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ORIGINAL PAPER

Applying ANN – PSO algorithm to maximize the compressive strength and split tensile strength of blended self curing concrete on the impact of supplementary cementitious materials

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Abstract

This study was intended to get the optimized Compressive strength and split tensile strength of Blended Self CuringConcrete(BSCC) on the impact of Supplementary Cementitious Materials (SCM's). The experiments were conducted by varying the quantity of Cement, Flyash, Ground Granulated Blast Furnace Slag (GGBFS), Silica Fume and Slump with fixed quantity of Fine aggregate, Coarse aggregate, S.P and Water. Totally 13 different mix proportions were prepared and tested for Compressive Strength (CS) and Split Tensile Strength (STS). Both strengths were calculated for 7, 14 and 28 days. To optimize the compressive strength and split tensile strength, a feed forward Artificial Neural Network (ANN) model was developed, and Particle Swarm Optimization (PSO) algorithm was used by optimizing the weighing factors of the network in the neural power software. Finally, with a root mean square error of 0.008223, 0.006559, and 0.009743 for CS and 0.008905, 0.006999, and 0.008745 for STS, the model was obtained for 7, 14, and 28 days. The percentage contribution of input parameters is also discussed separately for compressive strength and split tensile strength of 7, 14 and 28 days of curing. Finally, the optimized compressive strength and split tensile strength were found to be 42.3552 N/mm^2 and 4.3113 N/mm^2 respectively for 28 days.
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Keywords Blended self curing concrete · Cementitious materials · ANN · PSO

1 Introduction

Blended cement concrete is a mixture of cement replaced with supplementary cementitious materials with different proportioning mixes based upon the utility of concrete. SCMs like fly ash (FA), silica fume (SF), metakaolin (MK), bentonite, and ground granulated blast-furnace slag (GGBFS) were used to replace cement up to 60% without the need of alkaline solution in the investigation done by Halit Yazıcı [1]. Due to this SCMs the rheological, durability, and mechanical qualities of concrete can be enhanced by adding up to 40% mineral additive to the mixture and keeps costs down by reducing the amount of cement used in the concrete. Utilising pozzolanic materials and transforming them into useful materials can help conserve the environment while also assisting in the development of high-performance concrete thorough the literature on unary, binary, and triple blended pozzolans which was employed as concrete replacements explained by Athiyamaan [2].

Ternary blended concrete reveals the addition of several pozzolanic materials to the concrete, including cement acting as the primary binding agent. Metakaolin as well as fly ash from power stations are both important ingredients for modern concrete. Increasing the use of SCMs including such fly ash, silica fume, GGBFS, rice husk ash, and metakaolin during concrete production, precedes to the idea of blended cements and concretes. By reorienting the mix design parameters for enhanced structural characteristics of concrete, with an emphasis on regulating OPC content while increasing

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the overall cementitious material and limiting water content while obtaining chemical admixture for improved workability and compensating concerted hydration using SCMs. Due to the intensified utilization of performance built concrete, concrete incorporating self-curing agents could mean a new range of trend in construction throughout the modern era. For the inclusion of internal or self-curing water in concrete, newer techniques can also be used.

Most researchers suggested using saturated aggregates to perform internal concrete curing using polyethylene glycol PEG 400 mostly as self-curing agent for concrete mixes. Supplementary Cementitious Materials (SCMs) such as Flyash, Ground Granulated Furnace Slag, and Silica Fume improve the stiffness, ductility, and load bearing capability of concrete structures while reducing crack strengthening and dissemination. Thus according to the cement composite philosophy, a new composite material has high structural implementation and exceptional economic advantages can be produced by combining positive synergy with different admixtures. Suryawanshi et al. [3] investigated the incorporation of mineral admixtures to cement concrete enhances the amount of water required for curing, and this requirement can be much higher than those in ordinary Portland cement concrete mixes. Chemical shrinkage happens when there is water shortage for hydration also because inner relative humidity decreases.The key property of hardened concrete, durability, is profoundly affected by curing as it has a significant impact upon its hydration of Portland cement.

