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Research Paper

Enhanced soft computing for ensemble approach to estimate the compressive strength of high strength concrete

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High strength concrete (HCS) define as the concrete that meets unique mixture of performance uniformity requirements that cannot be reached routinely using conventional constituents and regular mixing, placing, and curing events. The modeling of such type of concrete is very difficult. In this investigation, the performance of the gaussian process (GP) regression, support vector Machine (SVM) and artificial neural network (ANN) were compared to estimate the 28^{th} day compressive strength of the HSC. Total data set consists of 83 data out of which 70 % of total dataset used to train the model and residual 30% used to test the models. The model accuracy was depend upon the five performance evaluation parameter which were correlation coefficient (R), Bias, mean square error (MAE), root mean square error (RMSE) and Nash-Sutcliffe model efficiency (E). The results recommend that ANN model is more accurate to predict the compressive strength as compare to GP and SVM based models. Sensitivity analysis indicated that Cement (C), Silica fume (SF), Fly ash (FA) and Water (W) are the most valuable constituents in which compressive strength of the HCS is mainly depend for this data set.

1 Introduction

High strength concrete (HSC) is a special type of concrete and used commonly in construction industries [1, 2]. It is special mixture of materials which meets particular requirements of a construction projects [3]. It is also more durable than normal strength concrete (NSC). The behaviour of HSC is more complex due to the using of different types of admixtures and chemicals for achieving the higher strength of the concrete [4]. Generally, the compressive strength of concrete considered on 7^{th} and 28^{th} days from the date of placing the concrete. The testing of the concrete for compressive strength at 28^{th} days measured as standard. The average compressive strength of the HSC on 28^{th} day is more than 60 MPa. These benefits decrease the cost of many large scale construction projects [5]. Knowledge of compressive strength of material/concrete is very significant for any construction project. Direct measurement of compressive strength of concrete is difficult, tedious, relatively costly, labour intensive and time-consuming. Thus, indirect methods using predictive approaches have been developed for estimation of compressive strength of concrete from easily measurable properties of the material.

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The recent scenario suggests the focus on nature of concrete and concrete mixture optimization instead of the concrete compositions versus strength relationship. Various researchers considered the characteristics parameters which affects the compressive strength of HSC. These parameters may be aggregates quality, cement strength, water–cement ratio and water content. Now a days, researchers gave the main focus on the utilization of industrial waste i.e. silica fume (SF), Fly ash (FA), Fibers (F) etc. [6]. To calculate the compressive strength (CS), the tests of concrete perform without supplementary cementitious materials such as SF, FA, F, SP (super plasticizers) according to the codes and standards in which the traditional approaches depends. These traditional approaches used for modeling the effect of compressive strength of high strength concrete with assumed analytical equations and it's followed regression analysis by experimental data set [7]. However, these approaches are not easy to use and no accurate prediction available in the codes regarding the compressive strength of HSCs.

In recent years, different artificial intelligence techniques such as nonlinear regression, GP, SVM, ANN, M5P, Random forest and ANFIS has become very trendy and has been used widely by the various researchers [8, 9]. Most of these studies recommend that the accuracy of these artificial intelligence techniques is very high. Several researchers used the GP [10], SVM [11] and ANN [12-15] and found that these model gave the best fit outcomes. The main objective of this investigation is to estimate the 28thdays compressive strength of the high strength concrete with supplementary cementitious using artificial intelligence techniques.

1.1 Overview of modelling techniques

1.1.1 Gaussian Process regression (GP)

Rasmussen and Williams [16] assumed, for the working of GP regression model that the adjoining observations give information about each other. It is a method to specify a prior directly over function space. The mean and covariance of Gaussian distribution are vector and matrix. The Gaussian process is over function.GP regression model is capable to recognize the predictive distribution analogous to check input information.

A GP is a collection of random variables in which any finite number has a joint multivariate Gaussian distribution. Assuming$x\ X\ y$ represents the domains of inputs and outputs, respectively. In which n pairs $(x_{i,}\ \ y_i)$ are drawn independently and identically distributed. For regression, let $y \subseteq \Re$; then, a GP on χ is defined by a mean function $\mu\!: \chi \rightarrow \Re$ and a covariance function $k : \chi \times \chi \rightarrow \Re$. For more information about GP regression and different covariance functions, it is recommended to refer to [17].

1.1.2 Support Vector Machines (SVM)

This method was introduced by Vapnik and Vapnik [18] and derived from statistical learning theory. Main principle of SVM is optimal separation of classes. From the separable classes SVM selects the one which have lowest generalization error from infinite number of linear classifier or set upper limit to error which is generated by structural risk minimization. This way the maximum margin between two classes can be found from the selected hyper plane and sum of distances of the hyper plane from the closest point of two classes will set maximum margin between two classes.

