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A Review on Artificial Neural Network Concepts in Structural Engineering Applications

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Abstract— The present study concentrates on a critical review on Artificial Neural Network (ANN) concepts and its applicability in various structural engineering applications. A detailed investigation is carried out on how ANN is used for the prediction of strength of concrete and Concrete Filled Steel Tubular (CFST) members. A comprehensive summary about the basic concepts of ANN and different software used to device ANN model are also discussed. The prospective use and application of ANN in the field of structural engineering is presented. The present study will be a helpful tool for design engineers to assess the mix proportions of concrete and estimation of its compressive strength.

Keywords— Artificial Neural Network; Compressive Strength of concrete; Concrete Filled Steel Tubular members; Structural Engineering Applications

I. Introduction

Artificial Neural Network (ANN) is a technique that uses existing experimental data to predict the behavior of the same material under different testing conditions.

ANN have emerged as a useful concept from the field of artificial intelligence, and has been used successfully, over the past decade, in modeling engineering problems in general, and specifically those relating to the mechanism behavior of composite materials. Neural networks can be used as a powerful regression tool. They are highly nonlinear and can capture complex interactions among input/output variables in a system without any prior knowledge about the nature of these interactions. They do not involve complicated derivations, but are able to analyze problems involving a large number of variables. Once the neural network has been properly trained and verified with a fairly comprehensive set of experimental data, it can routinely provide reasonable results without incurring much computational effort. This can enable the designer to investigate a wide range of design possibilities in a very short time and to make an informed decision on the choice of final design (Leung, 2006). McCulloch and Pitts (1943), first introduced the simplified neurons. These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform the computational tasks. A neural network consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. Artificial neural networks may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system (Van Der Smagt and Krose, 1996). A biological neuron has major parts which are of particular interest in understanding an artificial neuron and include: dendrites, cell body, axon, and synapse. A computational neuron has input variable weight, neuron cell, and output. Dendrites are represented by input lines. Every artificial neuron has one output line that represents the axon of the neuron. The biological neuron associated with computational neuron is presented in Fig. 1.

In computational neurons, the net function determines how the network inputs $\{ y_j ; 1 \leq j \leq N\}$ are combined inside the neuron. In Fig. 2, a weighted linear combination is adopted:

$$u = \sum_{j=1}^{n} w_j \, y_j + \theta \qquad (1)$$

In which, $\{ w_j ;\ 1 \leq j \leq N\}$ are parameters known as synaptic weights. The quantity u is called the bias and is used to model the threshold. (M.Ahmadi, H. Naderpour and A. Kheyroddin., 2014). Figure 3 depicts a simple neuron model.

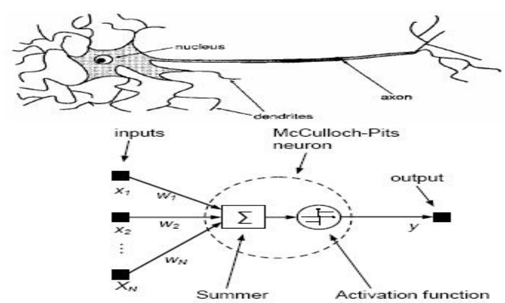

Figure 1. *A biological neuron model, which processes N inputs (xN) to arrive at the output(y).* (Source:http://www. controlglobal. com/ articles /2006/22)

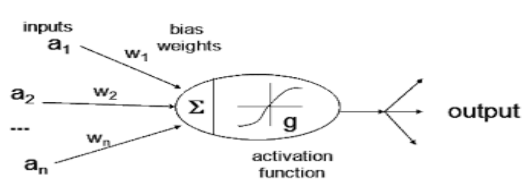

Figure 2. Schematic Computation of Neuron

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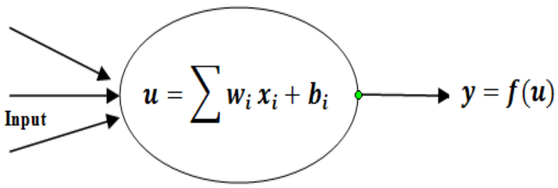

Figure 3. A simple neuron model

A feed-forward network has a layered structure; each layer consists of units which receive their input from units by a layer directly below and send their output to units in a layer directly above the unit. There are no connections within a layer. The N_i inputs are fed into the first layer of $N_{h,,l}$ hidden units. In the input units, no processing occurs. The output of the hidden units is distributed over the next layer of $N_{h,2}$ hidden units, until the last layer of hidden units, of which the outputs are fed into a layer of N_0 output units as shown in Fig 4 (Van Der Smagt and Krose, 1996).

