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Research Article

Applications of Artificial Neural Networks in Modeling Compressive Strength of Concrete: A State of the Art Review

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Abstract

Cement concrete is widely used throughout the world as a key construction material in civil engineering projects. Being a complex compound comprising of cement, sand, coarse aggregate, admixture and water, its compressive strength is a highly nonlinear function of its constituents, thereby making its modeling and prediction a difficult task. Nature inspired computational techniques, provide an efficient and easy approach for modeling complex, nonlinear or difficult to establish relationships between the independent and dependent variables. Artificial Neural Networks inspired by the learning ability of a human brain, can be regarded as an engineering counterpart of a biological neuron and its highly interconnected and parallel nature, gives them immense ability to learn from past examples capturing unknown relationships, making them a versatile tool for modeling the real world problems. The review paper is an attempt to provide an introduction to artificial neural networks, highlighting its applications as a computational tool for modeling complex functional relationships of various constituents influencing the compressive strength of concrete.

Keywords: *Artificial Neural Networks, Back-propagation algorithm, Compressive Strength of Concrete, Self Compacting Concrete, High Performance Concrete, Rubberized Concrete.*

1. Introduction

Concrete is an essential material in civil engineering, which is widely used all over the world. It is a composite material comprising of key constituents, namely, cement, sand (as fine aggregate), fly ash, coarse aggregate, admixture and water. The properties of concrete, including its compressive strength are a highly nonlinear function of its constituents. Various studies have shown that concrete's strength not only depend on water-to-cement ratio, but is also related to the other additive constituents (Oluokun, 1994). The lack of standard empirical relationships to judge the compressive strength of concrete based on its constituents has created the interest of the researchers towards soft computing tools. (Chaturvedi, 2008) has defined Soft Computing as an emerging collection of methodologies which aim to exploit tolerance for imprecision, uncertainty and partial truth to achieve robustness, tractability and total low cost. Soft computing harnesses statistical, probabilistic and optimization tools for learning, predicting and classifying new patterns based on the past data. Artificial Neural Networks (ANNs) touted as the next generation of computing forms a sub-set of Soft Computing Tools. Artificial neural networks are massively parallel adaptive networks of simple nonlinear computing elements called neurons, which are intended to abstract and model some of the functionality of human nervous system in an attempt to partially capture some of its computational strengths (Kumar, 2013). As compared to conventional digital computing techniques, and procedural and symbolic processing, neural networks are advantageous because they can learn from example and generalize solutions to new renderings of a problem, can adapt to fine changes in the nature of a problem, are tolerant to errors in the input data, can process information rapidly, and are readily transportable between computing systems (Flood and Kartam, 1994).

The unconventional method of deriving information through learning has created immense interest in the field of neural networks. The capability of artificial neural networks to act as universal function approximator has been traditionally used to model problems in which the relationship between the dependent and independent variable is not clearly understood (Aggarwal and Aggarwal, 2011). Due to the black-box nature of neural networks, there is no need to assume any functional relationship among the various variables. ANNs automatically constructs the relationships and adapts itself based on the data used for training. ANNs modeling ability to derive meaning from unknown and non-linear interrelationships among variables have been harnessed to aid the prediction of behavior of engineering and natural systems. Concrete's compressive strength is one such problem that is unstructured in nature involving highly non-linear relationships among its constituents and compressive strength. The review paper presents the

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versatility and robustness of artificial neural networks in modeling compressive strength of concrete.

The review paper has been divided into sections. Section 2 deals with an introduction to neural networks and its use as a modeling tool. The applications of neural networks for modeling various kinds of concrete have been dealt in Section 3. Finally the review paper has been summarized and concluded in Section 4.

2. Artificial Neural Networks as a Modeling Tool

Artificial Neural Networks take their name from the networks of nerve cells in the brain. Although they represent a much simplified version of the human brain, yet these computational models inspired by biological neural network may provide new directions to solve problems arising in natural tasks. In contrast to digital computers, which offer sequential processing of information, ANNs parallel processing inspired by working of a human brain, gives computers an additional advantage to simultaneously process large volumes of data. ANNs are well suited for problems whose solutions require knowledge that is difficult to specify but for which there are enough data or observations (Zhang *et al*, 1998). The neural network's ability to learn from experience without seeking prior knowledge about the governing relationships and to generalize when presented with unseen data forms the backbone of its modeling ability, with which it approximates any functional relationship with reasonable accuracy. It has been reported that the ANN has the ability to extract the patterns in phenomena and overcome the difficulties due to the selection of the model form, such as linear, power, or polynomial (Tokar and Johnson, 1999). The common features of some of these successful applications of ANNs in prediction and modeling are that the quantities being modeled are governed by multivariate interrelationships and the data available are ‘‘noisy’’ or incomplete (Oreta and Kawashima, 2003).

(Haykin, 2009) has defined neural networks as "a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use". Neurons are the basic units used for computation in the brain, and their simplified abstract models are the basic, processing units of ANNs (Castro, 2007). In addition to the processing elements called "neurons", the neural networks comprise of the connections between the processing elements. The connections carry a "weight" parameter signifying importance of the link between the neurons. The synaptic weights store the knowledge of the neural networks and therefore in the training phase with a continuous flow of information, there is a gradual reorganization of weights within the neural network and subsequent comparison of target and predicted values in an attempt to reduce the network error to a minimum. The continuous updating of synaptic weights is undertaken by a learning algorithm called error back-propagation. Back-propagation provides a computationally efficient method for changing the weights in a feed forward network, with differentiable activation units to learn a training set of input-output examples (Shivanandam *et al*, 2012).