Vapnik anticipatedε-Support Vector Regression (SVR) by introducing an anotherε- insensitive loss function and it permits the concept of margin to be used for regression problems. The principle of the SVR is to discover a function having at most εdeviation from the actual target vectors for all specified training data and it should be as flat as possible [19]. Cortes and Vapnik [20] gives the idea of kernel function for non-linear support vector regression.

1.1.3 Artificial neural network (ANN)

The artificial neural network (ANN) is a machine learning method widely used for numerical prediction of concrete problems [8]. It is inspired by the functioning of the neurons system and brain architecture. ANN has one input, one or more hidden and one output layers. Each layer consists of the number of nodes and the weighted connection between these layers represents the link between the nodes. Input layer having nodes equal to the number of input parameters, distributes the data presented to the network and does not help in processing. This layer follows one or more hidden layers which help in the processing of data. The output layer is the final processing unit. When an input layer is subjected to an input value which passes through the interconnections between the nodes, these values are multiplied by the corresponding weights and summed up to obtain the net output (P_j) to the unit

$$P_j = \sum_i X_{ij} \times y_i \tag{1}$$

Where, X_{ij} is the weight of interconnection from unit i to j, y_i is the input value at input layer, P_j is output obtained by activation function to produce an output for unit j. The detailed discussion about ANN is provided Haykin (1999). In present analysis an ANN based on two hidden layers is used.

2 Performance evaluation criteria

To analyse the capability of various modeling methods in estimating the 28th day compressive strength of the HSCcorrelation coefficient (R), Bias, mean square error (MSE), root mean square error (RMSE) and Nash-Sutcliffe model efficiency (E) values were calculated using the training and the testing dataset.

$$R = \frac{n\sum HF - \left(\sum H\right)\left(\sum F\right)}{\sqrt{n\left(\sum H^2\right) - \left(\sum H\right)^2}\sqrt{n\left(\sum F^2\right) - \left(\sum F\right)^2}} \tag{2}$$

$$Bias = \frac{1}{n}(\sum_{i=1}^{n}\left(H - F\right) \tag{3}$$

$$MSE = \frac{1}{n}(\sum_{i=1}^{n}\left(H - F\right)^2 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}(\sum_{i=1}^{n}\left(H - F\right)^2} \tag{5}$$

$$E = 1 - \frac{\sum_{i=1}^{n}\left(H - F\right)^2}{\sum_{i=1}^{n}\left(H - \bar{H}\right)^2} \tag{6}$$

Where:

H : observed values

F : predicted values

$\bar{H}$: mean of observed values

n : number of observations

3 Data set

The data set for this study was collected from published creditable journals. Data were derived from a number of resources [21-37]. Data was assembled for the high strength concrete containing cement (C), sand (S), course aggregate (CA), Silica fume (SF), Fly ash (FA), Fiber (F), super plasticizers (SP), water (W), aspect ratio (AR) and 28th days compressive strength (CS). The range of the CS was from 50.78 to 105.7 MPa. The total dataset consists of 83 data in which 70 % used for the training and 30 % used for the testing. Table 1 furnished the features of the training and testing dataset in which C, S, CA, SF, FA, F, SP, W and AR were the input parameters whereas CS was considered as the output parameter.

Table 1 - Features of the training and testing dataset

Variable	*Units*	**Minimum**	**Maximum**	**Mean**	**Std.**	**Skewness**	**Kurtosis**
			Training data set				
C	*Kg/m³*	32	643	437.0017	85.0443	-1.4600	8.4951
S	*Kg/m³*	425	891	709.5029	104.1028	-0.4634	0.6528
CA	*Kg/m³*	812	1203	1033.932	96.4101	-0.1447	-0.4024
SF	*Kg/m³*	0	73	17.9121	23.8001	0.7897	-1.0110
FA	*Kg/m³*	0	192	33.3538	58.3153	1.4943	0.8290
F	*Kg/m³*	0	80	14.7931	26.3171	1.5483	1.0330
SP	*Kg/m³*	0	18	7.6755	4.7451	0.1079	-1.0563
W	*Kg/m³*	126	214	163.4655	21.9213	0.2253	-0.2997
AR	*%*	0	80	20.8448	33.1847	1.0306	-0.8538
CS	*MPa*	52.44	105.7	75.7855	13.5172	0.1274	-0.8960
			Testing data set				
C	*Kg/m³*	255	576	413.0375	73.6616	0.4691	0.7224
S	*Kg/m³*	425	891	734.3750	125.2271	-1.0946	0.7186
CA	*Kg/m³*	786	1203	1005.975	125.4611	-0.1667	-1.0389
SF	*Kg/m³*	0	75	21.0458	23.6225	0.7733	-0.4999
FA	*Kg/m³*	0	224	59.9583	79.7406	0.9223	-0.6030
F	*Kg/m³*	0	80	25.7917	34.8412	0.8281	-1.1898
SP	*Kg/m³*	0	13.34	4.7563	3.7227	0.9770	0.3819
W	*Kg/m³*	132	214	165.5833	24.0772	0.7702	-0.1886
AR	*%*	0	80	30.2083	37.1097	0.4537	-1.8545
CS	*MPa*	50.78	98.5	74.0567	13.5621	-0.1928	-0.7823

4 Detail of kernel functions

There are many kernel functions in GP and SVM, so how to select a better kernel function is also a research concern. However, for general purpose, there are two common kernel functions.

