcomes, the network can learn to predict buckling behavior based on the provided inputs. The backpropagation algorithm is then used to adjust the network's weights, iteratively improving the prediction accuracy.

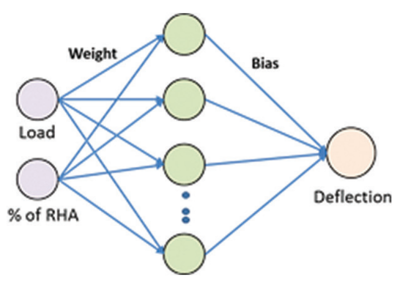


**Figure 1:** Schematic representation of Neural Network.

### 2.2. Particle Swarm Optimization (PSO)

Particle swarm optimization is an advanced computation approach developed in 1995 by EBERHART and KENNEDY [25], [13]. The social behaviour of the animals like bird flocking and swarm of fishes was the underlying motive for the creation of PSO algorithm. A hypothesis that social exchange of knowledge between the consecrated persons provides an evolutionary advantage is the key to the creation of PSO. Velocity, Cognitive and social are the three components exhibiting in PSO algorithm. The PSO algorithm's mode of operation is based on personal experience ($P_{best}$), overall experience ($G_{best}$) and to optimize a problem, PSO is used by considering a population of candidate solutions called "Particles" and the present particle movement is to assess their next location in the space to find a desired target. Stochastic component and deterministic components are used to adjust the movement of the particle [26]. The main advantage of the particle swarm optimization algorithm is that prior to the common statistical models, no prior knowledge is required concerning the type of relationship between the input and output data [27]. PSO works with the following simple equations [Eq.(1)–Eq.2)]

$$\overrightarrow{V_{new}} = \vec{V} + r_1 c_1 \times \left(\overrightarrow{P_{best}} - \vec{P}\right) + r_2 c_2 \times \left(\overrightarrow{G_{best}} - \vec{P}\right) \tag{1}$$

$$\overrightarrow{P_{New}} = \vec{P} + \overrightarrow{V_{New}} \tag{2}$$

Here $V_{New}$ is the new velocity, V is the Current velocity, $P_{New}$ is the new position and P is the current position for the given set of particles. In addition to this, C1 and C2 are the acceleration constant, and the best position of the particle and the particles in the set are given as $P_{best}$ and $G_{best}$. The range of the arbitrary constants $r_1$ and $r_2$ is 0 to 1.

The changes on the position of the one particle and other particles are determined by assigning ANN weights to the velocity and the position of the particles and they are updated to reach the termination criteria [28]. If "t" is the time interval, the new position of the particle is given by Eq. (3),

$$x^p(t+1) = x^p(t) + v^p(t+1) \tag{3}$$

Here, $x^p$, position of the particle P at time "t", $v^p$ (t + 1) is the new velocity of the particle at the time t + 1. The New velocity vector is obtained as follows [Eq. (4)],

$$V_j^p(t+1) = i(t)V_j^p(t) + \mu\omega_{1j}(t)(y_j^p(t) - x_j^p(t)) + V\omega_{2j}(t)(\hat{y}_j(t) - x_j^p(t)) \tag{4}$$

For i =1 to n, $\mu$ is the cognitive parameter and $i(t)$ is the weight factor and V is the social parameter. $\omega_{1j}(t)$ and $\omega_{2j}(t)$ are the random numbers obtained from the uniform distribution $y_j^p(t)$ is the personal best objective function and the $\hat{y}_j(t)$ is the best goal function of the population.

## 3. EXPERIMENTAL WORKS

### 3.1. Materials

Cement, Aggregates (Fine Aggregate and Coarse Aggregates), Rice husk ash, Super plastizers are the various materials used in this experimental work on SCC.

#### 3.1.1. Cement

The cement used in this experimental work is Ordinary Portland cement conforming the grade 53.