The appealing nature of ANN is its closeness to human perception that has led to diversifications of its applications. The modeling technique employed by ANN is far more superior to statistical regression as it can derive complex, non-linear and unknown relationships among independent and dependent variables through a learning process, thereby working as a universal function approximator. ANN thus finds its application in the field of engineering, which is always faced with unstructured problems. ANN methodology has been harnessed for modeling a variety of problems and phenomenon encountered in the field of Civil Engineering. Some of the most cited of them are (Mukherjee and Despande, 1995) who applied neural networks to the initial design of reinforced concrete rectangular beams, conceptual stage resource requirements using ANN by (Elazouni *et al*, 1997), modeling of ultimate shear strength of reinforced concrete deep beams by (Sanad and Saka, 2001) predicting the settlement of shallow foundations on cohesionless soils and comparing ANN with traditional methods to prove its robustness by (Shahin *et al*, 2002). (Abrahart and See, 2007) showed that the neural networks are appropriate tools for hydrologic modeling and (Xie *et al*, 2011) created an earthquake prediction model using ANN and validated using the observed data.

3. Modeling Compressive Strength of Concrete using Artificial Neural Networks

Concrete's compressive strength is its most important characteristic and has a strong relationship with quality. The key constituents of concrete, namely, cement, aggregate and water influence the behavior of the concrete as they impart strength and durability. The composite nature of concrete and nonlinear relationship among its ingredients and compressive strength has diverted the attention of the researchers towards nature inspired computational tools. ANN through its learning ability is used to model the compressive strength, which gives an insight into the factors affecting its strength. The following paragraphs give a detailed literature review on the application of ANN in modeling the compressive strength of various types of concrete.

3.1 Applications in Modeling Compressive Strength of Self Compacting Concrete

Self Compacting Concrete (SCC) is a type of High Performance Concrete (HPC). Self-compacting concrete can be defined as the concrete which requires no vibrations and can flow around obstructions, encloses the reinforcement and fills up the formwork completely under its self weight (Aggarwal *et al*, 2005). (Aggarwal and Aggarwal, 2011) used back-propagation neural networks for developing two neural network models ANN-I and ANN-II based on data taken from the literature and experimental data for Self Compacting Concrete (SCC) containing bottom ash as partial replacement of fine aggregates respectively. ANN-I showed reasonable prediction of 28 days compressive strength with a correlation coefficient above 0.9. ANN-II was used for predicting compressive strength at various ages viz., 7 days, 28 days, 90 days and 365 days. For ANN-I the Powder Cement (cement + fly ash) contributed the maximum importance factor. Whereas for ANN-II, fine aggregates (sand + bottom ash) showed the maximum importance. (Suryadi *et al*, 2011) used artificial neural network to evaluate the compressive strength of self compacting concrete (SCC) for the data collected from the ready-mix factory and concrete laboratory. The data were randomized and divided into training, validation and testing data sets. The SCC mix proportions namely, cement, coarse aggregate, fine aggregate, fly ash, chemical admixture and water-cement ratio formed the neural network inputs and 28 days compressive strength was treated as neural network output. The ANN predicted compressive strength of SCC was compared with the experimental results. The error between the predicted and observed strength was found to less than 10%, thereby proving effectiveness of ANN modeling.

(Uysal and Tanyildizi, 2011) predicted the core compressive strength of self-compacting concrete (SCC) mixtures with mineral admixtures (limestone, marble powder and fly ash) using ANN. The SCC mixtures with mineral admixtures were compared with conventional concrete (without mineral admixture) by applying them on the curtain wall element by pouring them down by 1.5 metres. The experimental study showed that the conventional concrete has significant variation among the water absorption and compressive strength of bottom specimens and top specimens. As compared to conventional concrete, the SCC showed effective consolidation under its own weight in case of narrow reinforcement construction elements. The ANN model with ten inputs, namely, the amount of cement, amount of fly ash, amount of limestone, amount of marble powder, amount of fly ash, amount of natural aggregates I and II, the amount of super-plasticizer, unit weight and water absorption and one output variable viz., compressive strength of concrete was developed with one hidden layer containing fourteen and fifteen neurons. The results from ANN modeling showed promising results in the prediction of compressive strength of SCC. (Raheman and Modani, 2013) used Artificial Neural Network for prediction of properties of Self Compacting Concrete (SCC). ANN proved to be efficient technique for predicting properties of SCC from neural network close to the actual properties of SCC measured experimentally. The ANN model can be applied for obtaining optimal mix proportions catering to specified strength and workability.