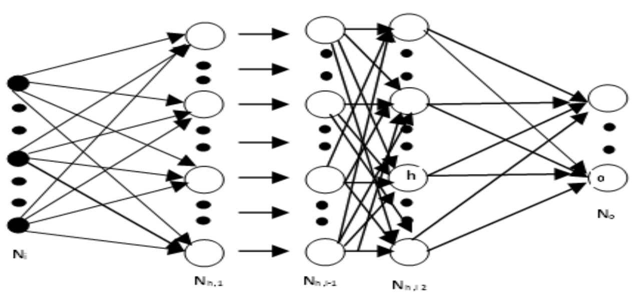

Figure 4. A Multilayer feed forward network

II. Application of ANN in modelling slump value, Mix design and compressive strength of concrete

Guang and Zong (2000) carried out study on predicting the compressive strength of concrete using neural networks. The fresh concrete data are routinely collected and used for quality control, was used to estimate the long term behaviour of concrete. The variables considered for the study were 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, effect of admixtures, dosage of admixtures. The above 11 parameters that readily develop the strength of the concrete were expected to possess a non-linear relationship. Back propagation algorithm is implemented to determine the concrete strength. A C++ coding was used to construct the Back propagation algorithm and neural network model. Learning phase and testing phase of the model was done and the consistency of the simulated results were checked with the consistency between NN modelling and the experimental data collected. Multi-layer feed forward neural network (MFNN) computational intelligent method will be helpful to civil engineers, technologists, ready - mix operators and concrete mixture designers in civil engineering and concrete mixing and batching plants. They also observed that some effects of concrete compositions on strength are in accordance with the rules of mix proportioning.

Tao Ji, Tingwei Lin, Xujian Lin (2006) investigated concrete mix proportion design algorithm based on artificial neural networks. Modified Tourfar's Model was introduced to transform five parameters of nominal water – cement ratio, equivalent water– cement ratio, average paste thickness, fly ash– binder ratio and grain volume fraction of fine aggregates and mix proportion of concrete. The prediction models of strength and slump of concrete were built based on artificial neural networks (ANN). The learning algorithm adopted to train the network model in this study is the Levenberg–Marquardt algorithm. Concrete mix proportion design algorithm based on ANN was formulated. The concrete designed by the proposed algorithm is expected to have lower cement and water contents, higher durability, better economical and ecological effects. The grade of cement and the nature of aggregates were considered in the connection weights and biases of the ANN models as these parameters were kept constant in the prediction models of strength and slump of concrete built based on artificial neural networks and if these parameters change, another prediction model based on ANN should be derived. The future scope to enhance it can be attributed to predict the adiabatic temperature rise, creep and shrinkage, durability of concrete, and to design the mix proportion of high performance concrete (HPC), whose strength, workability and durability satisfy specific requirements.

Yeh (1998) conducted study on modeling of strength of high-performance concrete using artificial neural networks. The compressive strength of concrete is a function of the following eight input parameters: cement, fly ash, blast furnace slag, water, superplasticizer, coarse, fine aggregate, age of testing. Experimental data from 17 different sources was used to check the reliability of the strength model and the neural network developed in the investigation had eight units in the input layer and one unit in the output layer. In random sampling the training set values were better with R^2 values nearing 0.9 for all the four set of data. The strength model based on the artificial neural network was observed to be accurate than the model based on regression analysis. The strength model could be used to determine the strength effects of age or water-to-binder ratio.

Lee (2002) predicted the strength of concrete using artificial neural model. I-PreConS (Intelligent PREdiction system of CONcrete Strength) model was developed to identify the in-place strength of the concrete to aid in the removal of formwork and scheduling for construction. Modular ANN was proposed. Condensation technique and weighing technique were used to increase the accuracy and precision of the model. Modular neural networks are more suitable rather than single one for predicting the concrete strength. It was also observed that the Multiple architectures composed of five ANNs solved the problem occurred in single one. Both weighting and condensation techniques were efficient for searching the best performance network.

Lai and Serra (1997) developed a model based on neurocomputing to predict concrete strength. The experimental data obtained during the construction of Alto Slucis Thermal Power station at Protovesme, Italy were used in the tests. Different kinds of activation function such as step fuction, ramp function and sigmoid function were discussed. It was observed that if the neural network possesses number of hidden layers in the range of 4-8, its performance is independant of the number of neurons.