#### 3.1.2. Coarse aggregate and fine aggregate

The local sand which has been washed and sieved to remove particles larger than 5mm was used in this research work and coarse aggregate of 20mm size aggregate is used for the Self-Compacting Concrete.

#### 3.1.3. Water

In line with the quality standards of drinking water, mixing water quality is needed. Fresh and clean water was used for casting and curing of specimens. The pH value of the water was found to 7.2.

#### 3.1.4. Admixture

The Superplasticizer (Ceraplast 400) and Viscosity Modifying agent (Auromix V100) were used in this investigation.

#### 3.1.5. Rice Husk Ash

The main element of this research is the decision to use rice husk ash (RHA) as a cement substitute material. Pictorial view of Rice Husk Ash shown in the Figure 2. RHA has pozzolanic properties and similar characteristics to other cement substitute materials that are typically used in the production of SCC, to assess its suitability for producing SCC. The chemical and physical properties of the materials used in this research activity are given in the Table 1 and Table 2.

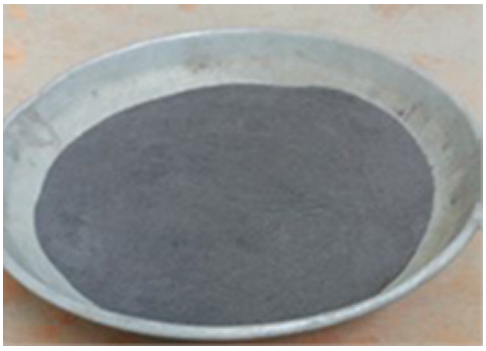

**Figure 2:** Rice Husk Ash.

**Table 1:** Chemical properties of cementing materials.

| COMPONENTS | CHEMICAL ANALYSIS (%) | |
|---|---|---|
| | CEMENT | RHA |
| $SiO_2$ | 17.12 | 86.94 |
| $Al_2O_3$ | 4.16 | 0.2 |
| $Fe_2O_3$ | 3.53 | 0.1 |
| CaO | 67.47 | 1.32 |
| MgO | 1.39 | 0.6 |
| $K_2O$ | 0.74 | 1.65 |
| $Na_2O$ | 0.11 | 0.16 |
| $SO_3$ | 4.05 | 0.43 |

**Table 2:** Properties of concrete constituents materials.

| CONSTITUENT MATERIALS | PROPERTY |
|---|---|
| Cement (C) | Specific Gravity: 3.16 |
| | Initial Setting Time: 28 min |
| | Consistency: 36% |
| Fine Aggregate (FA) | Specific Gravity: 2.54 |
| | Fineness modulus: 2.61 |
| Coarse Aggregate (CA) | Specific Gravity: 2.56 |
| | Fineness modulus: 6.90 |
| Rice Husk Ash (RHA) | Specific Gravity: 2.30 |
| | Fineness (Blaine's): 16000 $cm^2/gm$ |
| | Loss of Ignition: 3.6% |

### 3.2. Mix proportions

The mix proportions of SCC for M30 grade of concrete are designed based on EFNARC [29] guidelines and are presented as 1: 2.17: 1.66 with the water/cement ratio of 0.45 (Table 3). In all the mixtures the w/c ratio was kept as constant value. The control mixture containing no admixture and the test mixture, the cement is replaced with 5%, 10%, 15%, 20%, 30% and 40% with the Rice Husk Ash.

### 3.3. Tests for fresh concrete

According to the procedure recommended by the EFNARC committee, to obtain the self-compacting fresh properties the slump flow, T50 slump, V- Funnel and L-box test were performed in these present investigations. The average of the measurements was given from all the measurements of the fresh test. The properties of the fresh state mixes were obtained within the time period of 30minutes after mixing of the concrete, to reduce the effect of losses in workability. The testing order follows as (i) Slump Flow test, (ii) V-Funnel Test (iii) L- Box test.