3.2 Applications in Modeling Compressive of High Performance Concrete

High Performance Concrete (HPC) has certain distinct features that distinguish it from an ordinary Portland cement concrete. These features can be categorized as high strength, high frost and abrasion resistance, early strength etc. (Yeh, 1998) was the first to model the compressive strength of HPC using neural networks by drawing a relationship between the compressive strength and eight input parameters namely, cement, fly-ash, blast furnace slag, water, superplasticizer, coarse aggregate, fine aggregate and age of testing. The ANN predicted compressive strength was compared with statistical regression models based on water-cement ratio and water-binder ratio. The results of the study showed that the neural network models are supported better by experimental data than the regression analysis. However the neural network models cannot be used for extrapolation beyond the domain of the collected data.

(Muthupriya *et al*, 2011) showed that neural networks are capable of learning and generalization from examples and experiences. They employed feed-forward neural networks and trained them for determining the 3, 7, 28, 56 and 90 days compressive strength and durability of HPC containing metakaolin and silica fume. The predicted value of trained neural networks had close resemblance with actual compressive strength and can be used for quick determination of compressive strength without attempting any experiments. Moreover ANN can be used for predicting the durability properties like saturated water absorption, porosity, acid resistance and permeability values of concrete containing metakaolin and silica fumes.

3.3 Applications in Modeling Compressive Strength of Rubberized Concrete

The waste material rubber from scrap tyres is used in rubberized concrete. This can affect the unit weight and compressive strength of concrete and is used in pavements, sidewalks and sound barriers. (Abdollahzade *et al*, 2011) showed the ability of back-propagation neural network to predict the compressive strength of rubberized concrete based on test measurements. The results indicate that back-propagation neural network have the ability to predict the strength of rubberized concrete with an acceptable degree of accuracy in comparison to Multiple Linear Regression (MLR) model. The ANN methodology proved to be an accurate and quick tool for estimating the compressive strength of rubberized concrete.

3.4 Applications in Modeling Compressive Strength of Ferrocement Concrete

Ferrocement is a type of thin wall reinforced concrete, commonly constructed of hydraulic cement mortar reinforced with closely spaced layers of continuous and relatively small size wire mesh. It possesses exceptional elasticity, flexibility, strength and capable of for resisting high impacts and cracking. (Khan *et al*, 2013)used multilayer feed forward artificial neural network model to predict the compressive strength of plain concrete confined with ferro cement. The results showed that the ANN estimated compressive strength was very close to the experimental results than the existing mathematical model proposed by some researchers. The study proved that the ANN methodology is a suitable alternative to replace the hectic experimental work for computing the compressive strength of concrete.

3.5 Applications in Modeling Compressive Strength of Concrete using Non-Destructive testing data

Non-destructive testing is generally defined as a method of test that does not impair the intended performance of the element or member under investigation and it determines the existence of flaws, discontinuities, leaks, contamination, thermal anomalies, or imperfections in materials, components or assemblies without impairing the integrity or function of the inspected component. (Hola and Schabowicz, 2005) employed non-destructive methods viz., ultrasonic method, sclerometric method and pull out method for determining longitudinal velocity, reflection number, impression and pulling force respectively. The tests were conducted on 7 specimens (A to G) and compressive strength was determined after 3, 7, 14, 21, 28 and 90 days. The non-destructive test results were presented as input neurons, while compressive strength designated the output neuron of the ANN architecture. In all, five neural network architectures were trained and tested to find the best one. The relative error was found to be low in case of choosing a neural network model. The study showed that by incorporating non-destructive test results and training neural networks based on such data, one can reliably identify the compressive strength of similar concretes.

(Kewalramani and Gupta, 2006) compared multiple regression analysis and ANN for prediction of uniaxial compressive strength of concrete using the weight and UPV of concrete specimens as predictive variables. The study was conducted on specimens of two different shapes and size. An ANN model was created consisting of two inputs (weight and UPV) and one output (compressive strength). Three hidden layers were used with first two hidden layers having three neurons while the last hidden layer has only one neuron. For the present study 864 data were generated containing UPV and compressive strength at a period of 7, 28, 183, 365 days. A comparison was made between prediction ability of four different regression equations with two predictor variables and ANN. The study shows that experimentally evaluated values of compressive strength are in strong coherence with the values predicted through ANN than multiple regression analysis for most of the samples. Thus the study suggests an alternative approach of compressive strength assessment against destructive testing methods.

(Lande and Gadewar, 2012) modeled the relationship between concrete compressive strength and non-destructive test (ultra pulse velocity UPV) readings using multilayer feed forward back propagation neural network. The ANN model was able to construct a relationship between compressive strength of concrete and UPV readings. The ANN model helped in the interpretation of results and was found to be a successful alternative to empirical relationships provided by the manufacturer of UPV instrument. The study showed that ANN technique is a good modeling tool and can predict compressive strength to a sufficient degree of accuracy based on the UPV readings.

3.6 Applications in Modeling Compressive Strength of Recycled Aggregate Concrete

In the world of limited resources, there is always been a challenge to strike a balance between the optimal use the resources for protecting environment and cater to the changing demands of construction industry. The demolition waste comprising of concrete, brickwork and other impurities can be used for preparing recycled aggregate concrete, which forms a good substitute to conventional concrete. The environmental friendly nature of recycled aggregate concrete and its immense applications in the sustainable growth of concrete industry, has created immense interest among the researchers to model its properties. (Duan *et al*, 2013) used ANN modeling to predict the compressive strength of recycled aggregate concrete (RAC). Back-propagation neural network was employed for modeling the compressive strength with fourteen input parameters and one output parameter. ANN model is constructed using 146 available sets of data obtained from 16 different published literatures. The study showed the applicability of ANN for modeling the compressive strength of concrete containing of recycled aggregates which have composition and properties substantially different from natural aggregates.