Using soft computing techniques, Feizbakhsh et al. [4] investigated the prediction model of compressive strength of self–compacting concrete (SCC). Adaptive neuro–based fuzzy inference method (ANFIS), artificial neural network (ANN), and PSOPC–ANFIS, a combination of particle swarm optimization with passive congregation (PSOPC) and ANFIS, are among the techniques used. Khademi et al. [5] developed three different models of multiple linear regression (MLR), artificial neural network (ANN), and adaptive neuro-fuzzy inference system (ANFIS), trained, and tested in the MATLAB programming environment for forecasting the 28-day compressive strength of concrete for 173 different mix designs, based upon the experimental results. Numerous regression, neural networks (NNT), and ANFIS models are developed, trained, and tested using concrete constituents as input variables in determining the 28-day compressive strength of no-slump concrete (28-CSNSC) by Sohbani et al. [6]. When the results are compared, perhaps the NNT and ANFIS models are more capable of predicting the 28-CSNSC than the conventional regression models suggested.

Nikoo et al. [7] studied about numerous experimental data patterns were used to build models from observations of cylindrical concrete components with different aspects. Uysal [8] researched the forecasting of the loss in compressive strength of SCC, an artificial neural network (ANN) model based specific formulation had been proposed, which would be defined in terms with cement, mineral additives, aggregates, heating degree, and with or without PP fibres and the analytical model developed with ANN appeared to have a strong prediction capability of CS. Ahmet Raif Boğaa [9] investigated concrete containing GGBFS and CNI, the effects of cure form and curing time were investigated along with compressive strength, splitting tensile strength, and chloride ion permeability were all tested extensively and formulated four-layered artificial neural network approach (ANN) and adaptive neuro-fuzzy inference system (ANFIS). Lingam et.al [10] developed Artificial Neural Networks (ANN) to forecast the compressive strength of HPC comprising binary and quaternary blended mixes. Gulbandilar et al. [11] formulated the prediction models for flexural strength of cement mortars were created using Artificial Neural Networks (ANN) and Adaptive Network-based Fuzzy Inference Systems (ANFIS)with four input parameters Portland cement, GGBFS, WTRP, and sample age and one output parameter flexural strength of cement mortars.

2 Materials and methods

In this investigation, the self curing blended concrete was planned to prepare with the following ingredients such as Cement, Fly ash, Ground Granulated Blast Furnace Slag, Silica Fume, Fine Aggregate, Coarse Aggregate, S.P, Water and Slump. To prepare the SCBC, different quantities of cement, fly ash, ground granulated blast furnace, silica fume, and slump were maintained, while the remainder of the materials were kept constant. Table 1 shows the proportioning of standard self-curing concrete of M30 grade, while Table 2 shows the various mix proportions of Blended Self Curing Concrete for M30 Grade as per IS10262:2019 [12] codal provisions. It should be noted that the slump was measured from the bottom of the mould. Finally compressive and split tensile strength tests were performed on the specimens for seven, fourteen, and twenty-eight days of curing.

From the literature, the factors which are having considerable influence on the performance of Compressive Strength and Split tensile Strength for 7, 14 and 28 dayswere identified. They are (i) Cement (kg/m^3), Fly Ash (kg/m^3) (iii) GGBFS (kg/m^3) and (iv) Silica Fume (kg/m^3) and these factors were controlled during mixing process. A series of trial experiments were undertaken to determine the functional range of the supplementary Cementitious Materials (SCM's). Totally 13 different combinations was mentioned as M1 to M13 in Table 2 of BSCC specimens in Cube and Cylindrical forms were prepared. Each cube mould of the size is 150 × 150 × 150 mm for CS and STS with cylinder 150 mm in diameter and 300 mm long. For each blended mix, in a fresh state, the slump value (in mm) and for a hardened state, the strength

Table 1 Proportioning of Standard Self Cured mix for M30 Concrete (unit expressed as kg/m^3)

Materials	Cement	Fine Aggregate	Coarse Aggregate	PEG 400	Water	Water-Cement Ratio
Quantity	350	744.3	1314.2	2.28	175	0.4

