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Prediction of fly ash concrete compressive strengths using soft computing techniques

Rajeshwari Ramachandra*[1] and Sukomal Mandal[1,2a]

[1]*Department of Civil Engineering, PES University, 100 feet Ring Road, Bengaluru-560040, India*
[2]*CSIR-NIO, Dona Paula, Goa- 403004, India*

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Abstract. The use of fly ash in modern-day concrete technology aiming sustainable constructions is on rapid rise. Fly ash, a spinoff from coal calcined thermal power plants with pozzolanic properties is used for cement replacement in concrete. Fly ash concrete is cost effective, which modifies and improves the fresh and hardened properties of concrete and additionally addresses the disposal and storage issues of fly ash. Soft computing techniques have gained attention in the civil engineering field which addresses the drawbacks of classical experimental and computational methods of determining the concrete compressive strength with varying percentages of fly ash. In this study, models based on soft computing techniques employed for the prediction of the compressive strengths of fly ash concrete are collected from literature. They are classified in a categorical way of concrete strengths such as control concrete, high strength concrete, high performance concrete, self-compacting concrete, and other concretes pertaining to the soft computing techniques usage. The performance of models in terms of statistical measures such as mean square error, root mean square error, coefficient of correlation, etc. has shown that soft computing techniques have potential applications for predicting the fly ash concrete compressive strengths.

Keywords: concrete; fly ash; compressive strength; soft computing techniques

1. Introduction

The compressive strength of concrete is a crucial decisive parameter for design engineers to measure the capability of any concrete structure. The concrete compressive strength being the backbone of the construction industry is usually measured the 28 days characteristic compressive strength of standard specimens tested under standard curing conditions, its prediction established from ages is a tedious procedure from the laboratory investigation. The modern-day construction industry focuses on meeting the population demands with escalating land value in developing countries, has led to the age old tradition of using industrial by-products or waste materials for concrete manufacture. The use of abundantly available industrial spinoffs like fly ash, targets the disposal and storage issues, which would otherwise pose a huge environmental threat. Alternate cementitious materials like fly ash in varying percentages have been used without compromising in the quality of construction and satisfying the durability requirements. Fly ash is an inert waste material from coal calcined thermal power plants with pozzolanic properties, which in concrete reacts with lime in presence of water and produces a binding gel further enhancing the mechanical and durability properties of concrete. With ever growing technology, conventional concrete has evolved from normal to high strength and further to ultra-high performance concrete. Research has been carried out to further improve the strength and durability properties of heterogeneous material i.e., concrete by incorporating abundantly available fly ash to suit the requirements of the construction industries.

The traditional method of testing the concrete compressive strength with laboratory investigations poses many drawbacks associated with the cost and time effectiveness, which has led to the development of many prediction models. Many numerical models have been proposed to interpret the complex nature of concrete, but with limited success. With the use of alternate replacement materials, it is difficult to design mixes without availability of any standard guidelines. In numerical analysis, it becomes extremely difficult to develop mathematical equations for these new concretes and the same may not hold good for new data. To address the drawbacks of these conventional prediction models, in the last few decades researchers have proposed the use of soft computing techniques in the field of Civil Engineering.

2. Soft computing

Soft computing is a transpiring multidisciplinary computing paradigm administering solutions to real situations. Soft computing provides the opportunity to represent ambiguity in human thinking with the uncertainty in real life (Ko *et al*. 2010). The advantages of using soft computing are its capability to tolerate imprecision, uncertainty, and partial truth to achieve tractability and robustness on simulating human decision-making behavior

*Corresponding author, Ph.D. Student
E-mail: rajeshwarir@pesu.pes.edu
[a]Formerly Chief Scientist

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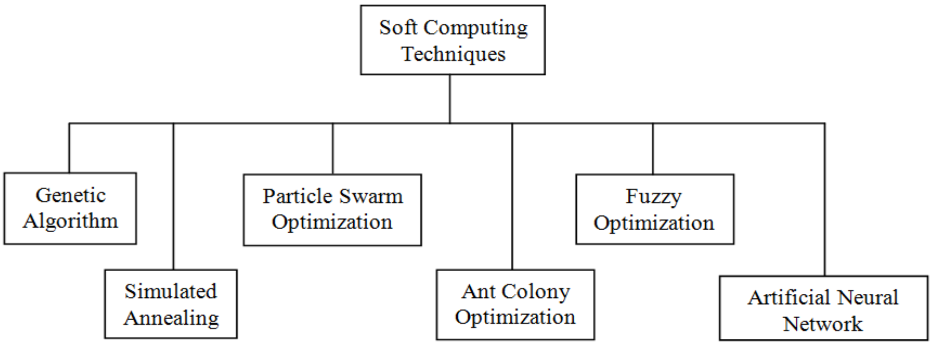

Fig. 1 Classification of soft computing techniques

with low cost. Soft computing is a group of unique methodologies, contributed mainly by Expert System, Fuzzy Logic (FL), Artificial Neural Networks (ANN) and Evolutionary Algorithms, which provide flexible information processing capabilities to solve real-life problems (Pal and Ghosh 2004).

Soft computing methods are theoretically different from long-established mathematical formulating methods, which imitate certain virtues and actions of biological, atomic, swarm of insects and neurobiological ideology. Fig. 1 shows a general classification of soft computing methods, most of which have been recently developed for solving complicated problems in reality (Rao 2009). The genetic algorithms (GA) depend on familiar genetics and choice whereas simulated annealing has the likeliness of thermal annealing of critically heated solids. Both these two methods are speculative and are highly applicable for discrete optimization situations which have high feasibility of achieving global minimum. Particle swarm optimization (PSO) depends on the actions of province of insects, birds or fish. Similarly, ant colony optimization (ACO) is based on the nature of real ant colonies to explore the shortest path from their nest to a food source.