(Despande *et al*, 2013) studied the use of ANN methodology for predicting the 28 day compressive strength of Recycled Aggregate Concrete (RAC) and compared the results with non-linear regression (NLR) technique. Five ANN and NLR models were created with five input parameters and three non-dimensional ratios. The study proved the efficiency of ANN in modeling the highly complex material behavior exhibited by RAC. The use of non-dimensional parameters contributed to the performance of ANN and NLR. There was noticeable increase in the correlation between predicted and actual compressive strength, with each addition of the non-dimensional ratio. The neural network weights were used for constructing the hinton diagram which highlighted the influence of each parameter on the compressive strength.

3.7 Applications in Modeling Compressive Strength of Concrete containing Nano-Silica

Nano-Silica is typically a highly effective pozzolanic material. It normally consists of very fine vitreous particles approximately 1000 times smaller than the average cement particle. It has proven to be an excellent admixture for cement to improve strength and durability and decrease permeability. Nanotechnology creates new possibilities to improve material properties for civil construction and provide pioneering solution to the complex problems of construction. (Gupta, 2013) used data from various literatures for predicting 28 day compressive strength of concrete with partial replacement of cement with nano-silica. The study showed that compressive strength of concrete can be predicted in a short period of time without performing any experimental study using ANN model.

3.8 Applications in Modeling Compressive Strength of FRP Confined Concrete

Fibre-reinforced polymer (FRP) made from carbon, glass, aramid, or other high performance materials embedded in polymeric matrices in the form of bars, tendons, and strands are being produced and used.FRP is the best alternative to steel meshes and FRP concrete provide good resistance towards corrosion, high strength, lower unit weight, good damping and fatigue behavior and convenient to use for repair structures. (Naderpur *et al*, 2010) modeled compressive strength of concrete confined with Fiber Reinforced Polymer (FRP) using ANN. Experimental data containing 213 test results were used as exemplar patterns for ANN modeling with diameter of circular concrete specimen, height of circular concrete specimen, total thickness of FRP, tensile strength of FRP, compressive strength of unconfined concrete and elastic modulus of FRP as six neural network inputs. The compressive strength of confined concrete was considered as the neural network output. The proposed ANN model was compared with the existing empirical models (linear, non-linear and second-order models). The comparative study showed that more than 90% of the simulated results are within ±20% of the experimental values for ANN but accuracy of other models is lower than 80%. Using the trained neural network model, an equation was derived for predicting the compressive strength. The results obtained from derived equation showed good agreement with the available experimental data.

3.9 Applications in Modeling Compressive Strength of Concrete containing Meta Kaolin and Silica Fume

Meta kaolin (MK) is a thermally activated alumino-silicate materials obtained by calcining kaolin clay within the temperature range 650-800°C. Silica fume is a byproduct of manufacture of silicon and ferrosilicon alloys. MK and FK act as mineral admixtures in combination with a super plasticizer and produce a high performance, high strength, dense and impermeable concrete and reduce the cement content in concrete production. The compressive strength of concrete with cement reducing admixtures namely, meta-kaolin and silica fume were modeled using feed-forward neural networks by (Saridemir, 2009). The neural network architecture comprised of age of specimen, cement, metakaolin, silica fume, water, sand , aggregate and super-plasticizer as inputs and compressive strength at 1, 3, 7, 28, 56, 90 and 180 days as output. The ANN predicted values were found to be very close to the experimental results and therefore proved the complex, non-linear functional modeling ability of neural networks.

3.10 Applications in Modeling Compressive Strength of High Strength Concrete

Conventional concrete can be designed for achieving strength upto 50 MPa. In contrast High strength concrete (HSC) having compressive strength up to 100 MPa can be design to cater to specific construction requirement. The main advantages achieved using HSC are high performance and uniformity in comparison to conventional concrete. The concrete is characterized by a superior level of workability and strength and uses chemical and mineral admixtures that reduce the water cement, thereby reducing porosity. The modeling of compressive strength and slump of HSC using ANN was shown by (Oztas *et al, 2006)*. Data were collected for HSCs containing water to binder ratio, water content, fine aggregate ratio, fly ash replacement ratio, air-entraining agent ratio, silica fume replacement ratio and super-plasticizer content. The trained ANN model showed close agreement with observed slump and compressive strength values. The study proved that ANN can be applied to model highly complex material like HSC and can therefore be applied for determination of slump and strength values in quick time without going for multiple trial mixes.

3.11 Miscellaneous Applications in Modeling Compressive Strength of Concrete

(Lai and Serra, 1997) utilized ANN for predicting the compressive strength of cement conglomerate. The neural networks consisted of eight input neurons namely, class of cement, fine sand/m^3, coarse sand/m^3, fine aggregate/m^3, coarse aggregate/m^3, cement/m^3, water-cement ratio and plasticizer. The compressive strength was modeled as the output neuron. The relative errors between the predicted and observed values were computed and were found to be less than 5%. The study showed the applicability of ANN in solving problems which are otherwise difficult to be formulated analytically.