### 3.4. Tests on hardened concrete

The concrete moulds were prepared after the completion of initial fresh concrete tests. Three cubes of size 150 × 150 × 150mm were prepared for each mixture to evaluate the compressive strength of the concrete and to determine the split tensile strength cylinders of size 150 × 300mm were prepared as per IS 516:1959 [30].

**Table 3:** Mix proportion.

| CEMENT | FINE AGGREGATE | COARSE AGGREGATE | w/c RATIO |
|---|---|---|---|
| 437 $kg/m^3$ | 949.45 $kg/m^3$ | 726.28 $kg/m^3$ | 0.45 |

**Figure 3:** Measurement of the slump.

**Figure 4:** V-Funnel test.

## 4. RESULTS AND DISCUSSION

### 4.1. Properties of fresh concrete

Slump Flow, T50 slump, V-funnel and L box test was conducted to determine to the Segregation, passing ability and deformability respectively according to the procedure recommended by European Federation for Specialist Construction Chemicals and Concrete Systems (EFNARC) [29]. The workability and the filling ability of SCC was assessed using slump flow test. The slump flow reflects the average concrete mass diameter which is determined by the release of the typical slump cone and measured in the two directions that are perpendicular [31], [28]. KHAYAT [32] summarized the basic workability criteria for an effective SCC as: Excellent, reasonable stability and low risk of obstruction. The slump flow value ranges between 650 -800mm is typically required for SCC [EFNARC]. The measurement of the slump is shown in Figure 3. The concrete will segregate if the slump flow is more than 700mm and the concrete will have insufficient flow to pass through the congested reinforcement if it is less than 500mm [33].

V- funnel test was performed in addition to the slump flow test to assess the flowability and stability of SCC. For SCC, the V funnel time which is less than 6sec is recommended. Viscosity can be assessed by the T500 time during the slump-flow test or assessed by the V-funnel flow test as shown in Figure 4. Low-viscosity concrete will have a very rapid initial flow and then stop. High viscosity concrete may continue to creep forward over an extended period of time [34]. To ensure the satisfactory properties of the fresh concrete L –box test was carried out as per the guidelines [35]. For the control mix, the passing ratio is 0.85 and for the other mixes is found to be 0.84 to 0.89. Moreover, the addition of RHC into SCC improves the passing ability [36]. Table 4 shows the fresh properties of self-compacting concrete.

**Figure 5:** Compression testing.

**Figure 6:** Split tensile strength test.

**Table 4:** Fresh properties of self compacting concrete.

| WORKABILITY PERFORMANCE (WORKABILITY TEST) | ACCEPTANCE CRITERIA FOR SCC AS PER EFNARC (REQUIREMENTS) |
|---|---|
| Slump Flow - 680mm | 650–800mm |
| $T_{50}$ Slump (sec) - 4 | 3–7 |
| V–Funnel (sec) - 6.5 | 8–12 |
| L–Box ($H_2/H_1$) - 0.85 | 0.8 to 1.0 |

### 4.2. Properties of hardened concrete

#### 4.2.1. Compressive strength

To calculate the compressive strength of concrete cube specimen of size 150 × 150mm in compliance with IS 516-1959 [30] a 1000kN capacity universal testing machine was used (Figure 5). At the ages of 7, 14 and 28days, the evaluation was performed [37, 38]. For each batch, three specimens were measured and the average value was determined in order to find the compressive strength. The Eq. (5) used to find the compressive strength calculation is;

$$compression\,strength\ (\mathrm{N/\,mm^2}) = \left(\frac{Load\ in\ \mathrm{kN}(P)}{Area\,of\ cross\,section\,in\ \mathrm{mm}^2\,(A)}\right) \tag{5}$$