1. Radial basis kernel (RBF) = $e^{-\gamma |x_i - x_j|^2}$

2. Pearson VII function kernel (PUK) = $\left(1 \Big/ \left[1 + \left(2\sqrt{\|x_i - x_j\|^2} \sqrt{2^{(1/\omega)} - 1} \Big/ \sigma \right)^2 \right]^{\omega} \right)$

Here Gaussian noise, γ, σ and ω are kernel parameters. It is well known that GP and SVM generalization performance (prediction precision) depends on a good setting of meta-parameters, parameters C, Gaussian noise, γ, σ and ω. The choices of C, Gaussian noise, γ, σ and ω control the prediction (regression) model complexity. In this study, a physical method (carrying out several trials by using different combinations of user-defined parameters) was implemented to select user-defined parameters (i.e. C, Gaussian noise, γ, σ and ω). In order to minimize the RMSE and to maximize the R suitable values of various user-defined parameters are selected. The same kernel-specific parameters were taken for GP regression and as well as for SVM. Table 2 enlists all the optimal values of the user-defined parameters for GP and SVM.

Table 2 - Optimal value of user-defined parameters for GP and SVM

Sr. No.	Classifiers used	User defined parameters
1	GP with PUK kernel	Gaussian noise = 0.1, ω = 0.5, σ = 2.0
2	GP with RBF kernel	Gaussian noise = 0.1, γ = 3.0
3	SVM with PUK kernel	C = 10, ω = 0.5, σ = 2.0
4	SVM with RBF kernel	C = 10, γ = 3.0

5 Results and discussion

5.1 Results of Gaussian Process regression (GP)

Developing the Gaussian process regression based models (Gaussian noise, γ, σ and ω) are a trial and error process. Two kernel functions (PUK and RBF) were used to develop models. Gaussian noise (0.1) was kept constant for both kernels for the fair comparison of models. optimum user define parameters are shown in Table 2. During the GP model development (Table 3), it was found that the Pearson VII kernel function has a better performance compared with RBF kernel function. The performance of GP models in every stage of development (training and testing) is presented in Figure 1. To examine the accuracy of these models, error indices for every stage of preparation were estimated and shown in this figure. The CC values of PUK kernel function based GP model were obtained 0.9923, 0.8851, Bias values 0.0006, 0.5457, MSE values 2.8964, 38.786, RMSE values 1.7019, 6.2278 and E values 0.9839, 0.78 for training and testing, respectively. Overall, assessing Figure 1 shows that the exactness of the PUK kernel function based GP model is suitable for prediction of compressive strength of the high strength concrete. It is notable that in these figures the actual is associated to actual values, GP_RBF is associated to the results of the RBF kernel function based GP model and GP_PUK is associated to the results of the PUK kernel function based GP model.