Table 2 Mix proportions of Blended Self Curing Concrete for M30 Grade

Mix Quantity in kg/m^3	Cement	FlyAsh	GGBFS	SF	Fine Agg	Coarse.Agg	S.P	Water	Slump (mm)
M1	350	0	0	0	744.3	1314.2	3.5	140	244
M2	227.5	87.5	35	0	744.3	1314.2	3.5	140	255
M3	227.5	0	87.5	35	744.3	1314.2	3.5	140	255
M4	227.5	87.5	0	35	744.3	1314.2	3.5	140	256
M5	227.5	70	52.5	0	744.3	1314.2	3.5	140	251
M6	227.5	0	70	52.5	744.3	1314.2	3.5	140	251
M7	227.5	70	0	52.5	744.3	1314.2	3.5	140	254
M8	227.5	35	0	87.5	744.3	1314.2	3.5	140	252
M9	227.5	35	87.5	0	744.3	1314.2	3.5	140	255
M10	227.5	0	35	87.5	744.3	1314.2	3.5	140	252
M11	227.5	70	0	52.5	744.3	1314.2	3.5	140	248
M12	227.5	70	52	0	744.3	1314.2	3.5	140	251
M13	227.5	70	0	52.5	744.3	1314.2	3.5	140	253

parameters were calculated and noted down. Finally, the characteristic compressive strength and split tensile strength was calculated by using formula shown in Eqs. (1)and (2) [13] respectively.

$$CS\left(\frac{N}{mm^2}\right) = \frac{\text{AppliedLoad overCubeSpecimen}}{\text{CrossSectionalArea}} \tag{1}$$

$$STS\left(\frac{N}{mm^2}\right) = \frac{2^*\text{AppliedLoad over Cylindrical Specimen}}{\pi\ ^*\text{diameter of cylinder}^*\text{length of cylinder}} \tag{2}$$

The calculated (experimental) values of compressive strength and split tensile strength for BSCC are displayed in the Table 3 for 7, 14 and 28 days. Figs. 1 and 2 show specimens in Cube and Cylindrical forms of BSCC, whereas Figs. 3 and 4 are the tested specimens of compressive strength and split tensile strength respectively.

3 Developing a model and an optimization

In this investigation, it was planned to optimize the characteristic compressive strength and split tensile strengthfor 7, 14 and 28 days of Blended SCC using SCMs and finding the optimized process parameters after the model was created. Here, the model was created by Artificial Neural Network (ANN) and the model was optimized by Particle Swarm Optimization (PSA) algorithm. The role played by ANN and PSO in the field of modeling and optimization is discussed below. Figure 5 illustrates the integrated attempt of artificial neural network and particle swarm optimization algorithm.

3.1 Artificial neural network

The ANN methodology outperforms all other model, including linear and exponential regression. Many researchers have supported the use of ANN as a forecasting model because of its exceptional learning algorithm and balancing of input and output associations, including for non-linear and complicated systems [15, 16]. According to Ebrahimpour et al. [17], the ANN methodology has tremendous modelling potential due to its ability to identify the relationships at the core of complex systems. HadiMashhadban et al. [18] investigated whether a neural network could be designed to perform a specific role by changing the values of the connections (weights) between the components. Tavakoli et al. [19] explored into the use of artificial neural networks (ANN) to forecast the mechanical properties and energy dissipation capacity of fibre reinforced self-compacting concrete. They mentioned that now the ANN outcomes are really like the experimental information. To train the data, ANN uses various learning algorithms such as "Fast Propagation," "Batch Back

Table 3 Experimental Results of various Mix Proportions of Blended Self Curing Concrete

Mix	Compressive Strength (N/mm^2)			Split Tensile Strength (N/mm^2)		
	7 days	14 days	28 days	7 days	14 days	28 days
M1	12.48	20.15	31.21	1.34	2.1	3.4
M2	16.04	26.67	41.12	1.48	3.11	4.21
M3	16.79	25.6	38.16	1.54	3	4.18
M4	15.52	25.89	37.85	1.47	2.99	4.13
M5	13.06	24.52	35.21	1.42	2.6	4.03
M6	13.97	22.52	36.76	1.39	2.48	4.1
M7	14.03	20.78	35.07	1.35	2.56	4.19
M8	13.36	21.42	34.25	1.47	2.49	3.94
M9	14.08	20.76	33.53	1.49	2.44	3.91
M10	14.64	23.78	34.86	1.45	2.5	3.86
M11	15.97	25.29	38.95	1.33	2.24	3.54
M12	15.17	23.9	35.29	1.29	2.19	3.68
M13	14.25	21.19	33.93	1.3	2.28	3.79