Table 5 shows the compressive strength of the SCC + RHA. The control concrete develops 25.102, 30.48, 35.86 MPa at the age of 7, 14 and 28days respectively. The range of the SCC developing the compressive strength is 20.064 to 27.59Mpa, 25.02 to 33.34Mpa and 28.26 to 38.33Mpa at 7, 14 and 28days. Furthermore, the findings show the rapid and highest growth in intensity at the age of 7days and 28days. The maximum compressive strength (38.33Mpa) obtained at 70% of FA and 30% RHA at the age of 28days which is more than the strength of the control concrete and more than the target mean strength (38.25MPa) of SCC. It was observed that 6.44% of strength was increased compared to the control concrete at 28days curing. The compressive strength of control specimen at 28days of curing is 35.86MPa which is higher than compressive strength of 95% FA +5% RHA by 21.19%. The compressive strength of 90% FA + 10% RHA is 15.11% lower than control specimens (Figure 7). But the compressive strength of 70% FA + 30% RHA has 6.88% greater than the control specimen. This is due to pozzolonic activity of the concrete. The integration of FA and RHA blends enhanced the production of compressive strength as the smaller particles of FA filled voids within the mixture and decreasing the porosity [45, 46].

#### 4.2.2. Split tensile strength

The split tensile strength at the age of 28days of the self-compacting concrete cylindrical specimen of size 150mm × 300mm was carried out as per IS 5816-1999 [30].This specimen was shown in the Figure 6. The split tensile strength was obtained using the following relation [Eq. (6)],

$$f_{ct} = \left(\frac{2P}{\pi l D}\right) \tag{6}$$

Where, $f_{ct}$ is the split tensile strength, P is load in kN, l in Height of the Specimen in mm, D is Diameter of the Specimen in mm.

The results of the split tensile strength test which was determined after the period of 28days is shown in the Figure 8. The split tensile strength increases from 2.69 to 3.83MPa. The split tensile strength of the RHA induced SCC mixes was higher than those of normal SCC mixes at the age of 28days. The normal SCC exhibits the split tensile strength of 3.586MPa at 28days of curing. The equivalent splitting tensile strength values are obtained for 70%FA + 30% RHA SCC mixes (3.83MPa) and hence this mixture is considered as optimum value for tensile strength (Figure 8). RHA has not had significant changes in compressive strength and around 15 to 30% RHA as partial replacement of Cement is acceptable [35].

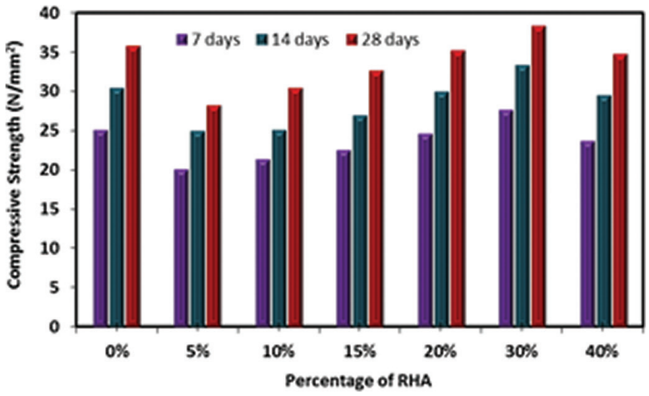


**Figure 7:** Comparison of compressive strength for different % of RHA.

**Table 5:** Compressive strength of RHA blended with concrete [39].

| RHA (%) | COMPRESSIVE STRENGTH (N/mm$^2$) | | |
|---|---|---|---|
| | 7 DAYS | 14 DAYS | 28 DAYS |
| 0 | 25.102 | 30.48 | 35.86 |
| 5 | 20.064 | 25.02 | 28.26 |
| 10 | 21.338 | 25.10 | 30.44 |
| 15 | 22.563 | 26.98 | 32.10 |
| 20 | 24.64 | 30.01 | 35.20 |
| 30 | 27.59 | 33.34 | 38.33 |
| 40 | 23.664 | 29.55 | 34.80 |