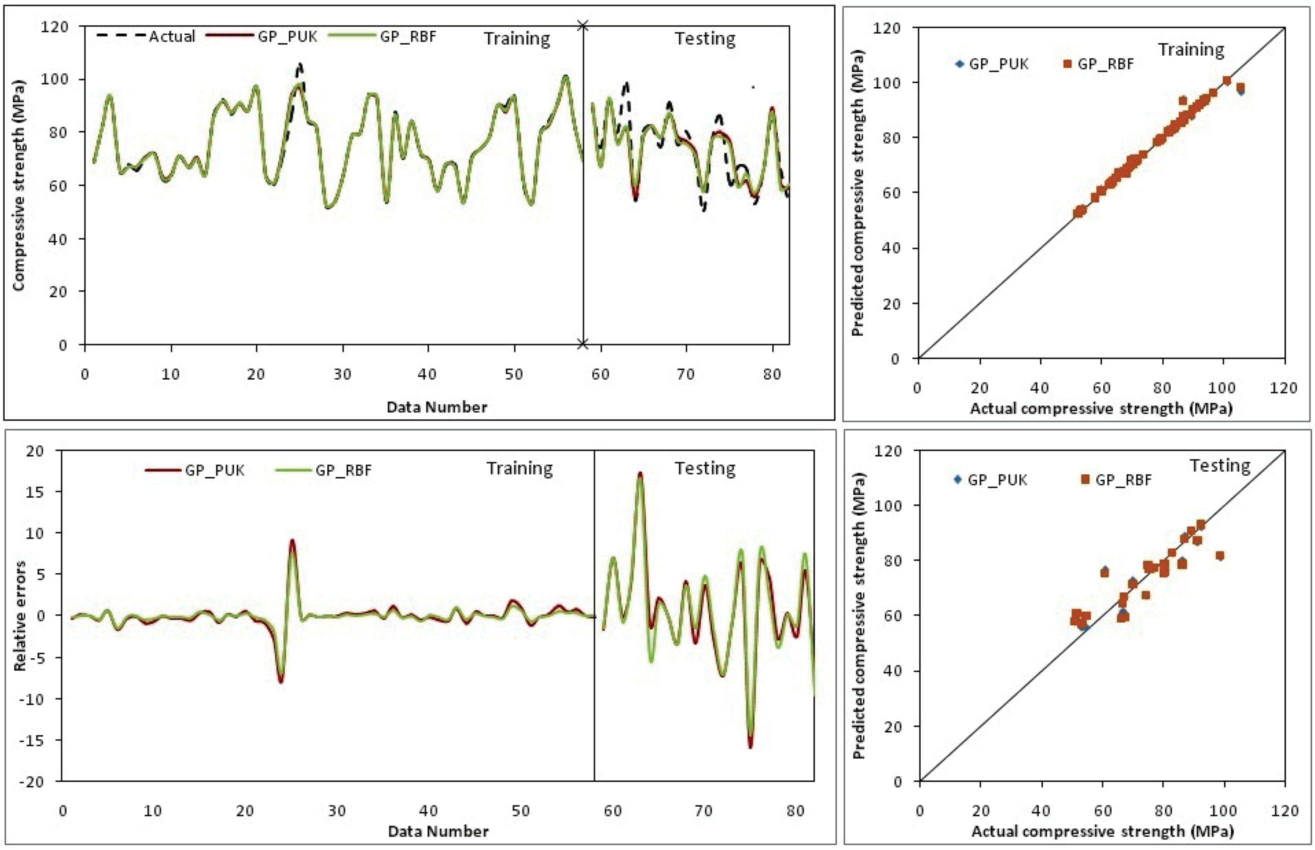

Fig. 1 – Performance of GP models during training and testing stages

5.2 Results of Support Vector Machines regression (SVM)

Developing the SVM model is similar to developing the GP model, based on the same data set. Developing the SVM based models (C, γ, σ and ω) are a trial and error process. Two kernel functions (PUK and RBF) were used to develop models. C (10) was kept constant for both kernels for the fair comparison of models. Optimum value of user define parameters (γ, σ and ω) were also kept constant for fair comparison of SVM and GP models. Optimum values of user define parameters model are shown in Table 2. During the SVM model development and validation (Table 3), it was found that the Pearson VII kernel function has a better performance compared with RBF kernel function. As shown in Figure 2, the performance and error are plotted as well as assessing the performance of the SVM models in training and testing periods. The R values of PUK kernel function based SVM model were obtained 0.9848, 0.8897, Bias values 0.2609, 0.7426, MSE values 5.6192, 37.5991, RMSE values 2.3705, 6.1318 and E values 0.9687, 0.7867 for training and testing, respectively. Overall, assessing Figure 2 shows that the exactness of the PUK kernel function based SVM model is suitable for prediction of compressive strength of the high strength concrete.