Fig. 1 Cubical test specimens for compressive strength

Fig. 2 Cylindrical test specimens for split tensile strength

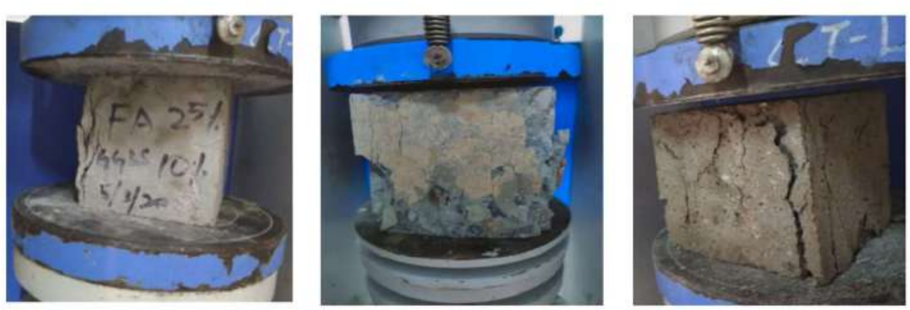


Fig. 3 Cubical tested specimens for compressive strength

Fig. 4 Cylindrical tested specimens for split tensile strength

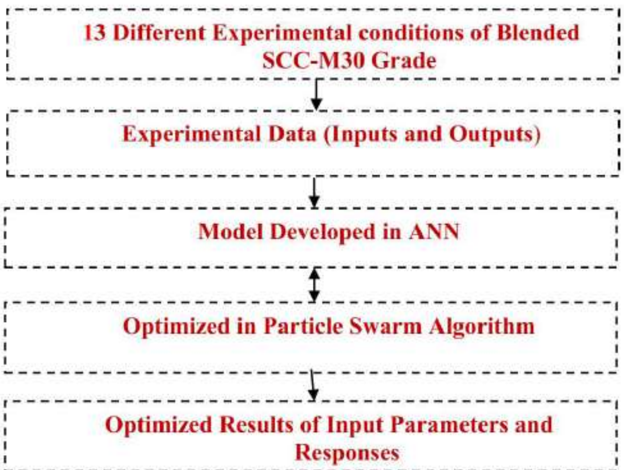


Fig. 5 Flow Chart of Hybrid ANN—PSO [14]

Propagation," "Incremental Back Propagation," and "Levenberg Marquadt." Nonlinear transfer functions such as Linear, Threshold Linear, Bipolar Linear, Gaussian, Tanh, and sigmoid are also included [20].This investigation's programme supports two separate link types: "multilayer regular feed forward" and "multilayer full feed forward." The RMSE divergence was used as a deciding factor as to when to stop training [21].

3.2 Particle swarm optimization

The PSO is a population-based optimization algorithm invented by Eberhart and Kennedy in 1995 and inspired by social behaviour such as bird flocking or fish schooling. In PSO, each particle in dimensional solution space is treated as an individual even amongst the population. The velocity and position of each particle are randomly chosen, and the very first position of each particle is determined using the target functions [22]. Then, amongst these results generated by all particles throughout the populations, gbest is found. The pbest particle is fixed which is based on the gbest. The pbest particle is assigned a velocity and a new population is formed, defining the new (second) position among all particles. Then gbest is discovered among the outcomes of the newly formed population, which is based on the most recent