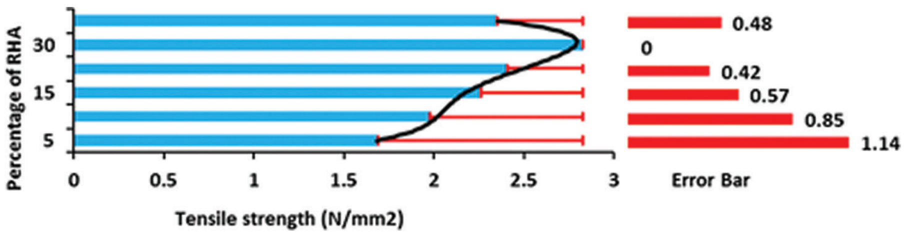


**Figure 8:** Variations of split tensile strength.

### 4.3. Validation of the model

Totally 80 data are used for predict the buckling deflection of the RHA column member, 70% and 30% of data sets are used for training and testing purpose of ANN-PSO model. In this data set, having two input; load and percentage of RHA and one output of deflection. The correlation between the input and output are shown in Figure 9.

Root Mean Square Error (RMSE) is used as the fitness function with the goal of minimizing the cost of function value. PSO parameters are set to: Population Size = 20; Maximum Number of Iteration = 100; Inertia weight = 1; Personal Learning co-efficient = 1.5; Global learning co-efficient = 2; Lower bound co-efficient = 5; Upper bound co-efficient = 5. The performance of model iteration with respect to RMSE value is shown in Figure 10. Root mean square error (RMSE), coefficient of determination ($R^2$) is the statistical parameters used for evaluating the performance of the ANN model. The more accurate prediction results and the greater fit between the experimental and the predicted value is obtained as lower of the RMSE value and the higher of $R^2$ value respectively. The parameter used for the ANN testing is given in the Table 6. After much iteration for training ANN, the model verified the best performance (RMSE) by the determination coefficient and the Figure 11 and Figure 12 shows the best regression coefficient R for the training, validation and the test data. From the plot, it is clear that there is a reasonable agreement between the expected results and the target results.