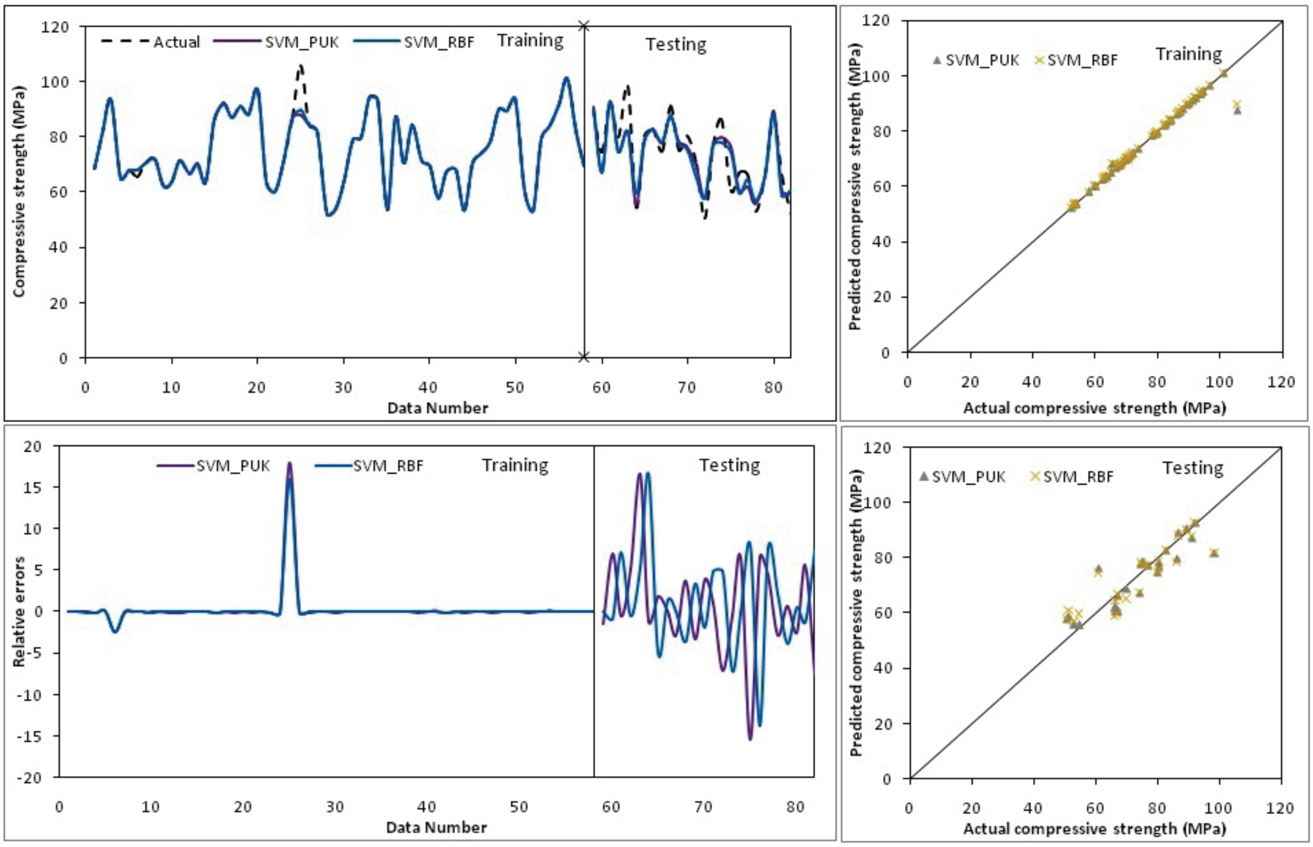

Fig. 2–Performance of SVM models during training and testing stages

5.3 Results of ANN

Developing the ANN model (e.g. number of neurons in hidden layer, number of hidden layers, momentum, learning rate, Iteration etc.) is a trial and error process. The ANN model contains two hidden layer. First hidden layer contain eleven neurons and second hidden layer contains eight neurons with momentum =0.2, learning rate =0.1 and Iteration =1500. The performance of the ANN model is shown in Figure 3. As shown in Table 3, the ANN model were obtained R=0.9093, Bias =1.9957, MSE =37.5576, RMSE = 6.1284 and E = 0.7869 for testing stage. Overall assessing Table 3 and Figure 3 shows that the accuracy of the ANN model is suitable for prediction of 28th day compressive strength of the HSC.