In reality, for most of our problems the purpose, boundary conditions and the arrangement of data available are not clear and in lingual terms, hence for such cases FL methods may be applied. In neural network based methods, the problems are formulated in the form of network made of many neurons and network is trained to evaluate the solutions with minimum error. Further most of these individual methods are combined together to form ensemble models such as Adaptive network-based fuzzy inference system (ANFIS), ANN-GA, ANN-PSO, ANN-ACO, etc. to further optimize the solutions and increase the prediction accuracy.

Soft computing approaches are used for the prediction of the 28-day compressive strength of cement. The stepwise regression analysis results are compared with ANN and gene expression programming to show the comparison between the prediction accuracy of soft computing over classical statistical methods (Baykasoglu *et al*. 2004). The applications of soft computing techniques to hydrologic and water resources engineering are reviewed where it is extremely difficult to formulate a physics-based model or to obtain the mathematical solution to the problem with increasing complexity (Tayfur 2012).

A review on applications of soft computing in civil engineering field is carried out by Chandwani *et al*. (2013), where ANN and GA have been discussed briefly along with their applications in the diversified field of civil engineering, further discussing on the hybridization of GA and ANN to get the best from these techniques. The state-of-the-art review on the concrete material characterization using computational intelligence techniques has been carried out. A summary on various techniques such as statistical, pattern recognition/ machine learning, evolutionary algorithms, and hybrid approaches used for the prediction of the concrete properties such as strength, adhesion, flow, slump and serviceability on previous experimental data has been gathered (Rafiei *et al*. 2016). Various available computational methods for modeling and problem formulations in the field of optimization of the design of concrete mixtures along with their applicability to design problems are discussed by DeRousseau *et al*. (2018).

In the present study, a literature survey is carried out on the prediction of the compressive strength of various fly ash concretes like control concrete, high strength concrete (HSC), high performance concrete (HPC), self-compacting concrete/self-consolidating concrete (SCC), polymer concrete, geopolymer concrete, etc. using various individual and ensemble soft computing techniques (SCT). The study is categorized under different fly ash concretes elaborating on the techniques used for predicting the compressive strength. Each study has applied different SCTs with varying number of datasets, input and output parameters, fly ash percentages with different methodology. This has been discussed briefly with the results in the form of tables incorporating the models' performance in terms of statistical measures such as mean square error (MSE), root mean square error (RMSE), coefficient of correlation (CC), average determination coefficient (ADC), etc.

3. Review of literature

In this study, an attempt has been made to highlight applications of various SCTs in the area of fly ash concrete. The compressive strength of different types of fly ash concrete, i.e., control concrete, HPC, HSC, SCC, etc. is presented with summarizing author's contribution on application of soft computing for the compressive strength prediction.

Table 1 Statistical values of compressive strength of Control concrete using SCTs

Author	SCTs used	Number of Datasets			Fly ash range (%)	Statistical measures		
		Train	Validation	Test		Type	Train	Test
Lee (2003)	ANN	24	NV*	4	10-12	ADC	NR	0.91 - 0.97
Sebastia *et al*. (2003)	ANN	NR*	NV	NR	1.3-95	CC	0.862-0.957	0.815-0.974
Yeh (2006)	ANN	390	NV	50	0-50	CC	0.94	0.93
Uygunoglu and Unal (2006)	FL	NR	NV	24	0-30	CC	NR	0.99
Pala *et al*. (2007)	ANN	130	NV	14	0-55	CC	0.9980	0.9990
Topcu and Saridemir (2008)	ANN, FL	120	NV	60	10-40	CC	0.9989-0.9990	0.9972-0.9986
Tsai (2010)	PSO	83	NV	20	0-60	RMSE	1.753-2.305	1.241-2.175
Tsai (2011)	GA	83	NV	20	0-60	RMSE	2.53-6.18	3.02-7.03
Atici (2011)	MRA, ANN	19	4	4	0-60	CC	0.871-0.999	0.87-0.995
Yuan *et al*. (2014)	ANN, GA-ANN, ANFIS	150	NV	30	0-20	CC	NR	0.8246 - 0.9747
Omran *et al*. (2016)	M5P model tree, M5-Rules, REPTree, ANN, SVM	65	NV	7	0-40	CC	NR	0.9217- 0.9843
Rebouh *et al*. (2017)	ANN-GA	288	62	62	0-50	CC	0.98	0.98

*NR: Not reported, NV: No validation

3.1 Control concrete

Concrete is a heterogeneous mixture of cementitious material, aggregates (coarse and fine) and water. The compressive strength of concrete is not only affected by parameters like maturity, methods of curing and mix proportioning but also by methods of mixing, laying, conveying and measuring. With the availability of abundant waste materials like fly ash, having cementitious properties, concrete is manufactured with partial replacement of cement by fly ash. Many researchers have demonstrated different replacement levels of fly ash with cement to get the maximum concrete strengths. Fly ash concretes show considerable increase in long-term mechanical properties and desirable durability aspects with low water to binder ratios. Concrete containing fly ash influences mainly on water demand and workability as credited by the spherical shape of fly ash particles in comparison with Portland-cement mix having same cementitious content. The fly ash concrete compressive strength prediction using SCTs is briefed below.