Topcu and Saridemir (2007) studied about waste crushed autoclaved aerated concrete aggregates that were used as crushed stone in concrete production. In order to predict the unit weight, cylinder compressive strength, ultrasound pulse velocity and dynamic modulus of elasticity values of the waste crushed autoclaved aerated concrete aggregated hardened concretes without attempting any experiments model was constructed in ANN method. The ANN used 7 input layer units, 2 hidden layers, 7 first hidden layer units, 8 number of second hidden layer units, 4 output layer units. The momentum rate, learning rate and error after learning were observed to be 0.99, 0.96 and 0.00016 respectively. ANN model predicted the expected results with good agreement.

Topcu and Saridemir (2008) used artificial neural networks and fuzzy logic models as a tool for predicting the 7, 28 and 90 days compressive strength of concrete containing high-lime and low-lime fly ash an found that the tools were efficient in predicting the compressive strength of concrete..

Topcu and Saridemir (2008) developed the models in artificial neural networks and fuzzy logic systems (FL) for predicting compressive and splitting tensile strengths of recycled aggregate concretes containing silica fume, have been developed at the age of 3, 7, 14, 28, 56 and 90 days. In the models constructed in ANN and FL methods, a multi-layered feed forward neural network with a back propaga-tion algorithm and Sugeno-type fuzzy inference system were used respectively. It was concluded by the researchers that artificial neural net-works and fuzzy logic were practicable methods for predicting the compressive strength and splitting tensile strength of concrete.

Oztas et al. (2006) studied the applicability of artificial neural network to predict the behaviour of strength and slump value of high strength concrete. 187 experimental data from various literature to construct, train and test network. The input parameters of the ANN network were the water to binder ratio, water content, fine aggregate ratio, fly ash content, air entraining agent, superplasticizer and silica fume replacement. MATLAB was used to program the ANN network. The two output variables were the compressive strength and slump values and to check the reliabilty of the ANN model, 18 samples were used as the test set and the remaining 169 samples were used to train the network. 7 input layers, 2 hidden layers, 5 first hidden layers, 3 second hidden layer units and 2 output layer units were adopted in the network. The learning algorithm that was used in the study is scaled conjugate gradients algorithm (SCGA). The activation function was a sigmoidal function, and number of epochs was 10,000. Step size mechanism of SCGA was used to avoid the time consuming line search per learning iteration. It was observed that the values of mean absolute percentage error (MAPE) were 2.617104% and 6.58954% in training set and 1.956208% and 5.782223% in test set for compressive strength and slump, respectively. The root-mean-squared R^2, values were 99.8977% and 99.2576% in training set and 99.931% and 99.3451% in test set for compressive strength and slump, respectively. ANN has strong potential and can be a feasible tool for predicting compressive strength and slump value. In order to obtain a desired high strength concrete and suitable workability, technical personnel must try several mix proportions and it was observed that the proposed ANN model would save time, reduce waste material and decrease the design cost. In construction, early determination of HSC strength and slump values is very important. Usually, determination of compressive strength takes 28 days but using the proposed ANN model, the compressive strength and slump values could be predicted in a short time.

Pala et al. (2007) investigated the effects of fly ash and silica fume replacement content on the strength of concrete cured for a long-term period of time, by neural networks. ANN model incorporated a format of eight input parameters that cover the flyash replacement ratio (FA), silica fume replacement ratio (SF), total cementitious material (TCM), fine aggregate (ssa), coarse aggregate (ca), water content (W), high rate water reducing agent (HRWRA) and age of samples (AS) and an output parameter the compressive strength of concrete. MATLAB software was used to devise the ANN model. The learning algorithm used was scaled con-jugate gradients algorithm (SCGA), developed by Moller. The important feature of the CGA was that the minimization performed in one step is not partially undone by the next, as it is the case with gradient descent methods. A significant drawback of CGA is the requirement of a line search, which is computationally time consuming. The activation function used was a sigmoid function, and number of epochs was found to be 10,000. 8 input layer units, 1 number of hidden layer, 9 numbers of first hidden layers and 1 output layer. The R^2 values are 99.85% in training set and 99.90% in test set for compressive strength. The model could be helpful in establishing the target engineering properties of concrete.

Yeh (2006) identified that artificial neural networks and optimisation technologies can be applied for searching the optimum mixture of concrete composition, a mixture with the lowest cost and required performance, such as strength and slump. Computer Aided Design (CAD) tool based on neural networks and optimization technologies could be used to concrete mix design as they covered wide range of strength and workability and their combinations; therefore, the results of these mixtures might be useful in forming general concepts about optimal concrete mixture design. The architecture of the system consists of six modules (1) User interface module that communicates between the user and the other five modules.