(Guang and Zong, 2000) prepared a multi layer feed-forward neural network to imbibe the complex non-linear relationship between the inputs (grade of cement, water-cement ratio, dosage of water, dosage of cement, maximum size of coarse aggregate, fineness modulus of sand, sand-aggregate ratio, aggregate-cement ratio, slump, admixture effect, dosage of admixtures) and compressive strength of concrete as output. The trained neural network was used to obtain the functional relations between strength and its corresponding factors. The functional relations showed that the compressive strength of concrete is nearly proportional to the dosage of cement at a constant water dosage of 190 kg/m^3 and higher the grade, the greater is the compressive strength. The fineness modulus of sand should prominent effect on compressive strength of concrete in comparison to the sand/aggregate ratio. It was presumed that this quick method of predicting 28 day compressive strength can be helpful to a vast community associated with concrete and construction activity.

(Lee, 2003) used ANN methodology to develop I-PreConS (Intelligent PREdiction system of CONcrete Strength). The purpose of I-PreConS was to provide in-place strength information of concrete to facilitate concrete form work removal and scheduling for construction. Five different ANN architectures were used having four categories of input neurons and seven output neurons designated as compressive strength at 16 h, 20 h, 24 h, 2 days, 3 days, 7 days and 28 days respectively. The training patterns were created experimentally by performing cylinder tests. The concrete compressive strength prediction of ANN was compared with that of traditional maturity method. The study showed that ANN-based model prediction is better than the maturity method and modular neural networks solved the problem conveniently and efficiently in comparison to a single neural network.

(Bai *et al*, 2003) used neural network as a universal model for predicting compressive strength at any age with high accuracy. However, other networks could give even better prediction if prediction of strength at specific age at 28, 90 days and 1 year only is needed. On the basis of the models developed, ISO-strength maps were plotted using trained neural networks. This makes it possible for the designer to produce mixtures with various blend compositions for a given range of strength specification. In addition, the models for predicting long-term strength with or without early strength results were recommended to save time and cost for construction contractors.

(Kim *et al*, 2004) proposed ANN methodology to quickly determine the 28 day compressive strength of concrete based on its mix proportions. The ready mix concrete (RMC) mix proportion data from two companies were used for the study. The validity of the neural network model was proved by comparing the predicted values with experimental compressive strength. The study demonstrated the effectiveness of the neural network based technique in estimating the compressive strength of concrete much earlier than its placement at the site.

(Gupta *et al*, 2006) developed a neural expert system based on a number of parameters like concrete mix design, curing techniques, shape and size of the concrete specimen, curing period, environmental conditions like surrounding temperature, relative humidity, wind velocity, etc. A total of 864 data were used for developing the neural expert system which included two different concrete mix grades (M20 and M30), two different curing periods (3 and 7 days), maximum temperature, relative humidity, wind velocity and compressive strength at 7, 28, 183, and 365 days. The study showed that the expert neural system not only predicts the strength of concrete based on the aforesaid parameters, but also suggests alternative ways in terms of curing temperature, curing period, concrete mix, etc., for achieving the desired compressive strength. The predicted data from the expert system are found to be in agreement with those observed experimentally.

(Noorzaei *et al*, 2007) proposed a method to predict 28-day high compressive strength of concrete by training multi layer feed forward neural network (MFNN) using concrete mix design data compiled from a technical literature. The inputs to the neural networks comprised of cement, water, silica fume, super-plasticizer, fine aggregate and coarse aggregates and 28 day concrete strength formed the neural network output. The results showed that trained ANN can recognize the concrete strength with a confidence level of about 95%, which denotes significant accuracy of the network.

(Ozturan *et al*, 2008) illustrated the use of neural networks for modeling 28 day compressive strength of low to medium strength ready mix concretes. A comparative analysis of ANN, Multiple Linear Regression (MLR) and Abrams' Law prediction models has been done based on coefficient of determination, for selecting the best system model for the prediction of the 28-day compressive strength. The study showed that for two system models containing fresh concrete data, the MLR are better in predicting the strength of concrete, whereas inclusion of early strength data gives ANN good prediction ability.

(Yousif and Abdullah, 2009) employed ANN for prediction of 28 day strength of concrete based on its mix constituents, maximum aggregate size (MAS) and slump of fresh concrete. The trained ANN model was successful in predicting the 28 day compressive strength and can be harnessed to predict compressive strength based on input parameters in quick time. The parametric study showed that water-cement ratio is a significant factor affecting the compressive strength of concrete. (Rasa *et al*, 2009) used artificial neural network of the feed-forward back-propagation for the prediction of density and compressive strength properties of the cement paste portion of concrete mixtures. They showed that concrete cement paste's compressive strength and density has a significant influence on the mechanical properties of concrete.

(Alilou and Teshnehlab, 2010) developed an artificial neural network for predicting 28 day compressive strength of concrete. A MISO (Multi Input Single Output) adaptive system was introduced which can model the proposed phenomenon by imparting a very important index to the 3-day compressive strength parameter. Using proposed method, the 28 day compressive strength can easily be predicted based on its 3-days compressive strength and this early prediction of compressive strength can be harnessed for reducing the duration of large civil projects.