The performance in terms of statistical measures (RMSE/CC/ADC) of SCT based models collected from literature to predict the compressive strength of control concrete using various individual and hybrid models are shown in Table 1. It shows the flexibility and discrepancies of each of these SCT based models in estimating the compressive strength of control concrete with varying percentages of fly ash. The data for models construction are either gathered from literature or experimental investigations are carried out for their respective works. The procedures used for the choice of input parameters are related to the mix proportions of concrete and laboratory testing of their compressive strength. The input parameters selected for model building are of varying numbers incorporating various constituents such as cement, blast furnace slag, fly ash, water, super plasticizer, fine aggregate, coarse aggregate, age of samples, crushed stone I (4-8 mm), crushed stone II (8-16 mm), high range water reducing agent replacement ratio, fly ash replacement ratio, calcium oxide, Rebound number, ultrasonic pulse velocity, etc. The percentage of cement replaced with fly ash in control concrete varies from 0 to 95. The datasets are divided into train and test groups in 70:30, 60:40, etc. ratios or a specific number of datasets are categorized for testing depending on the problem formulation. It can be seen that the noted models have shown good accuracy in the prediction of the compressive strength of control concrete trailing considerable tuning of parameters.

From Table 1, it is evident that ANN is widely used to predict the complex behavior of fly ash concrete achieving good correlations with experimental values. It is used for the prediction of the compressive strength of high volume fly ash (HVFA) concretes using varying methodologies relevant to specific studies such as the use of multiple ANN architectures, have shown better results in comparison to single architectures for different curing periods by achieving a maximum ADC of 0.97 (Lee 2003); the ANN model with sensitivity analysis based on Trajan ANN simulator is used to analyze the major inputs influencing the 28 days unconfined compressive strength with CC of 0.967 with 20 inputs which is further reduced to 0.815 for 5 inputs, emphasizing on maximum addition of coal fly ash established by European Standards (Sebastia *et al*. 2003). Simplex-centroid experiment design method with ANN's generalization efficiency is applied to obtain high correlation (CC=0.929) with the concrete compositions and compressive strength (Yeh 2006). Also, the ANN models are able to generalize the behavior of low- and high-lime fly ash concrete cured over short and long terms with highest CC of 0.99 (Pala *et al*. 2007, Topcu and Saridemir 2008). It is also seen that the ANN models have performed better than multiple regression analysis (MRA) when modeled with different mix proportions and curing methods showing good correlations in the range of 0.926-0.995. Other individual learning method such as, FL models have also shown performance similar to ANN with CC of 0.99 to estimate the low- and high-lime fly ash concrete

Table 2 Statistical values of compressive strength of HSC using SCTs

Author	SCTs used	Number of Datasets			Fly ash range (%)	Statistical measures		
		Train	Validation	Test		Type	Train	Test
Oztas et.al (2006)	ANN	169	NV*	18	0-20	CC	1	1
Baykasoglu et. al (2009)	RA, ANN, GEP	NR*	NV	104	0-20	MSE	NR	0.26
Lee and Yoon (2009)	ANN, HS algorithm	NR	NV	10	0-31	AE	NR	2.51
Tsai and Lin (2011)	WGP	84	NV	20	0-20	RMSE	1.628-3.853	1.863-3.750
Vakhshouri and Nejadi (2014)	ANN, ANFIS	240	NV	65	0-30	Error	5.7935, 5.4437	7.2018, 6.9088

*NR: Not reported, NV: No validation

compressive strength (Topcu and Saridemir 2008), which is found to increase with fly ash replacement percentage and water-binder ratio (Uygunoglu and Unal 2006). The overall prediction accuracy of the ANN models is better compared to other individual models and MRA; and the values are close to the experimental results.

The hybrid models, such as GA based ANN and ANFIS have surpassed the traditional ANN model's performance, showing better correlation of 0.9747 (Yuan *et al*. 2014) compared to ANN which is characterized by the surface being non-smooth and trapped in local minimum thus focusing on improving the model's tenacity and accuracy. Also, ANN-GA has shown better performance using same architecture when compared to the ANN model and experimental results with correlation of 0.979 (Rebouh *et al*. 2017) compared to the previous work (Yuan *et al*. 2014). PSO based hybrid models such as, hybrid multilayer perceptrons (HMLP) constructed with one-hidden layer using 3 higher order connectors have shown good prediction accuracy with least RMSE of 1.241, where HMLP has performed better than the linear traditional model (Tsai 2010). Weighted operation structures along with GA are used to achieve definite optimization showing performance similar to ANN with advantage of using weighted formula to solve real life scenarios (Tsai 2011). The hybrid models have shown good correlations with the experimental values in comparison to individual models.

Comparing advanced models such as Gaussian processes regression with support vector machine (SVM) based regression and ANN based multilayer perceptron, the former has performed better with CC of 0.9744 based on four input variables compared to the latter methods and other regression tree models (M5P, Reduced Error Pruning Tree, M5-Rules, decision stump) and ensemble models (additive regression and bagging with 10-fold cross validation) (Omran *et al*. 2016).

Table 1 gives an overview of various soft computing techniques applied for predicting the compressive strength of fly ash concrete, where comparison of the results between each study is not feasible due to various assumptions made during materials selection to casting and testing of concrete under conditions; highlighting on tuning of the parameters of SCT based individual or hybrid models to further improve the generalization capacity. Each study is focused on the individual or hybrid learning model with variation in the parameters or attempting to create more sophisticated methods to predict the concrete properties meeting success sometimes over traditional computational models. SCTs have shown potential to be used for the prediction of the fly ash concrete compressive strength with good correlation.