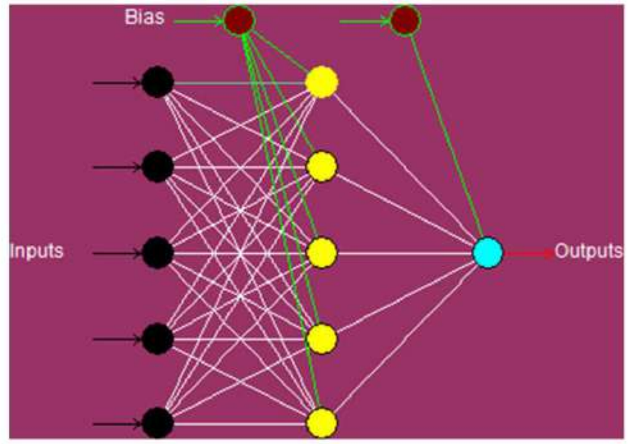


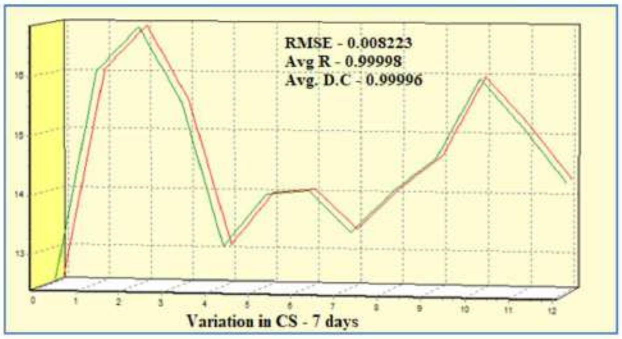
Fig. 6 Configuration of Three-Layered Neural Network

pbest particle. This process is repeated before the stop criterion, either the number of variables or no adjustments in the gbest value, take effect upon this algorithm.

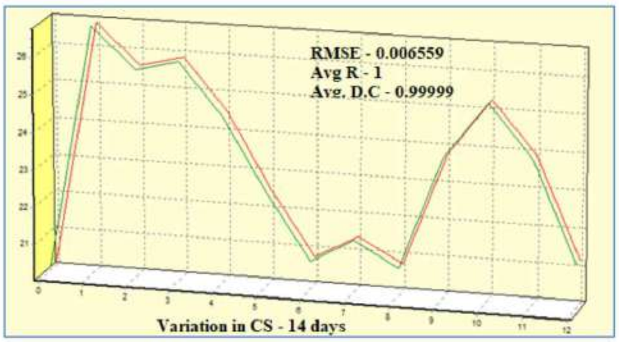
3.3 Solutions of ANN & PSO

CPC-X Neural Power [20] was used to model and optimize the problem in this study. Engineering fields are also aware of the implementation of ANN and PSOA throughout the engineering world [23]. In ANN, the Levenberg Marquadt algorithm and multilayer normal feed forward propagation have been used as learning algorithm and connection type, meanwhile.Both the learning rate and the momentum were set to 0.8. For the hidden layer and output layer, the sigmoid transfer feature has been used. The sigmoid function was found to be the most used function by Muthupriya et al. [24]. There is no standard method for determining the number of neurons in the network's hidden layer; instead, trial and error can be used, which was investigated by Singh et.al [25] and Kennedy et al.[26].

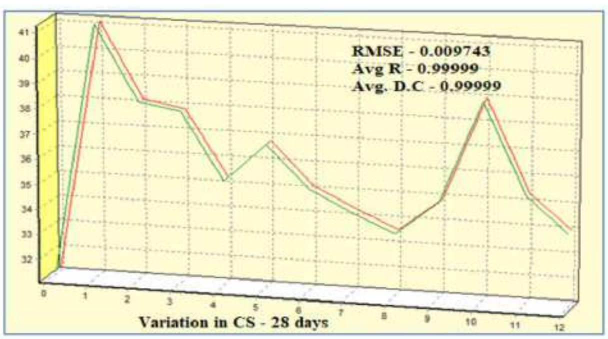
According to Das et al. [27], the number of neurons in the hidden layer can be based on the number of input sources n, and the number of neurons in the hidden layer can vary between n, n/2, 2n, 2n + 1, and 2n + 2. Kutanaei et al. [28] investigated PSOA's ability to model the mechanical properties of fibre reinforced cement sand. Xuesong [29] explained the use of the PSO algorithm to solve the TSP and the experiment results show that the new algorithm is successful for this problem, despite the drawbacks of genetic algorithms such as being easily locked into a local optimum. The total number of hidden layer is 1 and node on the hidden layer is 5. Finally, the model was achieved with the root mean square error of 0.008223, 0.006559 and 0.009743 for CS and 0.008905, 0.006999 and 0.008745 for STS respectively for 7, 14 and 28 days. Figure 6 shows the model which was used in this investigation.