(Erfani and Farsangi, 2010) demonstrated the capabilities and advantages of using Fuzzy Neural Networks (FNNs) in modeling and prediction of the Compressive Strength of Slag-Cement Based Mortars. FNNs automatically construct the relationships and adapt based on the training data presented. The more appropriate data in training and testing sets the better result and prediction. The study also shows the importance of validating the performance of FNN models in simulating physical processes especially when data are insufficient. Furthermore, the proposed fuzzy neural network model will save time, reduce waste material and decrease the design cost.

(Bilgehan and Turgut, 2010) proposed an approach of the multilayer back propagation neural network to evaluate the function relationship between concrete compressive strength, UPV (ultrasonic pulse velocity) and density values by using the experimental data obtained from many cores taken from different concrete structures of different ages. Using UPV and density data, the ANNs showed promising results for estimating compressive strength of concrete thereby presenting an alternative approach to destructive testing methods.

(Nath *et al*, 2011) constructed Multi Forward Neural Network (MFNN) for predicting 28-days compressive strength. The data used in the study comprised of mix design proportions which were separated into training, validation and testing data sets. The output of the trained neural network was compared with the experimental data to evaluate its performance. The study showed that the neural networks trained with raw data on concrete mix constituent contents make better predictions of strength and slump than those trained using non-dimensional ratios.

(Oztekin, 2012) investigated the application of ANN for prediction of confined compressive strength of square concrete columns. The ANN model consisted of input parameters comprising yield strength, numbers and diameters of longitudinal and transverse reinforcement, characteristic strength of concrete, concrete cover thickness, specimen dimension, transverse reinforcement spacing and six different transverse reinforcement configurations. The results obtained from the developed

ANN model were compared with those of analytical models and experimental studies. The developed ANN model predicted closer outputs to the experimental results than the analytical models with less error and can be used in compressive strength predictions of confined normal and high strength (f_{ck} = 20 to 184 MPa) square concrete columns for the 6 different transverse reinforcement confinement configurations defined in the study.

(Dantas *et al*, 2013) used ANN for predicting the compressive strength at the age of 3, 7, 28 and 91 days of concrete containing construction and demolition waste (CDW). A total of 1178 data were used to model compressive strength using ANN having 17 input parameters and one output parameter. The principal component analysis (PCA) was performed to separate out the 17 parameters into four groups consisting of variables catering to mix design proportions, CDW composition, physical characteristics and age of sample respectively. Using ANN an empirical equation was established between the variables of four groups and compressive strength of concrete. The ANN predicted values were in close agreement with that of experimental values and therefore the study proved that the equation derived using ANN provided a simplified approach of predicting the compressive strength of concrete based on the parameters included in the four important groups.

4. Summary and Conclusions

With the advent of computers, there is a strong inclination towards developing knowledge based computing tools that can harness the past knowledge to enable understanding of natural phenomenon. ANN's enormous ability to derive meaning from historical data can be coupled with large data handling capabilities of modern day computers to build decision support systems which can guide the user to make sensible decisions. ANNs with the capacity to model non-linear material behavior have created immense interest in neural networks. With its nature characterized by a black box approach, ANNs can model any functional relationship with reasonable accuracy. The robustness of ANNs is attributed to its immense capability of learning from past data and adaptability to change in the presented data. In contrast to conventional mathematical regression technique, in which a regression equation is either known or is assumed, ANNs do not require such underlying equations. This quality of ANN is harnessed to yield un-surpassing modeling capabilities for unstructured problems.

Cement Concrete's composite nature has always been a challenge to the researcher with regard to modeling its properties, namely, compressive strength, tensile strength, slump etc., based on its mix proportions. The solution to such unstructured problems lies with nature inspired soft computing tools. ANN inspired by the working of a human brain, can learn from past examples and derive meaningful explanations to the unstructured problems. The review paper has extensively dealt with the ANNs ability to model the compressive strength of concrete. The broad conclusions derived from the literature review are summarized as:

1) ANN are data intensive computational models and do not require any prior knowledge about the underlying relationships among input-output variables.
2) The Multilayer Feed Forward neural network with error back-propagation learning algorithm is the most efficient and widely neural network used for function approximation. The applications of ANN reviewed in the paper are a testimony to the extensive use of this type of neural network in modeling the composite material behavior of concrete.
3) ANNs are far more efficient in modeling unstructured non-linear problems in comparison to the conventional mathematical regression models.
4) The material models based on ANN methodology can be harnessed to yield decision support tool for explaining and deriving complex, unknown and non-linear functional relationships. This will enable sensible decision making and saving in time while designing concrete mix proportion catering to a customized compressive strength.
5) Using ANN modeling, one is able to have an insight into the composite nature of concrete. The factors that govern the compressive strength can be easily sorted out through sensitivity analysis. Moreover the effect of the variation in each constituent on the compressive strength of concrete can be easily evaluated using ANN modeling methodology.
6) The ANN can be used as a predicting tool based on historical data, to estimate the compressive strength of concrete based on mix proportions before placement of concrete. Moreover the prediction ability of ANN can be extended to much early prediction of 28 day strength, based on its 3 day strength.
7) The material modeling of ANN is so robust that it can be applied to different types of materials.