3.2 High strength concrete

The term high strength has evolved from normal strength with the use of ideal combination of mineral and chemical additives along with the basic composition to improve the strength properties of concrete yielding HSC. It has marked its place in the construction industry with distinguished workability, strength and durability properties. HSC has the compressive strength of 42 MPa and higher at 28 days helping builders to achieve the design requirements easily rendering huge cost savings in large scale construction projects (ACI 211.4R-08). With the use of more number of ingredients, lately SCTs have become the first preference for predicting the HSC strength to get an economic and workable mix.

The statistical measures (MSE, RMSE and Average Error % - AE) of various SCT based models used for the prediction of the compressive strength of HSC are shown in Table 2. It is seen that varying number of datasets is used for model construction with the test data either collected from literature or from experiments carried by researchers for the specific study in HSC. The input parameters used for model construction are cement, water/binder ratio, water, fine aggregate, coarse aggregate, fly ash, air entraining agent, super plasticizer, silica fume replacement ratio, etc. The percentage of cement replaced with fly ash in HSC varies from 0 to 31. From the results, it can be seen that ANN is successful in interpreting the complex behavior of the HSC compressive strength with CC close to 1 using scaled conjugate gradients algorithms and sigmoid activation function (Oztas *et al*. 2006). Also, ANN is able to predict with minimum MSE of 2.51% for 10 mixes which are experimentally carried out, by using MLR for model construction and mix proportions optimized using harmony search (HS) algorithm (Lee and Yoon 2009).

The hybrid models, such as gene expression programming (GEP) with the use of weights to create a new weighted genetic programming (WGP) and hierarchical approaches for function optimization have shown better performance with least MSE of 0.26 (Baykasoglu *et al*. 2009) and RMSE of 1.863 (Lee and Yoon 2009) compared to the regression analysis (RA) and ANN models. Where, the former adopted multi-objective optimization models combined with hierarchical approaches to interpret multiple objectives and the latter adopted optimized functional operators in binary tree topology with weight coefficients along with increase in layer number from 1 to 6. Also, the ANFIS models have shown least errors with 30 combinations of various factors investigated by sub-clustering method and obtaining the best combinations of the parameters in comparison to the ANN models using Sugeno fuzzy inference system and grid partition method (Vakhshouri and Nejadi 2014).

From Table 2, it is seen that the hybrid models have better optimization capacity of the complex behavior of HSC compared to traditional SCT methods. Comparison of the studies are not feasible with each other due to various methodologies adopted in specific studies, however a general overview of SCTs can be obtained from Table 2, from which it is seen that, SCTs can be well used for the compressive strength prediction of HSC.

3.3 High performance concrete

Concrete has revolutionized from normal to high strength with high performance characteristics improving the fresh and hardened properties. Research has been relentlessly carried out to enhance the concrete properties, with the use of abundantly available waste or recycled cementitious materials like fly ash, blast furnace slag (BFS) and chemical admixtures along with basic ingredients. With the increase in the number of parameters in manufacture of HPC, design of mixtures becomes extremely difficult without any standard guidelines. The HPC strength being experimentally achieved by trial and error has led to wastage of materials which is costly and time consuming. HPC being most suitable for the modern-day constructions has gained a lot of attention from researchers to further improve the material behavior making it ecofriendly and economical. The complex nature of HPC determined by the use of SCTs from literature is discussed below.

Various SCT based models performance in terms of commonly used statistical measures such as CC, RMSE, mean absolute percentage error (MAPE%), MSE (kg/m^3), AE%, median error (ME), correct prediction rate (CPR%), correct classification rate (CCR%), average accuracy (AA%). etc. for the prediction of the compressive strength of HPC are shown in Table 3. Several single and ensemble SCT based models have been developed to predict the HPC compressive strength. The commonly used input parameters for the model development are cement, fly ash, blast furnace slag, water, super plasticizer, fine aggregate, coarse aggregate, age of testing, etc. The mix proportions with different mineral and chemical additive materials along with their compressive strength values are collected from literature, data repositories or experiments carried out in laboratories for the specific study. The selected datasets are divided into train and test groups with k-fold cross-validation carried out to assess the generalization capacity of the models. The percentage of cement replaced with fly ash in HPC varies from 0 to 60. From Table 3, it is evident that HPC has gained a lot of attention from researchers to predict its behavior using variety of SCTs with single learning models like ANN, FL, etc. to sophisticated hybridized models such as smart firefly algorithm (SFA)-based least squares support vector regression (SFA-LSSVR), Deep Restricted Boltzmann Machine (DRBM), etc.

ANN is seen to be the preference from earlier to later years due to minimum parameter setting and has shown appreciable performance with CC values in the range of 0.90-0.97 (Yeh 1998, Yeh 1999, Yeh and Lien 2009, Slonski 2010, Chou *et al*. 2011, Khan 2012, Lingam and Karthikeyan (2014), Akpinar and Khashman 2017, Bui *et al*. 2018). Various methodologies have been used in modeling and parameter setting of the ANN model, such as random shuffling and combining of the datasets (Yeh 1998), use of software for design of mix proportions (Yeh 1999), various approaches such as validation set, maximum marginal likelihood and full Bayesian approach is used for the model selection (Slonski 2010), use of radial basis function for training the model (Khan 2012), use of many learning schemes with training-to-testing ratios of 40:60, 50:50, and 60:40 (Khashman and Akpinar 2017) and learning methods based on training period to classify the concrete strengths to low, moderate and high strength (Akpinar and Khashman 2017), use of modified firefly algorithm (MFA) to optimize the initial weights and bias (Bui *et al*. 2018), etc. It is seen that the ANN model has not performed with random shuffling of datasets (Yeh 1998) similar to classification based on durations of the learning methods (Akpinar and Khashman 2017) with moderate CCs. Also, ANN has predicted the compressive strength of quaternary blended HPC at 28 days with higher CCs compared to different ages (Lingam and Karthikeyan (2014).