(2) Design of experiment (DOE) module that plans the experiments for collecting the data of mixtures and their material behavior. (3) Data base module that stores the data of mixtures and their material behavior. (4) Modeling module that generates the models of mixtures-material behavior. (5) Model base module which stores the models of mixtures-material behavior. (6) Optimization module which generates the optimum mixture by lowering the cost while keeping the material behaviour predicted by the models in the required ranges. It was observed that CAD tool was able to find mix composition for a concrete with minimum cost of the components and satisfying the given strength and workability.

Yeh (2007) carried out modeling slump flow of concrete using second-order regressions and artificial neural networks. It was observed that the slump flow model based on ANN was predicting much more accurate results than that based on regression analysis. It was noted that ANN models were easy for examining numerical experiments and to review the effects of mix proportions on concrete flow properties. The response trace plots of slump flow derived with second-order regressions were confined to simple second-order curves, but derived from artificial neural networks, were more delicate; therefore, the latter were potentially more accurate.

Mustafa Sarıdemir (2009) used artificial neural network for predicting the compressive strength of concretes containing metakaolin and silica fume. In order to build hese models, training and testing using the available experimental results for 195 specimens produced with 33 different mixture proportions were collected from the technical literature. The eight input parameters that was considered for the study were the age of specimen, cement, metakaolin (MK), silica fume (SF), water, sand, aggregate and superplasticizer. The learning consists of changing the weights in order to minimize this error function in a gradient descent technique. The obtained conclusions had demonstrated that multilayer feed forward artificial neural networks are practicable methods for predicting compressive strength values of concretes containing metakaolin and silica fume.

Ozcan et al (2009) carried out a comparative study between artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete. Multilayer feedforward network models have been trained with Levenberg–Marquardt (LM) training algorithm. The parameters such as amount of cement (C), amount of silica fume replacement (SF), water content (W), amount of aggregate (AG), plasticizer content (P) and age of samples (A) were selected as input variables and the model output variable was the compressive strength of the concrete. A data set including 240 data samples obtained from experimental studies were used for training, testing and validation phases of the network models.

A multilayer feedforward network models containing one hidden layer were used. The ANN network was devised in MATLAB. 6 numbers of input layers, 1 hidden layer, 11 hidden layer neurons, 1 output layer and 28 epochs were modelled. The logarithmic sigmoid and pure linear functions used as activation function for the hidden and output layer neurons, respectively. It was observed that ANN provides better results than the FL results in terms of R^2 values.

Noorzaei(2007) focused on the development of Artificial Neural Networks (ANNs) in prediction of compressive strength of concrete after 28 days and in order to predict the compressive strength of concrete six input parameters considered were cement, water, silica fume, super plasticizer, fine aggregate and coarse aggregate. A total of 639 different data sets of concrete were gathered from the technical literature. For preventing unstable and oscillation network, a value called momentum was added in back propagation algorithm. Sigmoid function on average reaches lower MSE rates than the other activation functions. For this reason the sigmoidal transfer function is implemented between the input and hidden layers and also is selected in output layer. The MSE for the training set was 5.33% for the 400 training data points, 6.13 % for the 100 verification data points and 6.02 % for the 139 testing data points. From the results obtained for artificial neural network, it can recognize the concrete in terms of strength, with a confidence level of about 95%, which was considered as satisfactory from an engineering point of view.

Dantasetal.(2013) carried out prediction of compressive strength of concrete contains construction and demolition waste using artificial neural networks. A total of 1178 data was used for modeling ANN, 77.76% in the training phase, and 22.24% in the testing phase. The Component Analysis allowed establishing that ratio of recycled concrete and the absorption rate of fine recycled, and content of dry aggregate and fines modulus of aggregates are the main variables influencing the variance of the compressive strength (output).

Chandwani et al. (2014) have documented the applications of artificial neural networks in modeling compressive strength of concrete. This review made 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.

Chandawani et al (2014) presented a hybrid artificial neural networks and genetic algorithm approach for modeling slump of ready mix concrete based on its design mix constituents. In the present study, Levenberg-Marquardt back-propagation algorithm has been used along with learning rate 0.45 and momentum coefficient 0.85. Levenberg-Marquardt back-propagation training algorithm is the fastest converging algorithm preferred for supervised learning. It can be regarded as a blend of steepest descent and Gauss–Newton method, combining the speed of Newton algorithm with the stability of the steepest descent method. The algorithm has a dual way of approaching the solution to a function, behaving as steepest descent when the solution is far away from the local minimum and Gauss–Newton when the solution is near to the local minimum. The multiple neural network architectures created by varying the number of hidden layer neurons and its training parameters were trained using Levenberg-Marquardt BP training algorithm. In comparison to BPNN model, which provided NMBE values 0.2497%, 0.1950% and -0.5249%, the ANN-GA model gave 0.0004%, 0.0138% and 0.0531% values during training, validation and testing phases respectively that indicated the consistency of prediction provided by the hybrid ANN-GA model.