The review paper has dealt with vast number of ANN applications to Self Compacting Concrete (SCC), High Performance Concrete (HPC), Recycled Aggregate Concrete (RAC) and use of Non-destructive test data for modeling the compressive of concrete. The multi-disciplinary application of ANN proves its robustness to deal with multi-faceted problems faced in different walks of life.

References

F.A.Oluokun, (1994), Fly Ash Concrete Mix Design and the Water-Cement Law, *ACI Material Journal*, 91(4), 362-371.

D.K. Chaturvedi, (2008), Soft Computing Techniques and its applications in Electrical Engineering, in *Studies in Computational Intelligence*, 103, 1-10.

S. Kumar, (2013), Artificial Neurons, Neural Networks and Architectures, in *Neural Networks A Classroom Approach*, 2nd Edition, Tata McGraw-Hill Education Private Limited, New Delhi.

I. Flood and N. Kartam, (1994), Neural Networks in Civil Engineering–II: Systems and Application, *Journal of Computing in Civil Engineering*, 8(2), 149–162.

Y. Aggarwal and P. Aggarwal, (2011), Prediction of Compressive Strength of SCC Containing Bottom Ash using Artificial Neural Networks, *World Academy of Science, Engineering and Technology*, 5, 662-667.

G. Zhang, B.E. Patuwo and M.Y. Hu, (1998), Forecasting with Artificial Neural Networks The State of the Art, *International Journal of Forecasting*, 14, 35-62.

A.S. Tokar and P.A. Johnson, (1999), Rainfall–Runoff Modeling using

Artificial Neural Networks, *Journal of Hydrologic Engineering*, 4(3), 232-239.

A.W.C. Oreta and K. Kawashima, (2003), Neural Network Modeling of Circular Confined Compressive Strength and Strain of Circular Concrete Columns, *Journal of Structural Engineering*, 129 (4), 554-561.

S. Haykin, (2009), *Neural Networks A Comprehensive Foundation*, 8th Edition, Pearson Prentice Hall, India.

L.N. Castro, (2007), Fundamentals of Natural Computing: A Review, *Physics of Life Reviews*, 4, 1–36.

S.N. Shivanandam, S. Sumathi and S.N Deepa, (2012), Feed Forward Networks, in *Introduction to Neural Networks using Matlab 6.0*, 16th Reprint, Tata McGraw-Hill, India.

A. Mukherjee and J.M. Despande, (1995), Modeling Initial Design Process using Artificial Neural Networks, *Journal of Computing in Civil Engineering*, 9 (3), 194–200.

A.M. Elazouni, I.A. Nosair, Y.A. Mohieldin and A.G. Mohamed, (1997), Estimating Resource Requirements at Conceptual Design Stage using Neural Networks, *Journal of Computing in Civil Engineering*, 11(4), 217–223.

A. Sanad and M. Saka, (2001), Prediction of Ultimate Shear Strength of Reinforced-Concrete Deep Beams Using Neural Networks, Journal of Structural Engineering, 127(7), 818–828.

M.A. Shahin, H.R. Maier and M.B. Jaksa, (2002), Predicting settlement of Shallow Foundations using Neural Networks, *Journal of Geotechnical and Geo-environmental Engineering*, 128(9),785-793.

R.J. Abrahart and L.M. See, (2007), Neural network modeling of non-linear hydrological relationships, *Hydrology and Earth System Sciences*, 11, 1563-1579.

J. Xie, J. Qiu, L. Wei and J.W. Wang, (2011), The application of neural network in earthquake prediction in East China, *Advances in Intelligent and Soft Computing*, 106, 79-84.

P. Aggarwal, Y. Aggarwal, S.M. Gupta and R. Siddique, (2005), Properties of Self Compacting Concrete, in 30th Conference on OUR WORLD IN CONCRETE AND STRUCTURES, Singapore.

A. Suryadi, Triwulan and P. Aji, (2011), Artificial Neural Network for Evaluating the Compressive Strength of Self Compacting Concrete, *Journal of Basic and Applied Scientific Research*, 1(3), 236-241.

M. Uysal and H. Tanyildizi, (2011), Predicting the Core Compressive Strength of Self Compacting Concrete (SCC) mixtures with minerals additives using Artificial Neural Network, *Construction and Building Materials*, 25, 4105-4111.

A. Raheman and P.O. Modani, Prediction of Properties of Self Compacting Concrete Using Artificial Neural Network, (2013), *International Journal of Engineering Research and Applications*, 3(4), 333-339.

I.C. Yeh, Modeling of Strength of High Performance Concrete using Artificial Neural Networks, (1998), *Cement and Concrete Research*, 28(12), 1797-1808.

P. Muthupriya, K. Subramanian and B.G Vishnuram, (2011), Prediction of compressive strength and durability of high performance concrete by artificial neural network, *International Journal of Optimization in Civil Engineering*, 1, 189-209.

A. Abdollahzadeh, R. Masoudnia and S. Aghababaei, (2011), Predicting strength of rubberized concrete using Artificial Neural Network, *Civil Engineering and Built Environment Information Science and Technology*, 10(2), 31-40.