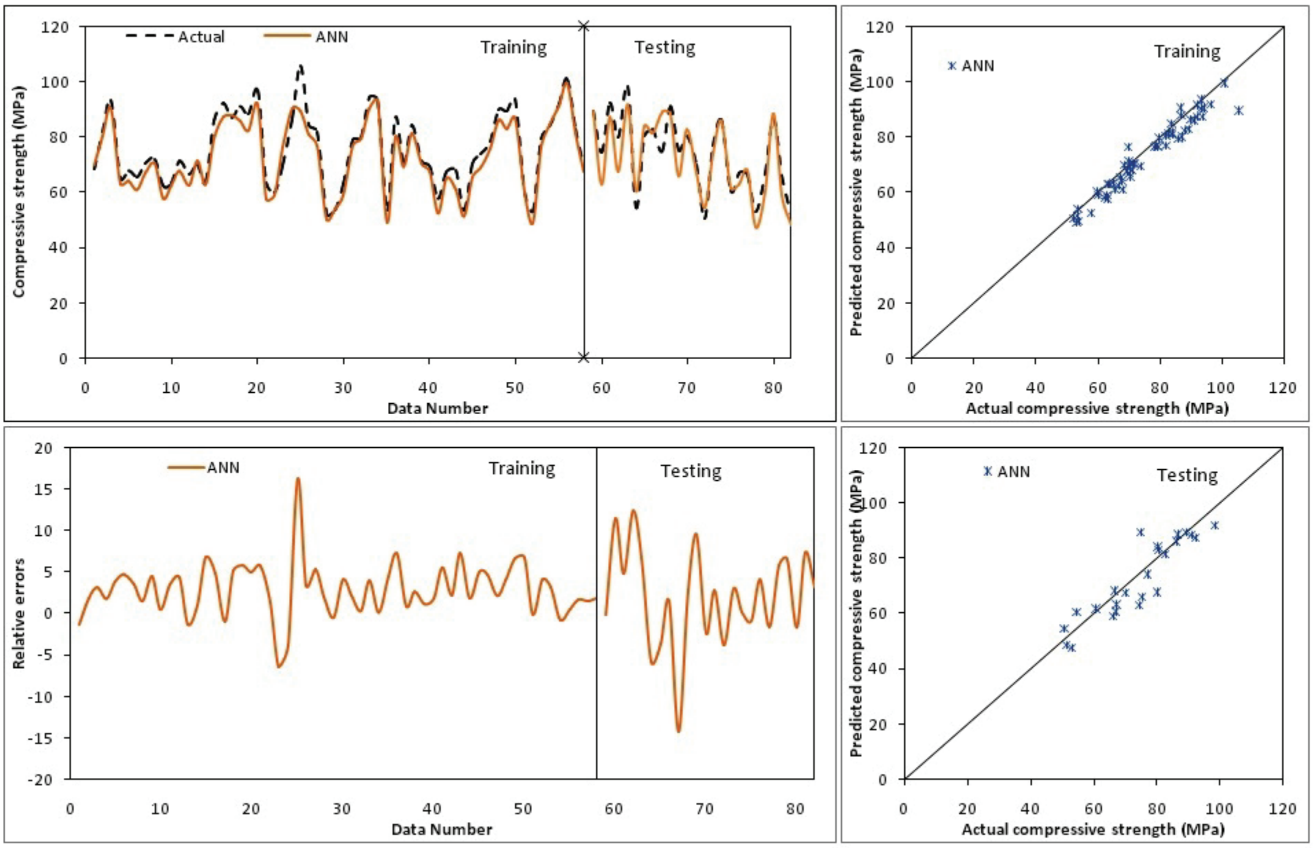

Fig. 3 – Performance of ANN models during training and testing stages

5.4 Comparison of models

Comparison of soft computing models indicates that ANN models works well than other soft computing based models. Table 3 indicates that PUK kernel based models works better than RBF kernel based models. Single factor ANNOVA results (Table 4) shows that *F*-values was less than *f*-critical and *P*-values was greater than 0.05 suggest that difference in estimated values using GP_PUK, GP_RBF, SVM_PUK, SVM_RBF, ANN models and actual values was insignificant. To compare the performance of GP, SVM and ANN model, agreement, performance and error were plotted in Figure 4 for both training and testing stages. It can be incidental from the figure that the estimated value produced by ANN were in extremely near proximity to the actual values and estimated values are found to chase the similar pattern as that of actual values.

Table 3 - Performance of GP, SVM and ANN models

	Performance evaluation Parameters									
	Training Data set					*Testing Data set*				
Approaches	***R***	***Bias (MPa)***	***MSE (MPa)***	***RMSE (MPa)***	***E***	***R***	***Bias (MPa)***	***MSE (MPa)***	***RMSE (MPa)***	***E***
GP_PUK	0.9923	0.0006	2.8964	1.7019	0.9839	0.8851	0.5457	38.7860	6.2278	0.7800
GP_RBF	0.9946	0.0009	2.0103	1.4179	0.9888	0.8819	0.5588	40.3935	6.3556	0.7708
SVM_PUK	0.9848	0.2609	5.6192	2.3705	0.9687	0.8897	0.7426	37.5991	6.1318	0.7867
SVM_RBF	0.9880	0.2408	4.4620	2.1123	0.9752	0.8816	0.9199	40.8293	6.3898	0.7684
ANN	0.9712	2.9187	18.7285	4.3276	0.8957	0.9093	1.9957	37.5576	6.1284	0.7869

Table 4 - Result of Single Factor ANOVA test for GP, GEP and GRNN approaches.