Akande et al. (2014) carried out a comparative study on Support Vector Machine (SVM) theory with ANN model for predicting the compressive strength of concrete which is very important in structure and building design, particularly in specifying the quality and in measuring performance of concrete and in determination of its mix proportion. ANN was set up using feed forward network and was trained with back propagation algorithms. Hence, the network consists of one hidden layer and by varying the number of neurons it was observed that the optimum performance was achieved. It was identified that SVM is a viable alternative to ANN in concrete strength prediction due to its stability and good performance.

III. UTILISATION OF ANN FOR PREDICTING THE STRENGTH OF CFST MEMBERS

Leung et al. (2006) developed an empirical approach for determining ultimate FRP strain in FRP-strengthened concrete beams. A comprehensive experimental database of 143 tests was used to model a neural network relating the ultimate FRP strain to various geometric and material parameters to train and validate. The validated network was used for an empirical design curve and several correction equations are generated to provide a simple means to find the debonding strain in practical design.

Sadoon et al. (2012) developed a model for predicting the ultimate strength of rectangular concrete filled steel tube (RCFST) beam-columns under eccentric axial loads using artificial neural networks (ANN). The available experimental results for (111) specimens obtained from open literature were used to build the proposed model. The predicted strengths obtained from the proposed ANN model were compared with the experimental values and with unfactored design strengths predicted using the design procedure specified in the AISC and Euro code 4 for RCFST beam-columns. The results revealed that the predicted values by the proposed ANN model were very close to the experimental values and were more accurate than the AISC and Euro code 4 values.

Kumar et al. (2013) carried out ANN study for composite Concrete Filled Steel Tubular (CFST) columns. Artificial Neural Network Model (ANN) was developed for the composite circular steel tubes- with recycled concrete infill with three different grades of concrete (M20,M40 and M60) were tested for ultimate load capacity and axial shortening , under axial monotonic loading for compression. A feed forward back propagation network having for 11 hidden layers as per Kolmogorov’s theorem had been used. The ANN technique was used to predict the crushing behavior of axial shortening and ultimate axial load in composite circular steel columns. It was observed that the ANN was able to successfully predict the crushing behavior of wide range of circular tubes.

Liu (2013) presented a new type of concrete-filled core steel tube with outer steel plank reinforced column. RBFNNs were employed for calculated the strength of the concrete-filled core steel tube with outer steel plank reinforced column, it was observed that the neural network forecasting the loading capacity of the columns has a clear advantage in terms of reasonable structure, quick convergence and high accuracy. The maximum and minimum error ratio of prediction was 11.32% and 4.17%, respectively. It revealed that the neural network has a wide application prospect in forecasting the loading capacity of the concrete-steel composite columns.

Kheyroddin (2013) used ANN model to compressive strength of confined concrete in circular CFST columns. The input parameters were selected based on past studies such as outer diameter of column, compressive strength of unconfined concrete, length of column, wall thickness and tensile yield stress of steel tube. After the learning step, the neural network can extract the relationships between the input variables and output parameters. The criteria for stopping the training of the networks were Regression values and Mean Square Error.

Ahmadi (2014) presented a new approach to predict the capacity of circular concrete filled steel tube columns under axial loading condition, using a large number of experimental data, by apply artificial neural networks. The effects of yield stress and wall thickness of steel tube, compressive strength of concrete and dimensions of column were examined. The Proposed equation was compared existing models and it was observed that the new model was able to predict the ultimate strength of axially loaded columns with a high level of accuracy.

IV. CONCLUSION

The present paper summarizes various ANN models used for predicting the strength of concrete and concrete filled steel tubular members. The various software used for devising the ANN model and the complementary theories to ANN is reviewed. This paper intensively concentrates on the variable parameters that have to be considered as inputs for the ANN network for predicting the strength of CFST members and concrete. The various learning algorithm adopted for training the network, their merits and limitations are also highlighted. This paper gives a thorough insight of applicability of ANN model to predict the strength of concrete and CFST members.

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