S.U. Khan, T. Ayub and S.F.A. Rafeeqi, (2013), Prediction of compressive strength of plain concrete confined with ferrocement using artificial neural network (ANN) and comparison with existing mathematical model, *American Journal of Civil Engineering and Architecture*, 1(1), 7-14.

J. Hola and K. Schabowicz, (2005), Application of artificial neural network to determine concrete compressive strength based on non destructive test, *Journal of Civil Engineering and Management*, 11(1), 23-32.

M. Kewalramani and R. Gupta, (2006), Concrete compressive strength prediction using ultrasonic pulse velocity through artificial neural network, *Automation in Construction*, 15(3), 374-379.

P.S. Lande and A.S. Gadewar, (2012), Application of Artificial Neural Networks in Prediction of Compressive Strength of Concrete by Using Ultrasonic Pulse Velocities, *IOSR Journal of Mechanical and Civil Engineering*, 3(1), 34-42.

Z.H. Duan, S.C. Kou and C.S. Poon, (2013), Prediction of compressive strength of recycled aggregate concrete using artificial neural networks, *Construction and Building Material*, 40, 1200-1206.

N. Despande, S. Londhe and S. S. Kulkarni, (2013), Modeling compressive strength of recycled aggregate concrete using neural network and Regression, *Concrete Research Letters*, 4, (2), 580-590.

S. Gupta, (2013), Using artificial neural network to predict the compressive strength of concrete containing Nano-Silica, *Civil Engineering and Architecture*, 1(3), 96-102.

H. Naderpour, A. Kheyroddin and G. Ghodrati Amiri, (2010), Prediction of FRP- Confined compressive concrete using artificial network, *Composite Structures*, 92, 2817-2829.

M. Saridemir, (2009), Prediction of compressive strength of concrete containing Meta Kaolin and Silica Fume by Artificial Neural Networks, *Advances in Engineering Software*, 40, 350-355.

A. Oztas, M. Pala, E. Ozbay, E. Kanca, N. Caglar and M. A. Bhatti, (2006), Predicting the compressive strength and slump of high strength concrete using neural network, *Construction and Building Materials*, 20(9), 769-775.

S. Lai and M. Serra, (1997), Concrete strength prediction by means of neural network, *Construction and Building Materials*, 11(2), 93-98.

N.H. Guang and W. J. Zong, (2000), Prediction of compressive strength of concrete by neural network, *Cement and Concrete Research*, 30, 1245-1250.

S. C. Lee, Prediction of concrete strength using artificial neural network, (2003), *Engineering Structures*, Vol. 25, 849-857.

J. Bai, S. Wild, B.B. Sabir, C.W. Morris and P. Angel, (2003), Concrete Strength Prediction with Neural Networks, *Proc. Of Seventh Int. Conf. on application of Artificial Intelligence to Civil and Structural Engineering*, Civil-Comp Press, Stirlingshire, UK, Paper 61.

J.I. Kim, D.K. Kim, M.Q. Feng and F. Yazdani, (2004), Application of Neural Networks for estimation of Concrete Strength, *Journal of Materials in Civil Engineering*, 16(3), 257-264.

R. Gupta, M. Kewalramani and A. Goel, (2006), Prediction of Concrete Strength Using Neural-Expert System, *Journal of Materials in Civil Engineering*, 18(3), 462–466.

J. Noorzaei, S.J.S. Hakim, M.S. Jaafar and W.A.M. Thanoon, (2007), Development of Artificial Neural Network for Prediction of Compressive Strength of Concrete, *International Journal of Engineering and Technology*, 4(2), 141-153.

M. Ozturan, B. Kutlu and T. Ozturan, (2008), Comparison of concrete strength prediction technique with Artificial Neural Network approach, *Building Research Journal*, 56, 23-36.

S. T. Yousif and S. M. Abdullah, (2009), Artificial Neural Network model for predicting compressive strength of concrete, *Tikrit Journal of Engineering Science*, 16(3), 55-66.

E. Rasa, H. Ketabchi and A.H. Afshar, (2009), Predicting Density and Compressive Strength of Concrete Cement Paste Containing Silica Fume Using Artificial Neural Networks, *Scientia Iranica*, 16(1), 32-42.

V.K. Alilou and M. Teshnehlab, , (2010), Prediction of 28-days compressive strength of concrete on the 3-day using Artificial Neural Network, *International Journal of Engineering (IJE)*, 3(6), 565-576.

M. Erfani, and E. N. Farsangi, (2010), Fuzzy Neural Network Utilization in Prediction of Compressive Strength of Slag-Cement Based Mortars, *Australian Journal of Basic and Applied Sciences*, 4(10), 4962-4970.

M. Bilgehan and P. Turgut, (2010), The use of neural network in concrete compressive strength estimation, *Computers and Concrete*, 7(3), 271-283.

U.K. Nath, M.K. Goyal and T.P. Nath, (2011), Prediction of compressive strength of concrete using Artificial Neural Network, *International Journal of Emerging Trends in Engineering and Development*, 1(1), 32-43.

E. Oztekin, (2012), Prediction of confined compressive strength of square concrete columns by Artificial Neural Networks, *International Journal of Engineering & Applied Sciences*, 4(3), 17-35.

A.T.A. Dantas, M. B. Leite, and K. J. Nagahama, (2013), Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks, *Construction and Building Materials*, 38, 717-722.