(a) ANN Model for CS – 7 days

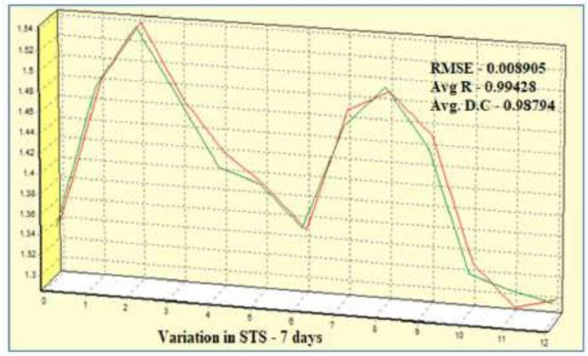


(b) ANN Model for CS – 14 days

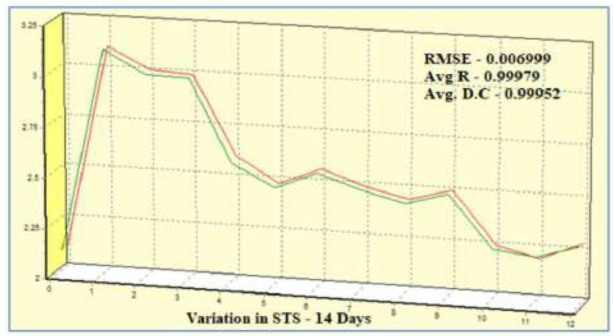


(c) ANN Model for CS – 28 days

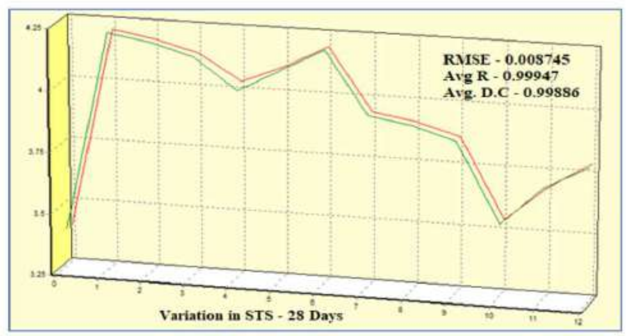
Fig. 7 **a** ANN Model for CS—7 days. **b** ANN Model for CS—14 days. **c** ANN Model for CS—28 days



(a) ANN Model for STS – 7 days



(b) ANN Model for STS – 14 days



(c) ANN Model for STS – 28 days

Fig. 8 **a** ANN Model for STS—7 days. **b** ANN Model for STS—14 days. **c** ANN Model for STS—28 days

Table 4 ANN Model's Statistical values of CS for different curing days

	7 Days	14 Days	28 Days
RMSE	0.008223	0.006559	0.009743
Avg R	0.99998	1	0.99999
Avg. D.C	0.99996	0.99999	0.99999

Figures 7(a) through (c) and 8(a) through (c) show the results of model created by ANN for CS and STS respectively, whereas Table 4 and 5 show the statistical significance of the model for CS and STS respectively.

To execute the optimization in PSO the following parameters were used [29]. The population size, inertia weight, learning factors such as cognitive factor (C1) and social factor (C2) are 10, 0.1, 2and 2 respectively. Finally, it was observed that the optimized values of Compressive strength are 17.3288, 27.4850 and 42.3553 N/mm^2 for 7, 14 and

Table 5 ANN Model's Statistical values of STS for different curing days

	7 Days	14 Days	28 Days
RMSE	0.008905	0.006999	0.008745
Avg R	0.99428	0.99979	0.99947
Avg. D.C	0.98794	0.99952	0.99886

Table 6 Optimized CS and optimized input values for different curing days

	7 Days	14 Days	28 Days
Compressive strength (N/mm^2)	17.3288	27.4850	42.3553
Cement	240.96	290.0097	229.4345
Fly ash	40.6751	86.0072	87.3342
GGBFS	67.3086	38.7017	2.4941
Silica fume	6.4172	73.4944	1.3895
Slump	253.3402	252.2067	251.1089