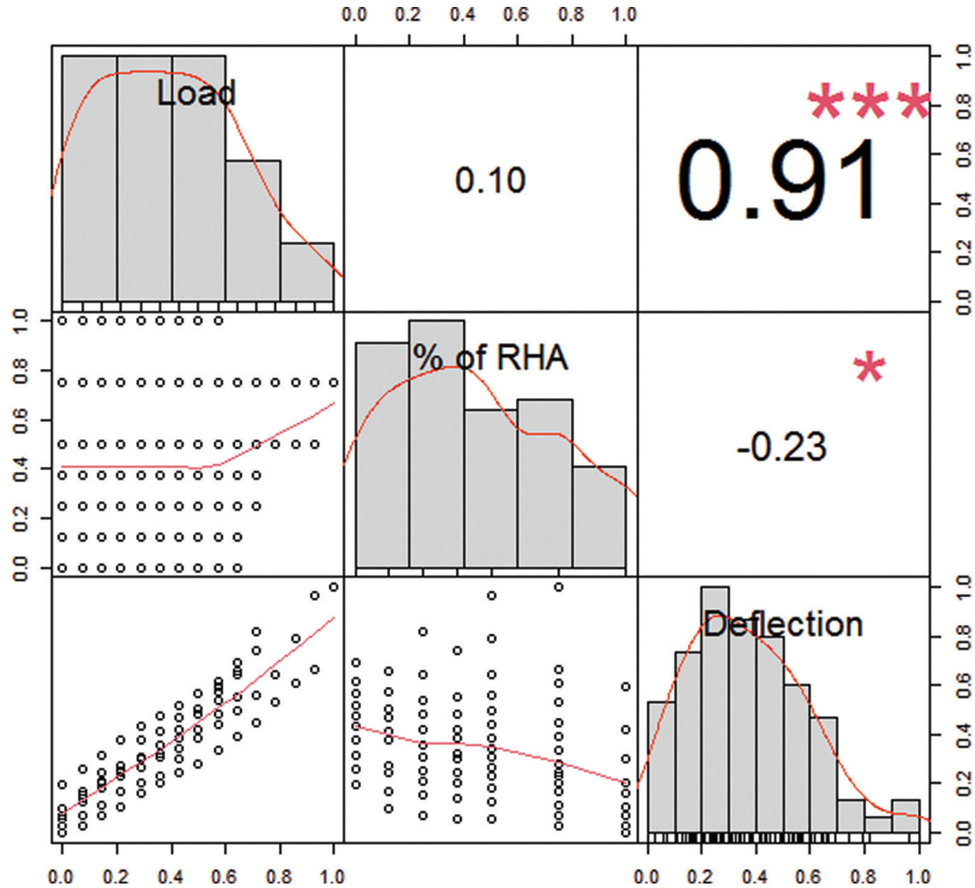


**Figure 9:** Correlation matrix for dataset.

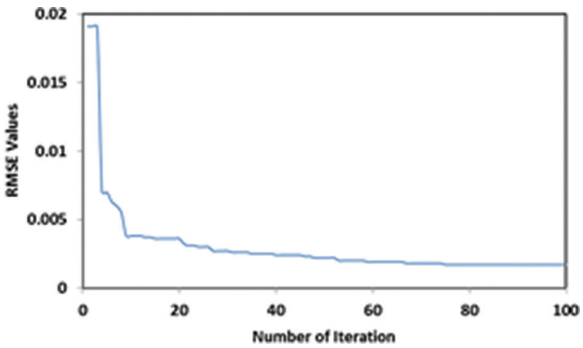


**Figure 10:** Performance of the ANN-PSO iteration.

### 4.4. Evaluation of the accuracy of the computing methods

The coefficient of $R^2$, Root Mean Square Error (RMSE), and Mean absolute Percentage Error (MAPE) are the criteria chosen to evaluate the performance of the soft computing methods [40]. $R^2$ shows how well the measured dependent variable account for the independent variables and it can be calculated as follows, [Eq. (7)–Eq. (11)]

$$R^2 = 1 - \frac{\sum_{i-1}^{n_i}(x_i - \bar{x}_i)(y_i - \bar{y}_i)^2}{\sum_{i=1}^{n_i}\bar{x}_i^2\bar{y}_i^2} \quad (7)$$

The root mean square Error is calculated using the following relations

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \quad (8)$$

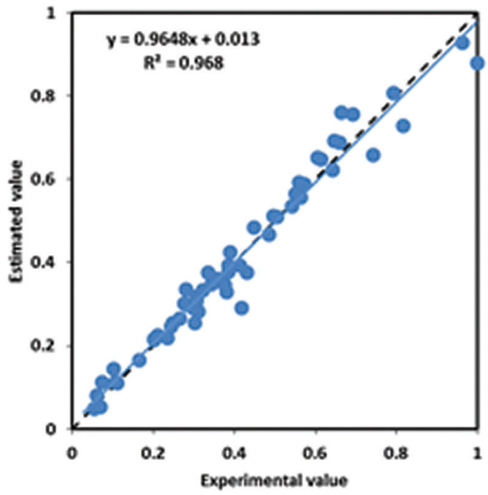


**Figure 11:** ANN- PSO training.

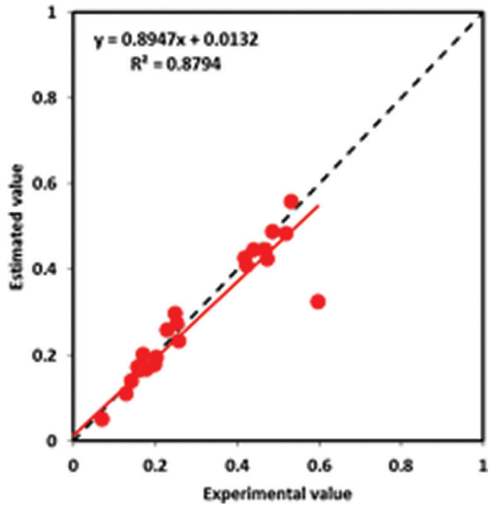


**Figure 12:** ANN- PSO testing.

The Mean absolute percentage Error (MAPE) are computed as follows

$$MAPE = \frac{1}{n_i}\sum_{i=1}^{n} 100 \times \left| \frac{x_i - \overline{x}_i}{x_i} \right| \tag{9}$$