Approaches	*F*	*P-value*	*F critical*	*Significant difference between actual and estimated values*
GP_PUK	0.022725	0.880834	4.051749	No
GP_RBF	0.024587	0.876087	4.051749	No
SVM_PUK	0.04182	0.838864	4.051749	No
SVM_RBF	0.066112	0.79823	4.051749	No
ANN	0.249516	0.619797	4.051749	No

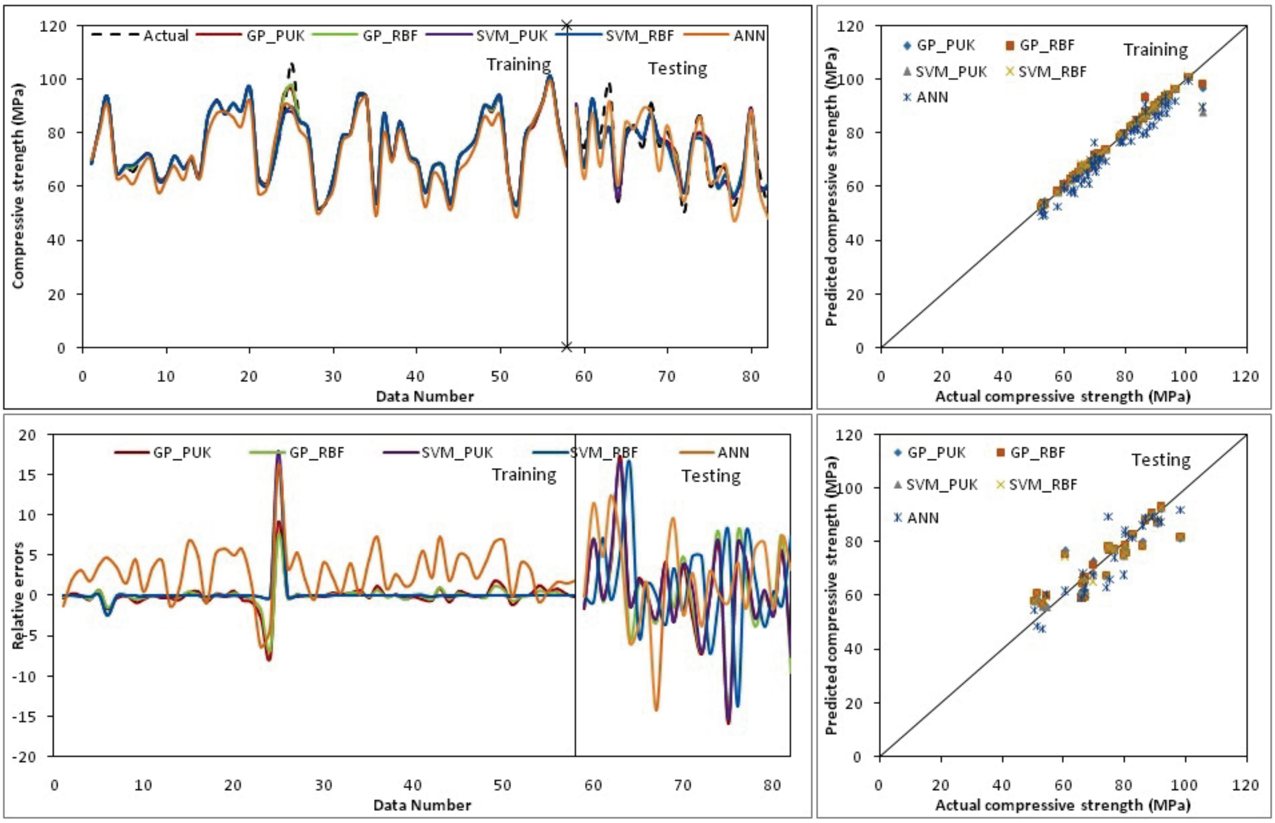

Fig. 4 – Performance of GP, SVM and ANN models during training and testing stages

6 Sensitivity analysis

The most effective parameters for estimation of 28th day compressive strength of the HSC by GP, SVM and ANN were defined by a simple approach. This approach explains the consequences of each parameter on the model to estimate the 28th day compressive strength of the HSC. At first, all parameters with regard to Table 2 except CS were considered as inputs for GP, SVM and ANN, and then one of the input parameters and again the model with the same structure was prepared. Data set was separated into two parts for training and testing. After adjusting the model structure, the sensitivity analysis of the models began in order to define the most effective parameters. The performance of the models in the deficiency of each input parameter was examined using estimation of indices including R and RMSE. Removing one of the input parameters caused a change in model performance. Depending on the degree of change in performance, the effect of each parameter was examined. The outcome of sensitivity analysis of GP, SVM and ANN are shown in the Table 5-7. Tables show that ANN model is more sensitive than other models. As seen in the Tables 7, the deficiency of the Cement (C) caused a dramatic decrease in the accuracy of the models, so it was found that this is the most significant parameter for modelling the 28th day compressive strength of the HSC. Silica fume (SF), Fly ash (FA) and Water (W) are also affecting the compressive strength of the HSC.