Application of genetic programming (GP) has been found extensively for the prediction of the HPC compressive strength with least error performances. GP has been further optimized with macro-evolutionary algorithm (MAGP) and grammatical evolution (GEGA) to determine the fittest function type with single and multivariable (Chen 2003, Chen and Wang 2010), also biological evolutionary process-natural selection and genetics are used to determine the proposed design of HPC mixtures (Lim *et al*. 2004), and basic arithmetic operators and mathematical functions are used to obtain the optimized model of GEP (Mousavi *et al*. 2012), geometric semantic genetic operators are used in the search process (Castelli *et al*. 2013), etc. Both the ANN and GP based models have shown good correlation in comparison to linear and non-linear regression methods. Genetic operation trees (GOT) have achieved CC of 0.93 and least RMSE of 5.74, almost similar to performance of the ANN models and better than non-linear regression (NLR) models. GOT can be used for practical purposes where self-organized regression formula is required to fit the experimental data set (Yeh 2009, Peng *et al*. 2010). K-fold cross validation with good generalization capability (Chou *et al*.2011) and hierarchical classification and regression approach (Chou and Tsai 2012) have been used upon individual models like linear regression (LR), ANN, SVM, SVR, etc. and metaclassifier models such as multiple additive regression trees (MART) and bagging regression trees (BRT) to improve the performance of the models achieving CC of 0.911 and MAPE of 3.62%.

Further, various ensemble techniques combining two or more models such as SVM, ANN, classification and regression trees (CART), chi-squared automatic interaction

Table 3 Statistical values of compressive strength of HPC using SCTs

Author	SCTs used	Number of Datasets			Fly ash range (%)	Statistical measures		
		Train	Validation	Test		Type	Train	Test
Yeh (1998)	ANN, RA	516-611	NV*	116-211	0-30	CC	0.917-0.945; 0.713-0.792	0.814-0.922; 0.683-0.779
Yeh (1999)	ANN	495	NV	200	0-30	CC	NR	0.903
Chen (2003)	MAGP, GP	400	NV	200	0-30	RMSE	4.56-9.30	4.64 - 10.60
Lim *et al.* (2004)	GA	181	NV	8	0-20	AE	NR	1.88 -5.40
Yeh and Lien (2009)	GOT, NLR, ANN	1000	NV	196	0-22	CC	0.8432-0.9407	0.8669 - 0.9338
Peng *et al.* (2010)	GOT, NLR, ANN	267, 383, 256	NV	133, 192, 128	0-25	RMSE	4.29-9.27	5.74 -10.53
Slonski (2010)	ANN	687	NV	343	0-60	CC	0.962-0.967	0.93 -0.955
Chen and Wang (2010)	GEGA, GP, BPN, MLR	760	NV	380	0-22	RMSE	NR	9.949- 22.861
Jayaram *et al.* (2010)	PSO	350	NV	NR	0-60	MSE	NR	1-10
Chou *et al.* (2011)	ANN, MLR, SVM, BRT, MART	927	10-fold	103	0-60	CC	NR	0.6112- 0.9108
Chou and Tsai (2012)	SVR, LR, ANN, Hybrid models	927	10-fold	103	0-60	MAPE	14.67 - 31.55	3.62 - 5.39
Cheng *et al*. (2012)	SVM, BPN, EFSMIT	927	NV	103	0-60	CC	0.722 - 0.910	0.752 - 0.927
Khan (2012)	ANN	NR*	NV	NR	0-40	CC	NR	0.95
Nedushan (2012)	ANN, stepwise regression	NR	NV	NR	0-20	CC	NR	0.9654 - 0.9844
Mousavi *et al.* (2012)	GEP	907	226	NR	0-50	CC	0.768-0.907	0.840 - 0.914
Chou and Pham (2013)	SVM, ANN, CART, CHAID, LR	927, 93, 94, 130	10-fold	103, 10, 10, 14	0-55	CC	NR	0.93 - 0.993
Erdal *et al*. (2013)	ANN, Wavelet ANN	927, 824	10-fold	103, 206	0-60	CC	NR	0.9088-0.9528, 0.8921-0.9326
Castelli *et al.* (2013)	GP	720	NV	308	0-60	ME	3.897 - 7.792	5.926 - 8.67
Chou *et al.* (2014)	ANN, SVM, CART, LR	1020	10-fold	113	0-55	RMSE	NR	1.51 - 7.11
Cheng *et al.* (2014b)	GA-ESIM, SVM, ANN	927	10-fold	103	0-60	RMSE	6.04-8.69	6.53 - 8.87
Cheng *et al.* (2014a)	SVM, ANN, ESIM, Hybrid models	824	5-fold	206	0-60	RMSE	3.294-7.117	6.379 - 7.170
Lingam and Karthikeyan (2014)	ANN	138	NV	46	0-25	CC	NR	0.925
Tsai (2015)	ANN	101/340	NV	25/85	0-60	RMSE	4.74-7.04	6.08 - 6.56
Chou *et al.* (2016)	SFA-LSSVR	NR	10-fold	NR	0-50	CC	NR	0.94
Khashman and Akpinar (2017)	ANN	412-618	NV	618-412	0-60	CPR	87.86-96.31	63.11 - 76.21
Akpinar and Khashman (2017)	ANN	515	NV	515	0-60	CCR	95.34- 97.09	68.16 - 73.40
Behnood (2017)	M5P model tree	1625	NV	287	0-50	CC	0.96	0.96
Rafiei *et al.* (2017)	DRBM, ANN, SVM	93-51	NV	10-52	0-60	AA	NR	91.8 - 96.6
Bui *et al.* (2018)	MFA-ANN	1020	10- fold	113	0-50	CC	NR	0.95