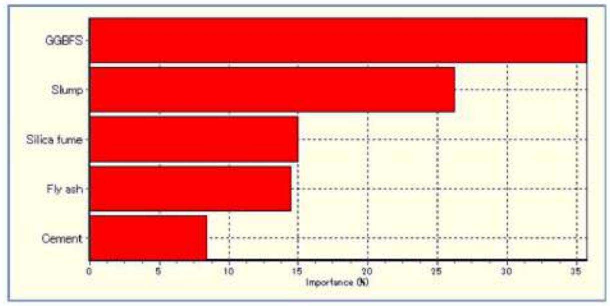
Table 7 Optimized STS and optimized input values for different curing days

	7 Days	14 Days	28 Days
Split Tensile Strength (N/mm^2)	1.5713	3.2363	4.3113
Cement	304.3145	319.9055	284.9032
Flyash	66.0441	20.6085	61.2320
GGBFS	59.6020	80.7960	83.9702
Silica fume	33.3184	32.2040	54.7132
Slump	251.3592	254.1756	247.2356

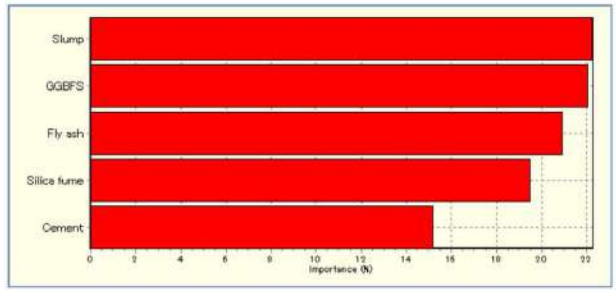
28 days respectively. Moreover it was found that the optimized values of Split Tensile Strength are 1.5713, 3.2363 and 4.3113 N/mm^2 for 7, 14 and 28 days respectively. Table 6 and 7 show the optimized input parameters for compressive strength and split tensile strength respectively for different curing days.

Figures 9(a) through (c) and 10(a) through (c) show process parameters importance (%) for CS and STS respectively. Whereas Tables 8 and 9 show the importance of each input factor (%) on compressive strength and split tensile strength respectively for different curing days. From the Tables 8 and 9 it can be found that the importance of cement contribution is low irrespective of strength and number of curing days.

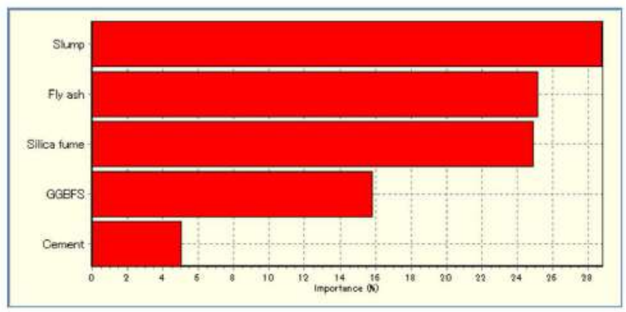
As the CS and STS are dependent on the quantity of GGBFS, fly ash, silica fume, and slump and the heat of hydration of concrete, the contribution of GGBFS, fly ash, silica fume, and slump vary in different curing periods (long



(a) Factors Importance (%) on CS – 7 days



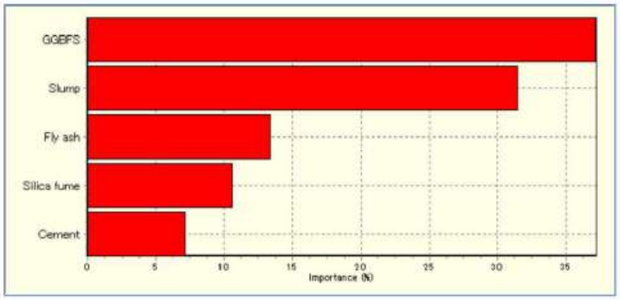
(b) Factors Importance (%) on CS – 14 days



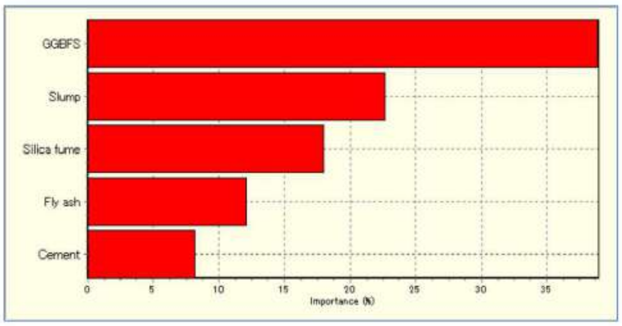
(c) Factors Importance (%) on CS – 28 days