Table 5 - Results of sensitivity investigation using GP_PUK

Sr. No.	*Inputs*	*Remove*	*Output*	*R*	*RMSE (MPa)*
1	*C, S, CA, SF, FA, F, SP, AR, W*	-	*CS*	0.8851	6.2278
2	*S, CA, SF, FA, F, SP, AR, W*	*C*	*CS*	*0.8774*	*6.4325*
3	*C, CA, SF, FA, F, SP, AR, W*	*S*	*CS*	*0.8855*	*6.1786*
4	*C, S, SF, FA, F, SP, AR, W*	*CA*	*CS*	*0.8516*	*6.9662*
5	*C, S, CA, FA, F, SP, AR, W*	*SF*	*CS*	*0.7014*	*10.0627*
6	*C, S, CA, SF, F, SP, AR, W*	*FA*	*CS*	*0.8448*	*7.181*
7	*C, S, CA, SF, FA, SP, AR, W*	*F*	*CS*	*0.8863*	*6.2008*
8	*C, S, CA, SF, FA, F, AR, W*	*SP*	*CS*	*0.8771*	*6.3854*
9	*C, S, CA, SF, FA, F, SP, W*	*AR*	*CS*	*0.8916*	*6.1189*
10	*C, S, CA, SF, FA, F, SP, AR,*	*W*	*CS*	*0.8351*	*7.4978*

Table 6 - Results of sensitivity investigation using SVM_PUK

Sr. No.	*Inputs*	*Remove*	*Output*	*R*	*RMSE (MPa)*
1	*C, S, CA, SF, FA, F, SP, AR, W*	-	*CS*	*0.8897*	*6.1319*
2	*S, CA, SF, FA, F, SP, AR, W*	*C*	*CS*	*0.8821*	*6.3559*
3	*C, CA, SF, FA, F, SP, AR, W*	*S*	*CS*	*0.8908*	*6.0746*
4	*C, S, SF, FA, F, SP, AR, W*	*CA*	*CS*	*0.8619*	*6.752*
5	*C, S, CA, FA, F, SP, AR, W*	*SF*	*CS*	*0.7073*	*10.148*
6	*C, S, CA, SF, F, SP, AR, W*	*FA*	*CS*	*0.8325*	*7.4935*
7	*C, S, CA, SF, FA, SP, AR, W*	*F*	*CS*	*0.8833*	*6.261*
8	*C, S, CA, SF, FA, F, AR, W*	*SP*	*CS*	*0.8851*	*6.2154*
9	*C, S, CA, SF, FA, F, SP, W*	*AR*	*CS*	*0.897*	*6.0306*
10	*C, S, CA, SF, FA, F, SP, AR,*	*W*	*CS*	*0.8503*	*7.1887*

Table 7 - Results of sensitivity investigation using ANN

Sr. No.	*Inputs*	*Remove*	*Output*	*R*	*RMSE (MPa)*
1	*C, S, CA, SF, FA, F, SP, AR, W*	-	*CS*	*0.9093*	*6.1284*
2	*S, CA, SF, FA, F, SP, AR, W*	*C*	*CS*	*0.7635*	*9.3796*
3	*C, CA, SF, FA, F, SP, AR, W*	*S*	*CS*	*0.9099*	*10.324*
4	*C, S, SF, FA, F, SP, AR, W*	*CA*	*CS*	*0.8597*	*8.8451*
5	*C, S, CA, FA, F, SP, AR, W*	*SF*	*CS*	*0.7929*	*10.3973*
6	*C, S, CA, SF, F, SP, AR, W*	*FA*	*CS*	*0.9057*	*6.6139*
7	*C, S, CA, SF, FA, SP, AR, W*	*F*	*CS*	*0.8773*	*7.7829*
8	*C, S, CA, SF, FA, F, AR, W*	*SP*	*CS*	*0.8246*	*9.7688*
9	*C, S, CA, SF, FA, F, SP, W*	*AR*	*CS*	*0.9091*	*6.8586*
10	*C, S, CA, SF, FA, F, SP, AR*	*W*	*CS*	*0.865*	*8.1898*

7 Conclusion

Estimation of the 28th day compressive strength of the HSC is an essential element of structural studies. Experimental investigation of compressive strength of the HSC is difficult, tedious, relatively costly, labour intensive and time-consuming. So in the study, indirect methods using artificial intelligence techniques approaches have been used for estimationthe 28th day compressive strength of the HSC. Results of this study showed that ANN model has a suitable capability to predict the the 28th day compressive strength of the HSC. The ANN model also provides better performance than the GP and SVM models. Another major conclusion was that Pearson VII kernel function based models work better than RBF kernel function based models. Single factor ANNOVA results also suggest that there is insignificant difference between actual and predicted values using different Artificial intelligence techniques based models. Sensitivity results suggest thatthe Cement (C) , Silica fume (SF), Fly ash (FA) and Water (W) are the most important parameters when ANN based modeling approach is used for prediction of the compressive strength of the HSC for this data set. ANN model is more sensitive model than GP and SVM based models.

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