*NR: Not reported, NV: No validation

detector (CHAID), LR and generalized linear methods (Chou and Pham 2013), ensembles with bagging, gradient boosting combined with discrete wavelet transform (DWT) (Erdal *et al*. 2013); and base learners like multilayer Perceptron (MLP) ANN, SVM, CART, LR are used to construct individual and ensemble learning classifiers along with the voting, bagging and stacking combination methods considered to integrate multiple classifiers (Chou *et al*. 2014) have been used to obtain the highest performance, CC of 0.99. PSO has also been applied to determine the optimum mix proportions (Jayaram *et al*. 2010) with its use in 3 layers high-order neural network (HONN) for parameter learning, avoiding over fitting and providing concise formula to get least RMSE of 6.08 (Tsai 2015).

Advanced sophisticated and hybrid algorithms like the artificial intelligence hybrid systems, fusing fuzzy logic, weighted SVMs and fast messy algorithms into an evolutionary fuzzy SVM inference model for time series data (EFSMIT) (Cheng *et al*. 2012); k nearest neighbor algorithm with differential evolution for 103 datasets (Nedushan 2012); genetic algorithm based evolutionary support vector machine (GA-ESIM) by combining the K-means and chaos genetic algorithm with ESIM (Cheng *et al*. 2014); Genetic Weighted Pyramid Operation Tree

Table 4 Statistical values of compressive strength of SCC using SCTs

Author	SCTs used	Number of Datasets			Fly ash range (%)	Statistical measures		
		Train	Validation	Test		Type	Train	Test
Nehdi *et al.* (2001)	ANN	25	NV*	4	0-35	CC	NR	0.9993
Ozbay *et al.* (2008)	GP	28	NV	16	0-60	CC	0.891-0.981	0.898-0.979
Nehdi and Bassuoni (2009)	FL	23	NV	NR	0-20	CC	NR	0.707-0.837
Prasad *et al.* (2009)	ANN	300	NV	12	27-87	CC	NR	0.91-0.92
Sonebi and Cevik (2009a)	GP	20	NV	6	0-82	CC	0.82-0.99	0.62-0.97
Sonebi and Cevik (2009b)	NF	21	NV	5	0-51	CC	0.99	0.81
Jin-li and Hai-qing (2010)	ANN	12	NV	NR	0-52	MSE	NR	1.30926e-007
Uysal and Tanyildizi (2011)	ANN	84	NV	84	0-30	CC	0.95	0.92
Aiyer *et al.* (2014)	LSSVM, RVM	56	NV	24	0-55	CC	0.974, 0.964	0.940, 0.953
Douma *et al.* (2016)	ANN	80	11	23	0-60	CC	NR	0.76-0.95
Yaman *et al.* (2017)	ANN	NR*	NV	59, 10	10-85	CC	NR	0.02- 0.46, 0.63-1.00
Vakhshouri and Nejadi (2018)	ANFIS	49	NV	6	0-30	AE	0.00463 - 15.643	18.479- 524.3267

*NR: Not reported, NV: No validation

(GWPOT), an advancement of genetic operation tree that includes GA, WOS, and Pyramid Operation (Cheng *et al.* 2014); SFA-LSSVR model (Chou *et al.* 2016), Restricted Boltzmann machine & deep belief concepts integrated to form DRBM (Rafiei *et al.* 2017) are developed and used for further increasing the computational efficiency and earlier convergence of overall results compared to flat models such as ANN and SVM. Also, mathematical equations are developed and implemented using M5P model tree algorithm to obtain CC of 0.96 (Behnood *et al.* 2017).

Various SCTs are applied to learn the complexity of HPC providing an insight to extent to which research has been carried out to predict its compressive strength. Comparison of various SCTs may not be possible due to wide range of the input parameters selection used in model construction, parameter tuning emphasizing on their performance, many such assumptions and constraints which could not have been specified in the particular study but plays an important role in the prediction of the HPC compressive strength. With the use of various SCT based models, the compressive strength predictions are close to experimental investigations with good correlation and least errors. The use of SCTs has led to reduction on wastages of materials, emerging with minimum prediction error, and hence demonstrating to have a great potential for the prediction of the compressive strength of HPC.

3.4 Self-compacting concrete

Self-compacting or self-consolidating concrete is a class of HPC, as the name suggests is a highly workable mix avoiding segregation and bleeding; filling the congested areas of reinforcement cages with its own weight saving on the use of mechanical vibrators. It eliminates the necessity for compaction while placing fresh concrete that saves time, reduces overall cost, better working environment, etc. With addition of superplasticizer to SCC its behavior becomes more complex to model which is solved using several SCT based models, are discussed below.