Fig. 9 **a** Factors Importance (%) on CS—7 days. **b** Factors Importance (%) on CS—14 days. **c** Factors Importance (%) on CS—28 days

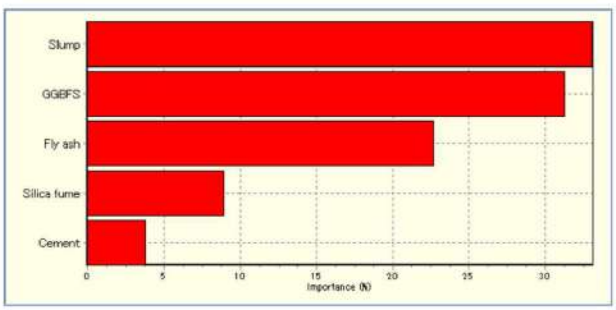
term and early-age). The CS of concrete mixtures including GGBFS increases when the amount of GGBFS is increased [30]. The presence of GGBFS provides greater early strength, whereas fly ash provides greater strength after a long time of curing. Fly ash particles interact with free lime in the cement to obtain more cementitious material, which improves long-term strength [31]. The type and quantity of cementing material, the water content, the aggregate grading, the existence of entrained air, and using chemical admixtures have a significant impact on the fresh and hardened properties of fly ash-based concrete [32].



(a) Factors Importance (%) on STS – 7 days



(b) Factors Importance (%) on STS – 14 days



(c) Factors Importance (%) on STS – 28 days

Fig. 10 **a** Factors Importance (%) on STS—7 days. **b** Factors Importance (%) on STS—14 days. **c** Factors Importance (%) on STS—28 days

4 Conclusions

- The self-curing blended concrete was prepared with the following ingredients such as Cement, Fly ash, Ground Granulated Blast Furnace Slag, Silica Fume, Fine Aggregate, Coarse Aggregate, S.P, Water and Slump.
- Cement, Fly ash, Ground Granulated Blast Furnace, Silica Fume and Slump were maintained with different proportions and the rest of the ingredients were fixed constant.
- The compressive strength and split tensile strength tests were conducted on the respective specimens for three different curing days of 7, 14 and 28.
- The model was constructed between the process factors and output values by artificial neural network. Finally, the model was achieved with the root mean square error of 0.008223, 0.006559 and 0.009743 for CS and 0.008905, 0.006999 and 0.008745 for STS respectively for 7, 14 and 28 days.
- The model trained by ANN was suitably incorporated with the evolutionary computational techniques of particle swarm optimization.
- It was observed that the optimized value of compressive strength is 17.3288, 27.4850 and 42.3553 N/mm^2 for 7, 14 and 28 days respectively. Moreover it was found that the optimized value of split tensile strength is 1.5713, 3.2363 and 4.3113 N/mm^2 for 7, 14 and 28 days respectively.
- The percentage importance was found separately for optimized compressive strength and split tensile strength. It was also found that irrespective of curing days cement has the least importance on compressive strength and split tensile strength.

Table 8 Importance of each input factor in % on CS for different curing days

Parameters	7 Days	Parameters	14 Days	Parameters	28 Days
GGBFS	35.73	Slump	22.27	Slump	28.84
Slump	26.3	GGBFS	22.09	Fly ash	25.24
Silica fume	15.01	Fly ash	20.93	Silica fume	24.95
Fly ash	14.52	Silica fume	19.52	GGBFS	15.87
Cement	8.439	Cement	15.19	Cement	5.106

Table 9 Importance of each input factor in % on STS for different curing days

Parameters	7 Days	Parameters	14 Days	Parameters	28 Days
GGBFS	37.23	GGBFS	38.95	Slump	33.12
Slump	31.55	Slump	22.69	GGBFS	31.29
Fly ash	13.42	Silica fume	18.01	Fly ash	22.76
Silica fume	10.62	Fly ash	12.13	Silica fume	8.98
Cement	7.175	Cement	8.23	Cement	3.85

Declarations

Conflict of interest On behalf of all authors, I hereby disclose that no potential competing interest is involved with this technical paper.

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