The mean absolute error is calculated using the relations

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(y - \overline{y}\right) \tag{10}$$

The variance account factor (VAF) is also estimated using the relation

$$VAF = \left[1 - \frac{var\left(x_i - y_i\right)^2}{var\left(x_i\right)}\right] \times 100 \tag{11}$$

The ANN-PSO model will be excellent when the value of $R^2$ is 1, VAF is 100 and RMSE is 0. From the Table 7 of the statistical parameters, it is observed that the values are $R^2$ is nearly equal to 1. In addition, the

**Table 6:** Training parameter for ANN – PSO models.

| PARAMETERS | VALUE |
|---|---|
| Population Size | 20 |
| Maximum Number of Iteration | 100 |
| Inertia weight | 1.0 |
| Personal Learning co-efficient | 1.5 |
| Global learning co-efficient | 2.0 |
| Lower bound co-efficient | 5.0 |
| Upper bound co-efficient | 5.0 |

**Table 7:** Statistical value of the optimum BPNN.

| PARAMETER | ANN-PSO | | IDEAL VALUES |
|---|---|---|---|
| | TRAINING | TESTING | |
| **$R^2$** | 0.9679 | 0.8659 | 1 |
| **RMSE** | 0.0408 | 0.0616 | 0 |
| **VAF** | 96.7954 | 86.5948 | 100 |
| **MAPE** | 10.6631 | 15.3750 | 0 |
| **MAE** | 0.0289 | 0.0314 | 0 |
| **MBE** | –0.0011 | –0.0146 | 0 |

values of VAF, PI, WI, WAE, MAPE and MBE indicate that there is no ambiguity between the results as all the patterns are followed by all the parameters.

The parameter used for the ANN testing is given in the Table 6. After much iteration for training ANN, the model verified the best performance (RMSE) by the determination coefficient is shown in Figure 6 and the Figures 7, 8 shows the best regression coefficient R for the training, and the test data. From the plot, it is clear that there is a reasonable agreement between the expected results and the target results. These results show that with the error of 2.86%, the ANN was effective in training the relationship between the input and output data.

## 5. CONCLUSION

The fresh and hardened property of the SCC containing RHA and buckling behaviour of the column by ANN was systematically investigated in this present study. The following conclusions were drawn based on the results.

- RHA's high silica content is a pozzolanic construction material that is ideal for SCC long-term strength production.
- Increasing the content of RHA in SCC decreases workability. The concrete mixtures containing RHA should therefore be applied with super plasticizers to achieve the concrete more workable.
- All the SCC mixtures remained within the target range for each test as per EFNARC in terms of slump flow (680mm), T50 slump (4sec), V- Funnel (6.5sec) and L-box test (h2/h1 = 0.85).
- SCC's compressive strength and split tensile strength improves with an increase of up to 30 percent in RHA content due to its pozzolonic impact and enhanced concrete pore structure.
- The addition of RHA enhances the compressive strength and tensile strength. The replacement of 30% RHA shows the best improving effects, increasing the compressive strength of 7, 14 and 28days by 9.017%, 8.578% and 6.440% respectively. Similarly, the tensile strength of the SCC has increased up to 6.37% for 30% of RHA and then it tends to decreased.
- The buckling behaviour of the axial loaded column was predicted using PSO integrated Artificial Neural Network model through back propagation technique with high level of accuracy.
- The results showed that, when predicting the buckling behaviour, the PSO-ANN technique could provide better performance.

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