The statistical measures such as CC, MAPE and AE of SCTs models used for the prediction of the compressive strength of SCC are shown in Table 4. Various SCT models are developed with the multi input and single or multi output parameters. The mix proportions are collected from literature and in most cases the laboratory investigations are carried out to be used as test datasets for evaluating the performance of the trained models. The input parameters commonly used for the SCC mixtures are cement, water, fly ash, slag, silica fume, limestone filler, sand, gravel, viscosity-enhancing admixture, and high-range water-reducing admixture, water/cement, water/binder, water/powder, fine aggregate/powder, fly ash/binder and silica/binder ratio, binder content, fine aggregate, coarse aggregate, super plasticizer, etc. The output of the models are considered as each ingredient of concrete or 28-day compressive strength, slump value, slump flow diameter, L-box blocking ratio, V-funnel time, etc. The percentage of cement replaced with fly ash in SCC varies from 0 to 87.

ANN is used to a larger extent for modeling the fresh and hardened properties of SCC due its simplicity and minimum parameters tuning. From Table 4, SCC properties are modeled individually using same ANN network architecture including all properties and the model has shown best performance with CC of 0.9993 (Nehdi *et al.* 2001). Also, the ANN models with low volume fly ash SCC data is used for predicting the behavior of SCC with high volume fly ash and also the same model is used for the HPC behavior prediction by intuitively relating with ratios like water- binder ratio, water-cement ratio, etc. which has shown high correlation with CC of 0.92 (Prasad *et al.* 2009). It is seen that researchers have applied various methodologies to maximize the performance of the ANN model, such as hidden layer nodes are varied and tested to achieve maximum correlation (Li and Qing 2010), use of various training algorithms such as Fletcher-Powell conjugate gradient and Levenberg-Marquardt back propagation algorithm with nonlinear sigmoid activation function (Aiyer *et al.* 2014), a multilayer feed forward model is developed to determine large number of outputs with minimum inputs which has performed satisfactorily with CC values in the range of 0.80 to 0.95 (Douma *et al.* 2016); also the two ANN models, one with multi input - multi outputs to predict the ingredients of SCC mixes and the other multi input - single output in each step are built

Table 5 Statistical values of compressive strength of other concretes using SCTs

Author	SCTs used	Number of Datasets			Fly ash range (%)	Statistical measures		
		Train	Validation	Test		Type	Train	Test
Tanyildizi and Coskun (2007)	FL	NR*	NV*	4	0-15	AE	NR	7.16
Barbuta *et al.* (2012)	ANN	11	NV	4	6.4 - 12.8	CC	0.98	0.91
Nazari and Khalaj (2012)	ANFIS	102	21	21	30-70	CC	0.9900 0.9911	0.9443 0.9592
Omran *et al.* (2014)	ANN	65	10-fold	7	0-40	CC	NR	0.9573-0.9678
Nazari and Sanjayan (2015)	ANFIS, ICOA-SVM	NR	NV	NR	0-50	CC	0.7419-0.8993	0.7017-0.8691
Hossain *et al.* (2016)	ANN, Regression	165	NV	15	0-40	CC	NR	0.989, 0.902
Lokuge *et al.* (2018)	MARS	68	NV	32	100	CC	0.768	0.123

*NR: Not reported , NV: No validation

where the latter has performed better (Yaman *et al*. 2017). The performance of GP models is in good correlation with CC of 0.97 (Ozbay *et al*. 2008, Sonebi and Cevik 2009). An attempt is made to determine a global durability index based on multiple performance measures of concrete using fuzzy inference systems based on accelerated tests achieving a correlation CC of 0.837 (Nehdi and Bassuoni 2009); also 7 properties are modeled using Neurofuzzy (NF) approach to characterize the SCC mixtures obtaining CC of 0.81 (Sonebi and Cevik 2009).

The hybrid model such as ANFIS is used based on the error size in each combination analysis, weighting factor and importance level of each parameter is evaluated to apply the correction factors to get the most optimized relationship resulting with minimum average error (Vakhshouri and Nejadi 2018). Individual models such as Least Square Support Vector Machine (LSSVM) and Relevance Vector Machine (RVM) models are better compared to ANN, providing prediction equations where RVM uses only relevant vectors for the prediction purpose showing best performance (Aiyer *et al*. 2014). Many SCTs have been used to predict the SCC behavior meeting limited success which is evident from the Table 4; also reverse modeling using ANN have been attempted to obtain optimum mix proportion, along with an effort to determine global durability index.

3.5 Other concretes

Sustainable constructions are attracting the construction industry for the use of waste and by-products of industries leading to the development of many concretes like light weight concrete, green concrete, geopolymers, etc. Geopolymers, an artificial synthetic alumino silicate material is a new material, which is fire, acid and heat-resistant, have been developed and used extensively as an alternate to Portland Cement concrete. Also, concretes using polymers are designed to replace lime-type cements as binder to obtain polymer concrete. The use of SCTs for predicting the compressive strengths of these concretes has been carried out to minimize cost and wastage of resources. SCTs for predicting the compressive strengths of these concretes are discussed below.

The performance measures (AE%/CC) of SCT models used for the prediction of the compressive strength of other concretes with the use of fly ash such as polymer concrete and geopolymers are shown in Table 5. Many single and metaheuristic algorithms have been used to learn the behavior of these concretes. The models are trained and tested using datasets selected from literature and the commonly used input parameters are measure of epoxy resin, filler content, aggregates, curing time, Calcium hydroxide content, superplasticizer, sodium hydroxide (NaOH) concentration, mold type, geopolymer type, water / sodium oxide molar ratio, cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, age of testing, sodium silicate, NaOH and potassium hydroxide (KOH), oven curing temperature, oven curing time and age of ambient temperature curing, etc. The percentage of cement replaced with fly ash varies from 0 to 100.

Single learning models such as ANN, have been used to predict the compressive strength of polymer concrete which has shown appreciable performance with CC of 0.91 (Barbuta *et al*. 2012) and the concrete composition is determined by reverse ANN modeling; also the ANN models are developed separately for numerical and relative input methods for Portland concrete (PC) and Portland limestone cement (PLC) concrete used to predict the behavior of Green concrete (Omran *et al*. 2014) and engineered cementitious composites (ECC) (Hossain *et al*. 2016) which has achieved CC close to 1 and outperformed the regression models. The use of metaheuristic algorithms such as genetic algorithm (GA), particle swarm optimization algorithm (PSOA), ant colony optimization algorithm (ACOA), artificial bee colony optimization algorithm (ABCOA) and imperialist competitive algorithm (ICOA) are attempted and the results are better compared to single models such as ANN, SVM (Nazari and Sanjayan 2015). Also, FL (Tanyildizi and Coskun 2007) and ANFIS models (Nazari and Khalaj 2012) are used to predict the compressive strengths of lightweight concrete and geopolymers achieving better correlation values. A Multivariate Adaptive Regression Spline (MARS) model is proposed to establish the relationship between the input variables and compressive strength of geopolymers with help of contours (Lokuge *et al*. 2018). It can be seen that with the use of SCTs, the compressive strength of other

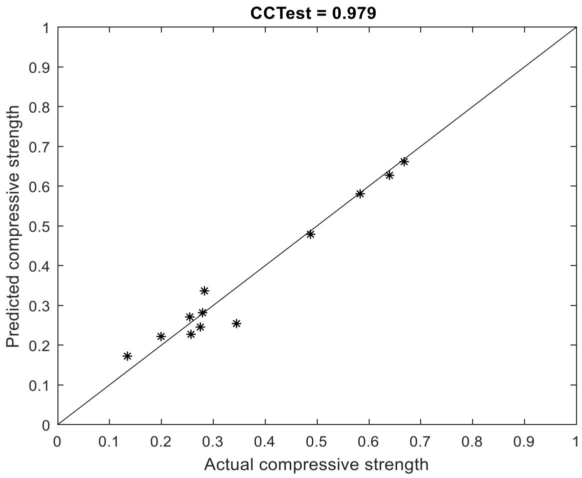

Fig. 2(a) Scatter plot of experimental vs. ANN predicted compressive strengths for test data

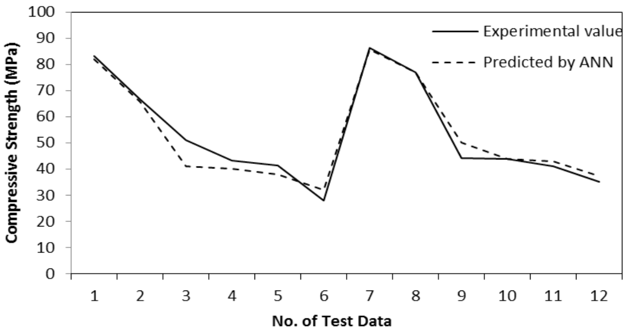

Fig. 2(b) Time series plot of experimental vs. ANN predicted compressive strengths for test data

types of concrete can be predicted eliminating the use of laboratory investigations.

3.6 Case study

In this study (Rajeshwari and Sukomal 2019), ANN is used to predict the 28 days compressive strength of high volume fly ash (HVFA) concrete. A total of 270 data sets is collected from the experimental investigations and developed the ANN model with 8 input parameters as cement, fly ash, water-binder ratio, superplasticizer, fine aggregate, coarse aggregate, specimen and fly ash type. The ANN model is trained with Levenberg Marquardt algorithm to test a dataset of 12 nos. from a particular study (Lam *et al.* 1998). The best ANN architecture for predicting the behavior of HVFA concrete is NN 8-11-1 (8-input nodes, 11 - hidden nodes and 1-output node).

The training results show that the proposed ANN model has successfully correlated the input parameters with the output. The statistical values for the 28 days compressive strength of HVFA concrete are expressed in terms of CC of 0.97, 0.979 for train and test data respectively. This shows that the trained ANN model is efficient in predicting the test data from a single study with good correlation (Figs. 2a and 2b). Hence ANN could be used as an efficient tool for predicting the HVFA concrete compressive strength of a single study.

4. Conclusions

Fly ash concrete promoting sustainable developments has gained attention not only from researchers to enhance its behavior but also the modern-day construction industry, have achieved targets within limited periods. Researchers have triumphed the classical compressive strength prediction methods by the development of many simple and hybrid computational models to save materials and man power. The statistical and computational methods of the compressive strength prediction are tedious and established equations are not good enough for new data sets with the use of many replacement materials. An emblematic form of computational method known as soft computing has been used in predicting the compressive strengths of the fly ash concrete.

The present study gives an overview of various single and ensemble learning models used for predicting the compressive strength of fly ash concretes such as control concrete, HSC, HPC, SCC, other concretes. The following conclusions are summarized from this study.

- Various single and ensemble learning SCT models have been used for the prediction of the compressive strengths of fly ash concretes such as control concrete, HSC, HPC, SCC, etc.
- It is evident that ANN has been able to learn faster the complex behaviors of different fly ash concretes compared to other individual models.
- Various advanced and hybrid models are developed in order to understand the complexity of fly ash concrete behavior achieving good prediction accuracy emphasizing on the importance of parameter setting.
- From the case study, it is observed that ANN could be used as an efficient tool which has potential for predicting the HVFA concrete compressive strength of the test data from a single study.
- SCTs have potential applications for the compressive strength prediction of different types of fly ash concretes.

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